Time series & financial analysis in the tidyverse

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Software Engineer
@rstudio

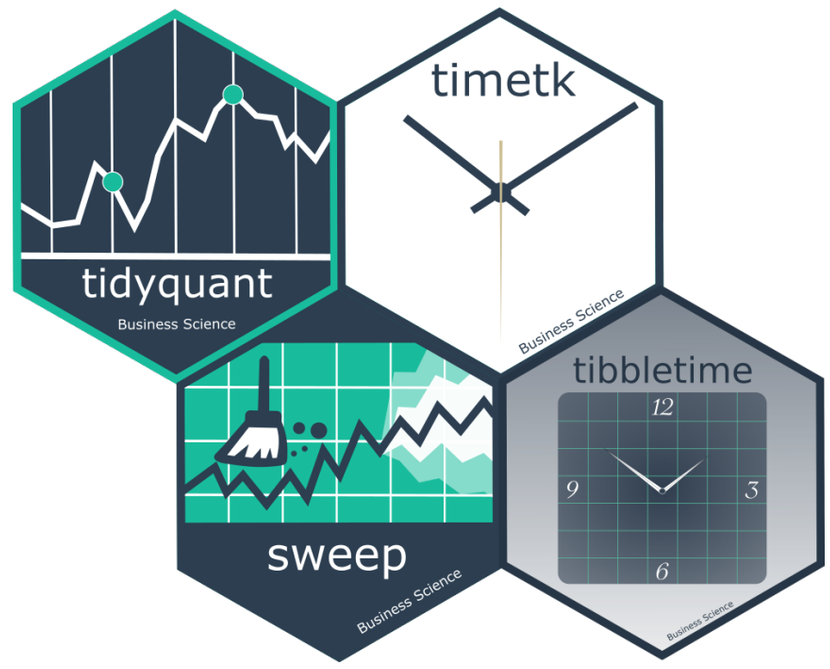
Disclaimer:

Most of what you see here
is not a product of RStudio…

…because I just started.

Who am I?

- Davis Vaughan
  - Software engineer @ RStudio
  - Quantitative finance
    - Master's @ UNC Charlotte
- **Obsessed with making your life easier**



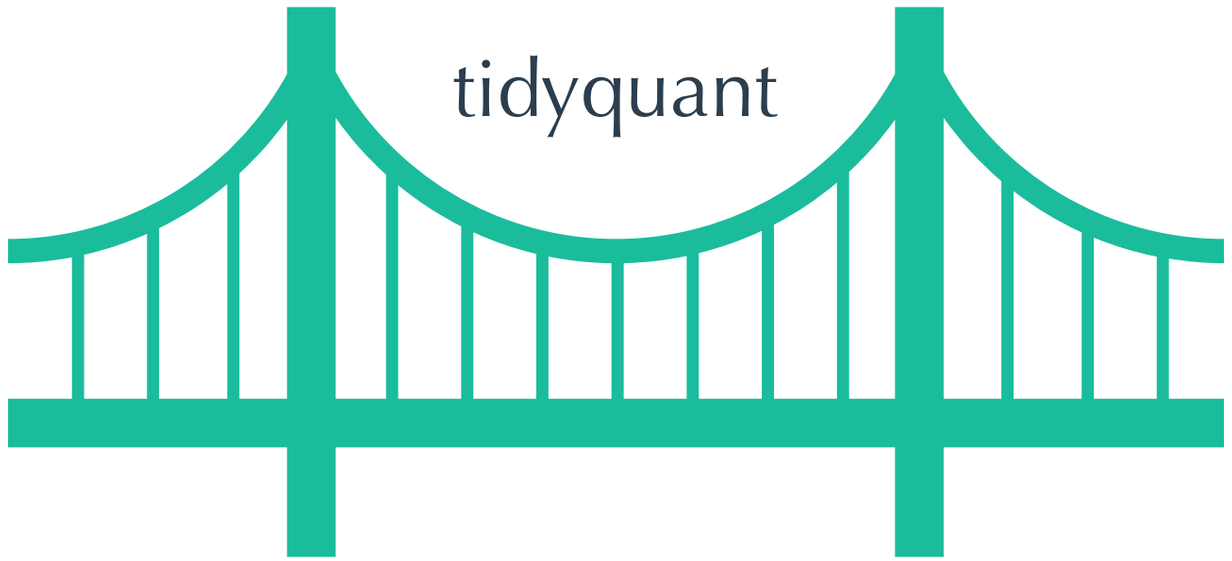
Agenda: Package overload

- `tidyquant`
- `tsibble`
- `rsample + furrr`

The current state of the world

xts	tibble
Native time-index support	Powerful generalized data manipulation
Specialized (& fast) time-based manipulation	Grouped analysis
Homogeneous data (built on matrices)	Readability > Performance
Packages for financial analysis (quantmod, PerformanceAnalytics, …)	Heterogeneous data + list-column support

tidyquant



Convert to xts

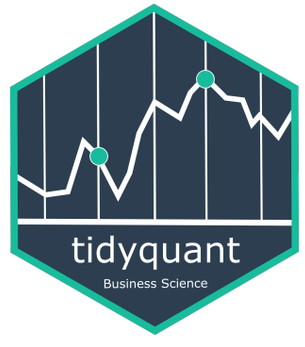
←

Apply time-based function

→

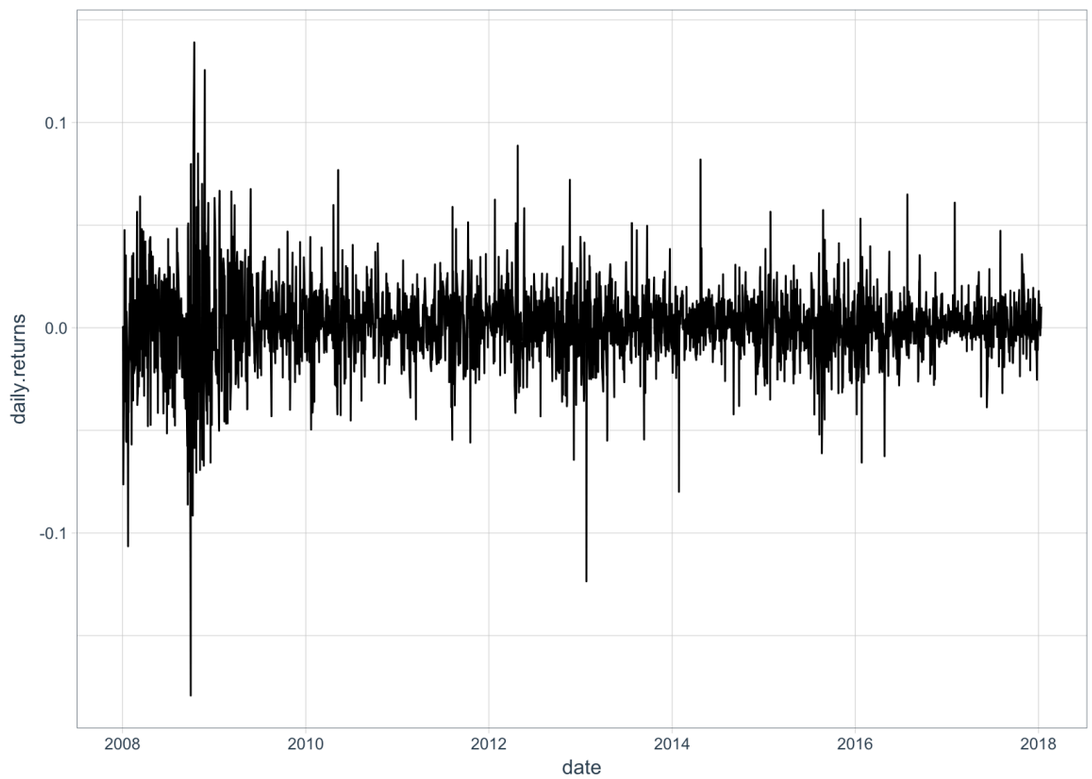
Convert to tibble

tidyquant




```
tq_get("AAPL") %>%
  tq_mutate(select = adjusted, mutate_fun = dailyReturn) %>%
  ggplot(aes(x = date, y = daily.returns)) +
  geom_line() +
  theme_tq()
```

- Quickly pull financial data as a tibble
- Apply any xts, quantmod, TTR, and PerformanceAnalytics function
- Pipe the result straight into other tidyverse packages



Mara Averick
@dataandme

Following

Replying to @mdancho84

What an overly gratifying activity. Like, pulling that stock data and plotting it was a minute-long affair (with thinking and getting distracted)! 💪 package *and* tutorial!

4:18 PM - 4 Jan 2018

Lots of functionality for free


```
> tq_mutate_fun_options()

$zoo
 [1] "rollapply"      "rollapplyr"    "rollmax"        "rollmax.default"        "rollmaxr"          "rollmean"
 [7] "rollmean.default" "rollmeanr"    "rollmedian"     "rollmedian.default"     "rollmedianr"       "rollsum"
[13] "rollsum.default"  "rollsumr"

$xts
 [1] "apply.daily"      "apply.monthly"  "apply.quarterly"  "apply.weekly"   "apply.yearly"   "diff.xts"        "lag.xts"
 [8] "period.apply"     "period.max"     "period.min"       "period.prod"    "period.sum"     "periodicity"     "to_period"
[15] "to.daily"         "to.hourly"      "to.minutes"       "to.minutes10"   "to.minutes15"   "to.minutes3"     "to.minutes30"
[22] "to.minutes5"      "to.monthly"     "to.period"        "to.quarterly"   "to.weekly"      "to.yearly"

$quantmod
 [1] "allReturns"       "annualReturn"   "ClCl"             "dailyReturn"  "Delt"           "HiCl"           "Lag"
 [8] "LoCl"             "LoHi"           "monthlyReturn"    "Next"         "OpCl"           "OpHi"           "OpLo"
[15] "OpOp"             "periodReturn"   "quarterlyReturn"  "seriesAccel"  "seriesDecel"    "seriesDecr"     "seriesHi"
[22] "seriesIncr"       "seriesLo"       "weeklyReturn"     "yearlyReturn"

$TTR
 [1] "adjRatios"        "ADX"              "ALMA"                "aroon"              "ATR"          "BBands"
 [7] "CCI"              "chaikinAD"        "chaikinVolatility"   "CLV"                "CMF"          "CMO"
[13] "DEMA"             "DonchianChannel"  "DPO"                 "DVI"                "EMA"          "EMV"
[19] "EVWMA"            "GMMA"             "growth"              "HMA"                "KST"          "lags"
[25] "MACD"             "MFI"              "momentum"            "OBV"                "PBands"       "ROC"
[31] "rollSFM"          "RSI"              "runCor"              "runCov"             "runMAD"       "runMax"
[37] "runMean"          "runMedian"        "runMin"              "runPercentRank"     "runSD"        "runSum"
[43] "runVar"           "SAR"              "SMA"                 "SMI"                "SNR"          "stoch"
[49] "TDI"              "TRIX"             "ultimateOscillator"  "VHF"                "VMA"          "volatility"
[55] "VWAP"             "VWMA"             "wilderSum"           "williamsAD"         "WMA"          "WPR"
[61] "ZigZag"           "ZLEMA"

$PerformanceAnalytics
[1] "Return.annualized"  "Return.annualized.excess"  "Return.clean"    "Return.cumulative"
[5] "Return.excess"      "Return.Geltner"            "zerofill"
```

What are we missing?

Conversion is **slow**

Limited in functionality

Indirectly using both the tidyverse and xts

No support for a **time-based index**

Wouldn’t it be nice to have a **tibble**

with **time-index support**,

fully leveraging the tools of the tidyverse?

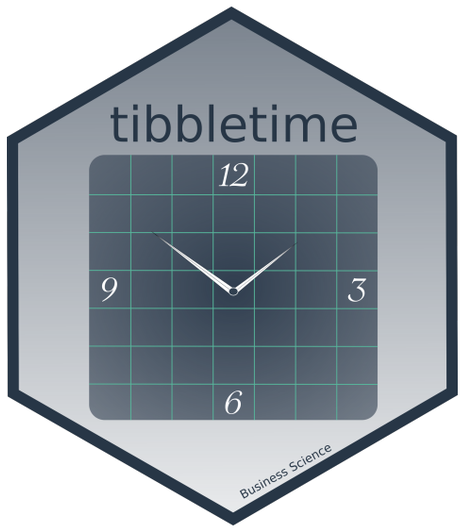
ts

+

tibble

=

A little history



Earo Wang
@earowang
https://github.com/earowang

What?

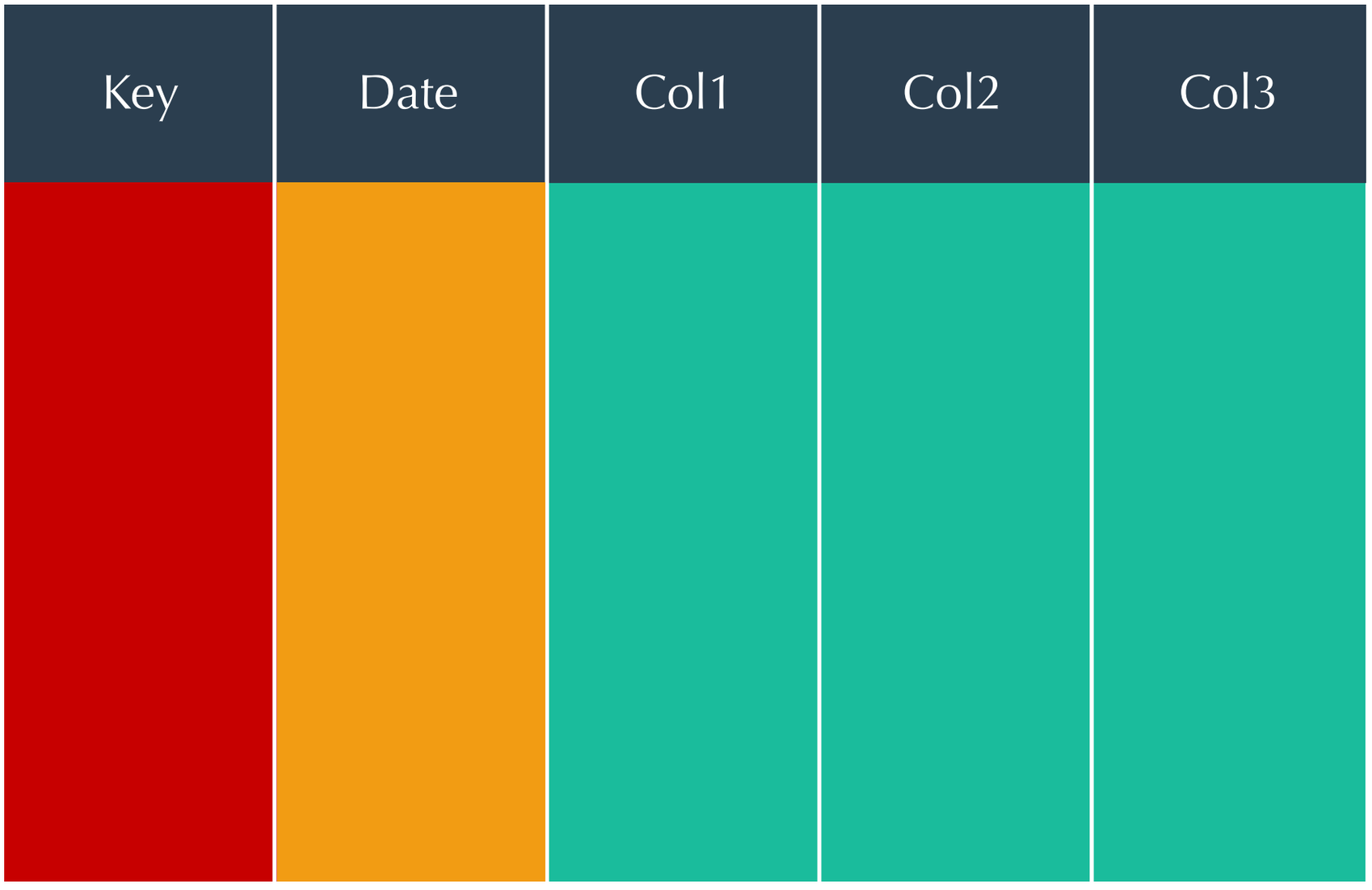
Utilizes extra knowledge

A **tsibble** consists of a time **index**, **key** and other measured **variables** in a data-centric format, which is built on top of the **tibble**.

Underlying data type is the same

Creation


```
as_tsibble(df, key = id(Key), index = Date)
```



Why?

1. Perform time-based manipulations on tibbles
2. Work more naturally with time series in the tidyverse

San Diego Airbnb bookings


```
airbnb
 # A tsibble: 9,111 x 5 [1s]
 # Key:       room_id [9,111]
    room_id last_modified       price latitude longitude
      <int> <dttm>              <dbl>    <dbl>     <dbl>
 1        6 2017-07-11 18:08:36   169     32.8     -117.
 2     5570 2017-07-11 20:01:30   205     32.8     -117.
 3     9731 2017-07-11 15:51:35    65     32.9     -117.
 4    14668 2017-07-11 15:09:38    55     32.9     -117.
 5    37149 2017-07-11 15:09:56    55     32.8     -117.
 6    38245 2017-07-11 15:18:00    50     32.7     -117.
 7    39516 2017-07-11 17:19:11    70     32.7     -117.
 8    45429 2017-07-11 18:18:08   160     32.7     -117.
 9    54001 2017-07-11 16:31:55   125     32.8     -117.
10    62274 2017-07-11 15:49:21    69     32.8     -117.

# ... with 9,101 more rows
```

http://tomslee.net/airbnb-data-collection-get-the-data

A new way to group


```
index_by(airbnb, two_hourly = floor_date(last_modified, “2 hour"))
```

	last_modified <dttm>	two_hourly <dttm>
1	2017-07-11 15:09:38	2017-07-11 14:00:00
2	2017-07-11 15:09:56	2017-07-11 14:00:00
3	2017-07-11 15:18:00	2017-07-11 14:00:00
4	2017-07-11 15:49:21	2017-07-11 14:00:00
5	2017-07-11 15:51:35	2017-07-11 14:00:00
6	2017-07-11 16:31:55	2017-07-11 16:00:00
7	2017-07-11 17:19:11	2017-07-11 16:00:00
8	2017-07-11 18:08:36	2017-07-11 18:00:00
9	2017-07-11 18:18:08	2017-07-11 18:00:00
10	2017-07-11 20:01:30	2017-07-11 20:00:00

A new way to group


```
airbnb %>%
  index_by(
    two_hourly = floor_date(last_modified, "2 hour”)
  ) %>%
  summarise(median_price = median(price))
```

```
# A tsibble: 8 x 2 [2h]

      two_hourly                    median_price
      <dttm>                               <dbl>
1     2017-07-11 14:00:00 [14-16)             55
2     2017-07-11 16:00:00 [16-18)            100
3     2017-07-11 18:00:00 [18-20)            199
4     2017-07-11 20:00:00 [20-22)            450
5     2017-07-11 22:00:00 [22-00)            152
6     2017-07-12 00:00:00 [00-02)            285
7     2017-07-12 02:00:00 [02-04)            882
8     2017-07-12 04:00:00 [04-06)             40
```

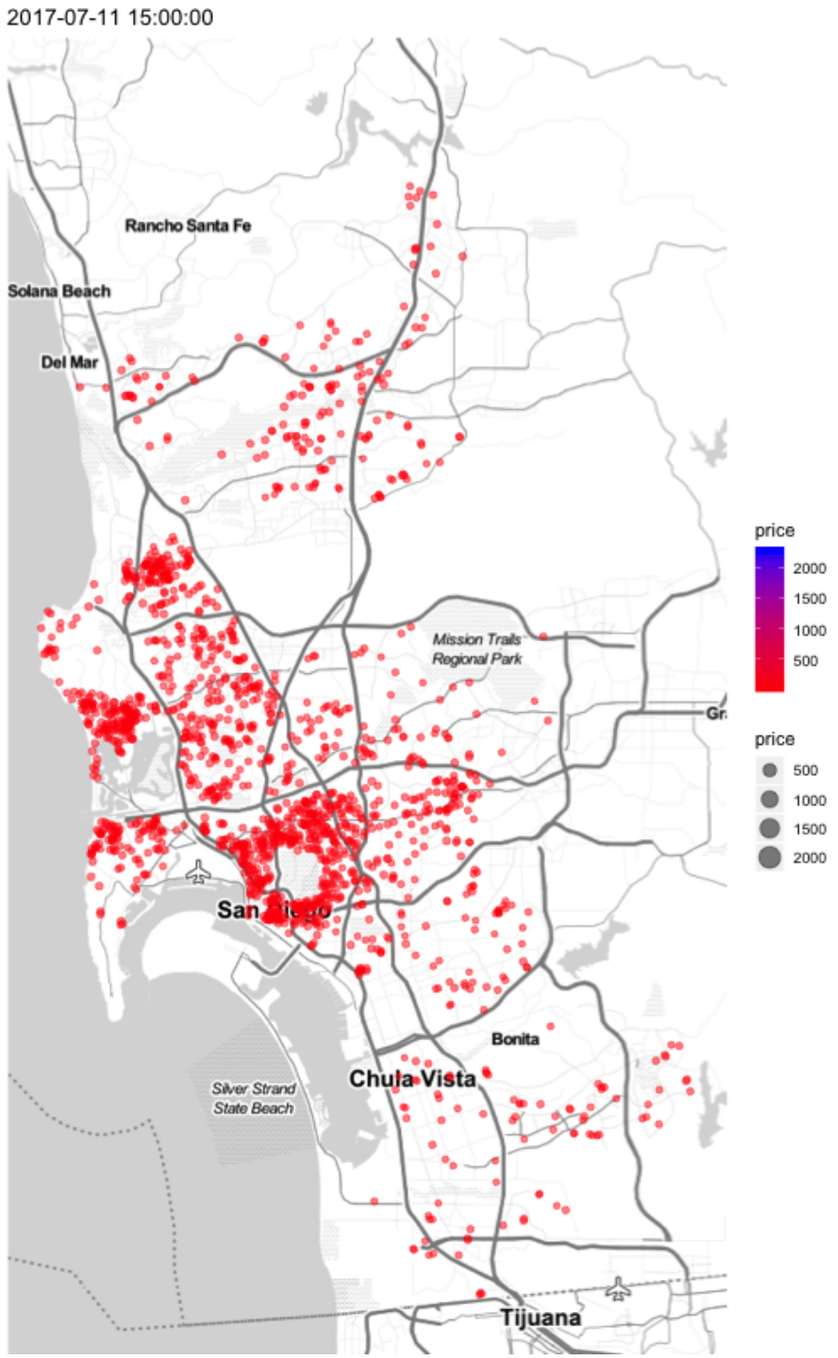
A new way to group


```
airbnb %>%
  index_by(
    two_hourly = ceiling_date(last_modified, "2 hour”)
  ) %>%
  summarise(median_price = median(price))
```

```
# A tsibble: 8 x 2 [2h]

      two_hourly                    median_price
      <dttm>                               <dbl>
1     2017-07-11 16:00:00 [14-16)             55
2     2017-07-11 18:00:00 [16-18)            100
3     2017-07-11 20:00:00 [18-20)            199
4     2017-07-11 22:00:00 [20-22)            450
5     2017-07-11 00:00:00 [22-00)            152
6     2017-07-12 02:00:00 [00-02)            285
7     2017-07-12 04:00:00 [02-04)            882
8     2017-07-12 06:00:00 [04-06)             40
```

The possibilities are endless


```
# Development versions of both
library(ggmap)
library(gganimate)

airbnb_plot ← airbnb %>%

  # Index by hour
  index_by(hourly = floor_date(last_modified, "hour")) %>%

  # Throw out a few outliers
  filter(
    between(price, quantile(price, .05), quantile(price, .95))
  ) %>%

  # Map and animate
  qmplot(longitude, latitude, data = ., geom = "blank") +

  geom_point(
    aes(color = price, size = price),
    alpha = .5
  ) +

  scale_color_continuous(low = "red", high = “blue") +

  transition_manual(hourly) +
  labs(title = "{current_frame}")

animate(airbnb_plot)
```



Extra functionality

Multi-class support

Date

Posixct

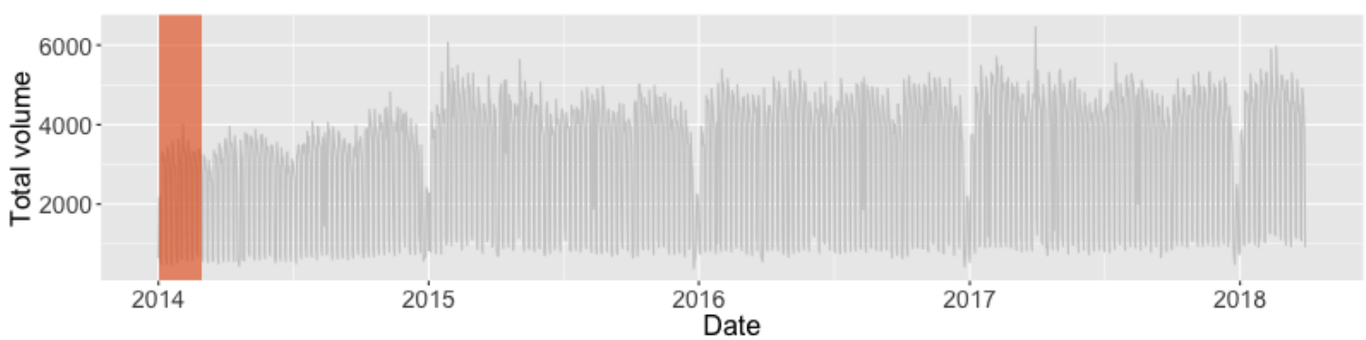
yearmonth

yearquarter

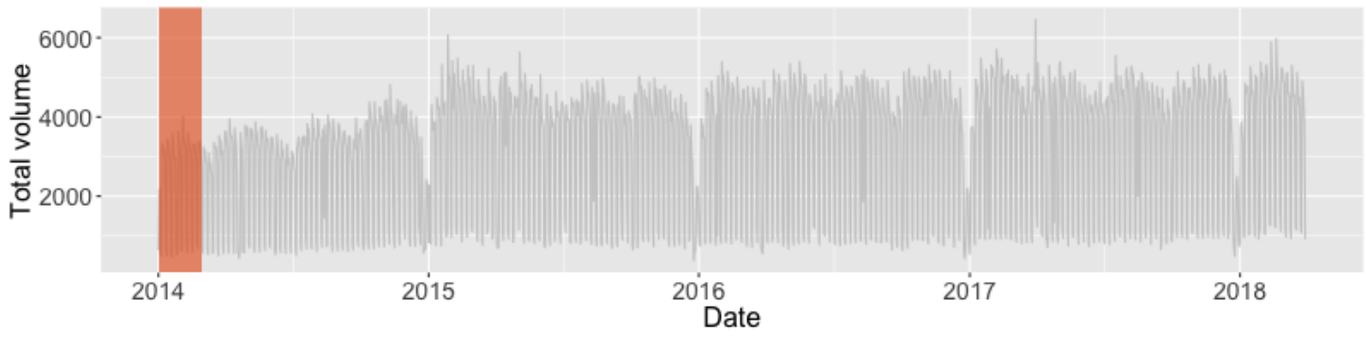
hms

A family of window functions

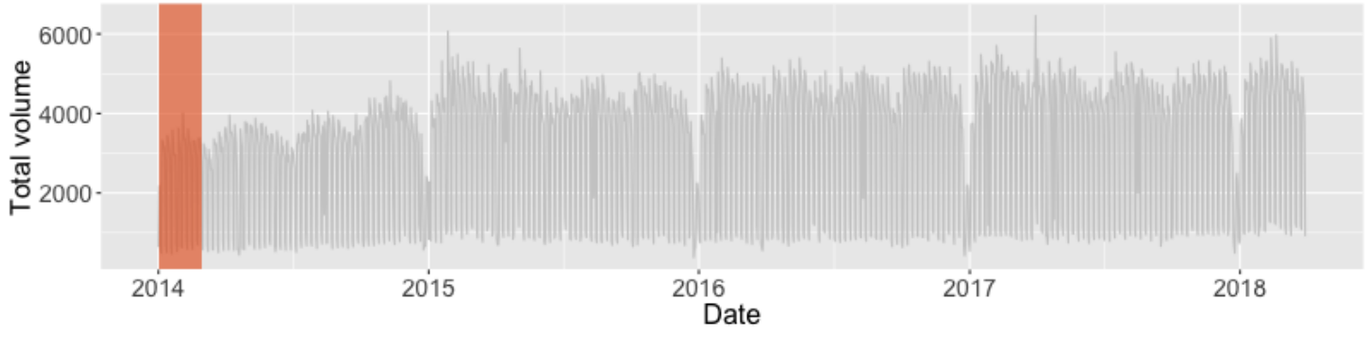
`slide()`, `slide2()`, `pslide()`



`tile()`, `tile2()`, `ptile()`



`stretch()`, `stretch2()`, `pstretch()`



1. `purrr`-like syntax
   - `~ .x + .y`
2. Type stable variants
   - default = list
   - `*_dbl()`
   - `*_int()`
   - `*_lgl()`
   - ...

Sliiiiiide to the left

`slide()`

Sliding window calculations without overlapping observations

Sliiiiide to the left

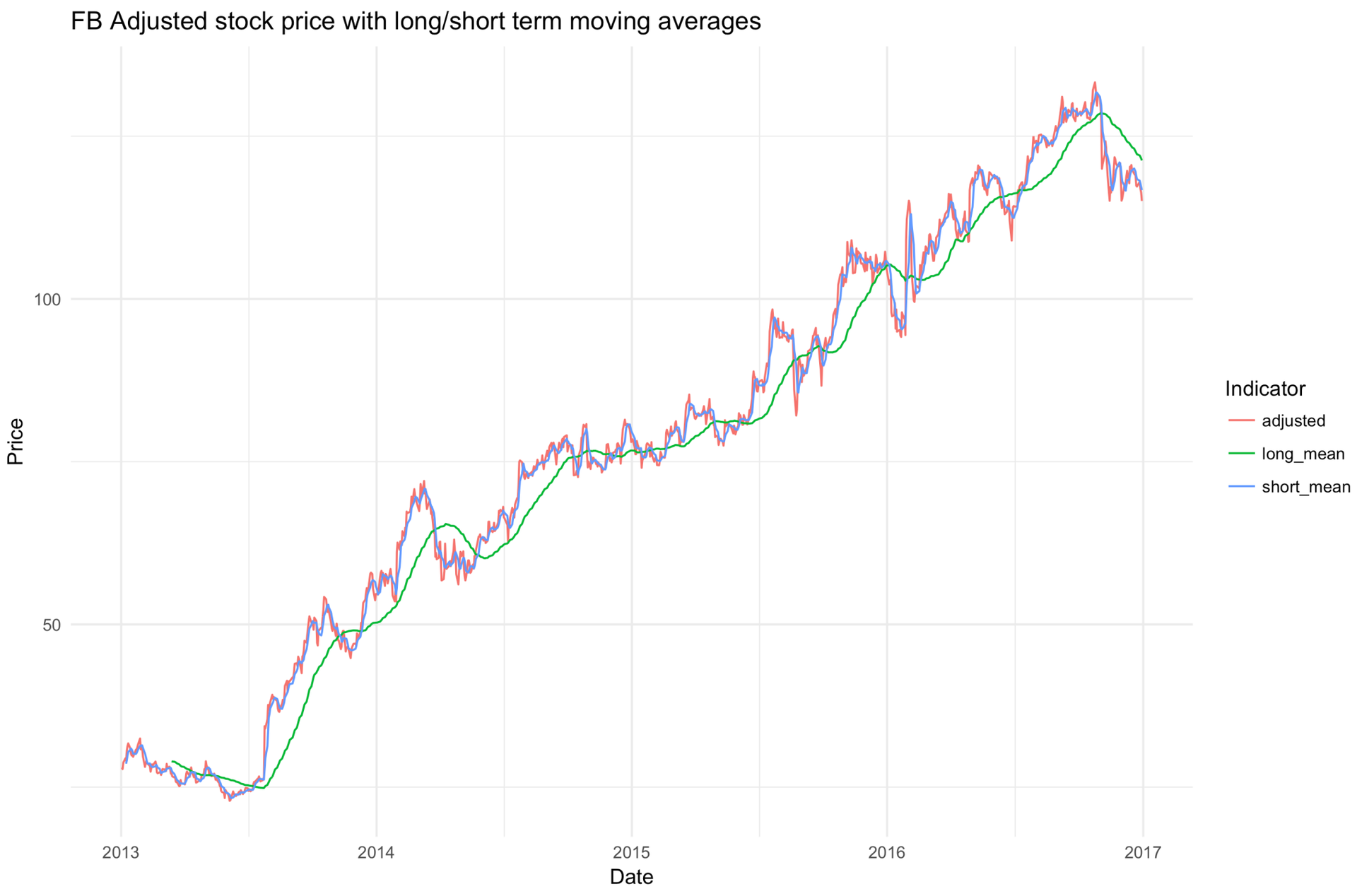

```
> FB
# A tibble: 1,008 x 3
   date       adjusted    volume
   <date>        <dbl>     <dbl>
 1 2013-01-02     28.0  69846400
 2 2013-01-03     27.8  63140600
 3 2013-01-04     28.8  72715400
 4 2013-01-07     29.4  83781800
 5 2013-01-08     29.1  45871300
 6 2013-01-09     30.6 104787700
 7 2013-01-10     31.3  95316400
 8 2013-01-11     31.7  89598000
 9 2013-01-14     31.0  98892800
10 2013-01-15     30.1 173242600
# ... with 998 more rows
```

Rolling averages


```
mutate(FB,
  short_mean = slide_dbl(adjusted, ~mean(.x, na.rm = TRUE), .size = 5),
  long_mean  = slide_dbl(adjusted, ~mean(.x, na.rm = TRUE), .size = 50),
)
```

```
# A tibble: 1,008 x 4
   date       adjusted  short_mean  long_mean
   <date>        <dbl>       <dbl>      <dbl>
 1 2013-01-02     28.0        NA         NA
 2 2013-01-03     27.8        NA         NA
 3 2013-01-04     28.8        NA         NA
 4 2013-01-07     29.4        NA         NA
 5 2013-01-08     29.1        28.6       NA
 6 2013-01-09     30.6        29.1       NA
 7 2013-01-10     31.3        29.8       NA
 8 2013-01-11     31.7        30.4       NA
 9 2013-01-14     31.0        30.7       NA
10 2013-01-15     30.1        30.9       NA
```

Rolling averages



Rolling linear models


```
FB_model ← FB %>%
  mutate(
    lag_volume = lag(volume),
    model = slide2(
      .x = lag_volume,
      .y = adjusted,
      .f = ~ lm(.y ~ .x),
      .size = 5)
)
```

Rolling equivalent of `map2()`.

.f can be anything.

Rolling linear models


```
FB_model ← FB %>%
  mutate(
    lag_volume = lag(volume),
    model = slide2(
        .x = lag_volume,
        .y = adjusted,
        .f = ~lm(.y ~ .x),
        .size = 5)
)
```

```
# A tibble: 1,008 x 5
   date       adjusted    volume lag_volume  model
   <date>        <dbl>     <dbl>      <dbl>  <list>
 1 2013-01-02     28.0  69846400         NA  <lgl [1]>
 2 2013-01-03     27.8  63140600   69846400  <lgl [1]>
 3 2013-01-04     28.8  72715400   63140600  <lgl [1]>
 4 2013-01-07     29.4  83781800   72715400  <lgl [1]>
 5 2013-01-08     29.1  45871300   83781800  <S3: lm>
 6 2013-01-09     30.6 104787700   45871300  <S3: lm>
 7 2013-01-10     31.3  95316400  104787700  <S3: lm>
 8 2013-01-11     31.7  89598000   95316400  <S3: lm>
 9 2013-01-14     31.0  98892800   89598000  <S3: lm>
10 2013-01-15     30.1 173242600   98892800  <S3: lm>
# … with 998 more rows
```

First 4 are NA

Built on top of tibbles

Wouldn't it be nice to have a **tibble** with **time-index support**, **fully leveraging** the tools of the tidyverse?

Learns about the index at creation

Seamless integration with the tidyverse

We now have

~~Wouldn't it be nice to have~~ a **tibble**

with **time-index support**,

fully leveraging the tools of the tidyverse!

Future plans

(aka my hopes and dreams)

Facebook, Amazon, Netflix, Google

```
FANG_time ← FANG %>%
  group_by(symbol) %>%
  as_tsibble(
    key = id(symbol),
    index = date
  )

slice(FANG_time, 1:2)
```

```
# A tsibble: 4,032 x 8 [1D]
# Key:       symbol [4]
# Groups:    symbol [4]
 symbol  date           adjusted
   <chr>   <date>          <dbl>
1 AMZN    2013-01-02        257
2 AMZN    2013-01-03        258
3 FB      2013-01-02       28.0
4 FB      2013-01-03       27.8
5 GOOG    2013-01-02        361
6 GOOG    2013-01-03        361
7 NFLX    2013-01-02       13.1
8 NFLX    2013-01-03       13.8
```

Calculate returns

```
FANG_time %>%
  index_by(yearly = floor_date(date, "year")) %>%
  calculate_return(adjusted) %>%
  mutate(drawdown = drawdown(adjusted_return),
         cum_ret  = cumulative_return(adjusted_return))
```

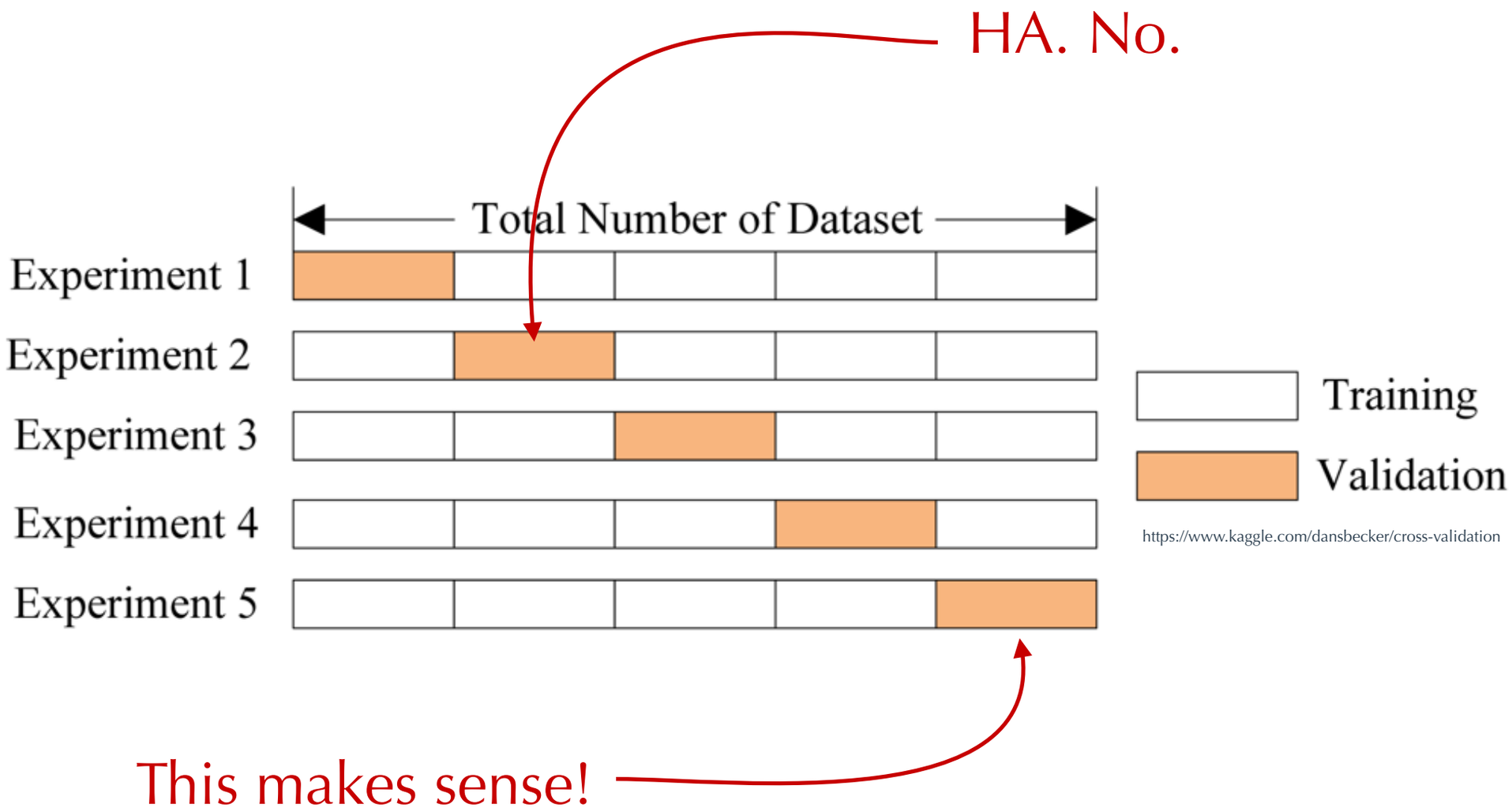
```
# A tsibble: 16 x 7 [1Y]
# Key:       symbol [4]
# Groups:    symbol [4]
   symbol date       adjusted yearly     adjusted_return
   <chr>  <date>        <dbl> <date>               <dbl>
 1 FB     2013-12-31     54.7 2013-01-01          0.952
 2 FB     2014-12-31     78.0 2014-01-01          0.428
 3 FB     2015-12-31    105.  2015-01-01          0.341
 4 FB     2016-12-30    115.  2016-01-01          0.0993
 5 AMZN   2013-12-31    399.  2013-01-01          0.550
 6 AMZN   2014-12-31    310.  2014-01-01         -0.222
 7 AMZN   2015-12-31    676.  2015-01-01          1.18
 8 AMZN   2016-12-30    750.  2016-01-01          0.109
 9 NFLX   2013-12-31     52.6 2013-01-01          3.00
10 NFLX   2014-12-31     48.8 2014-01-01         -0.0721
```

Switching gears

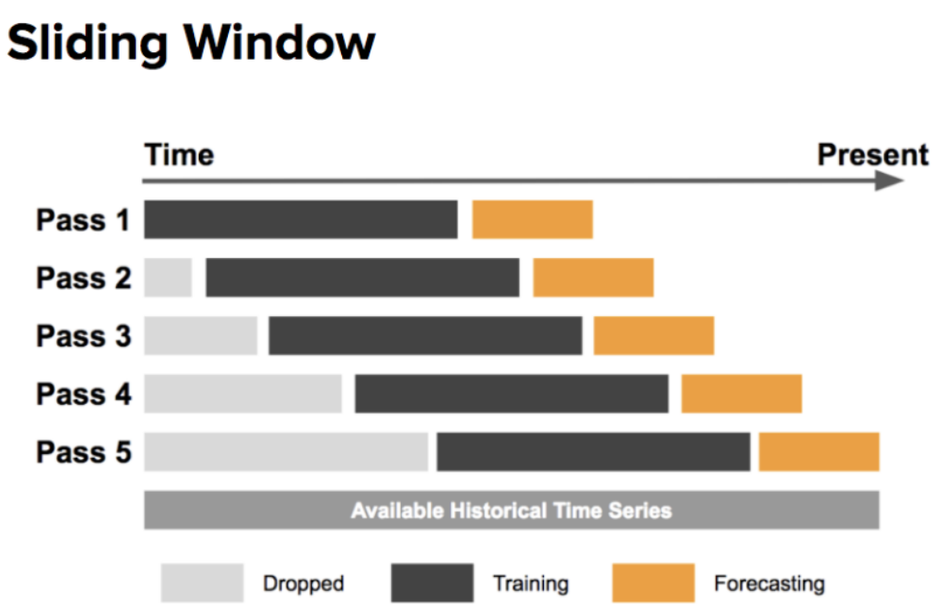
Problem:

You want to perform **cross-validation** in R with **time series**.

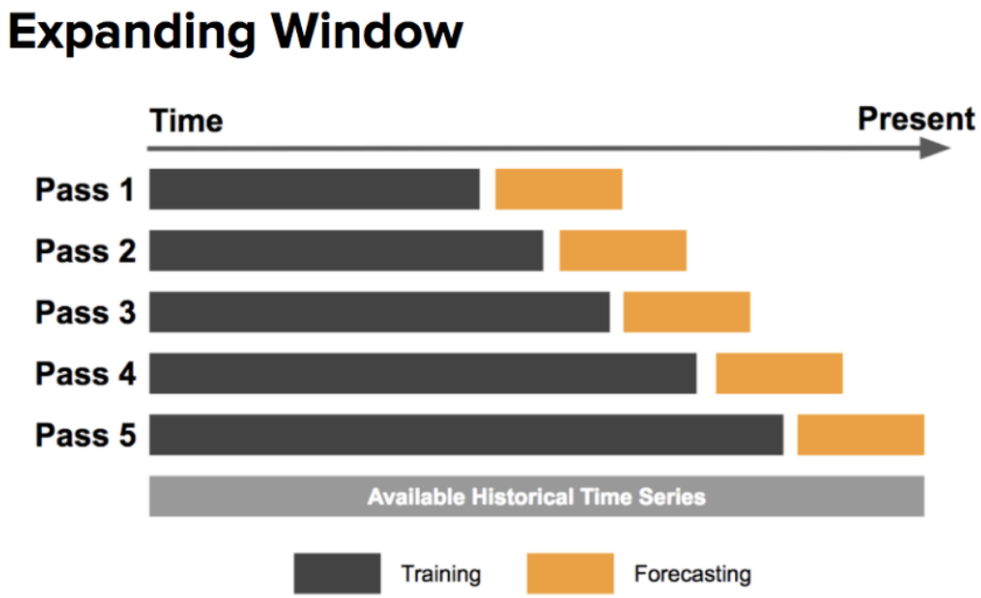
Cross-validation



Cross-validation for ~~the shit we do~~ time series



Training set is of fixed size



Training set size varies

https://eng.uber.com/forecasting-introduction/

Solution: `rsample`

Classes and functions to create and summarize different types of resampling objects.

Bootstraps

V-Fold Cross-Validation

Sliding & Expanding Window

rolling_origin()

```
rolling_origin(FB_adjusted,
  initial = 500,
  assess = 20,
  cumulative = FALSE
)
```

`initial` - The number of rows to start with.

`assess` - The number of rows to holdout for assessment.

`cumulative` - Sliding or Expanding?

```
> FB_adjusted
# A tibble: 1,008 x 2
   date       adjusted
   <date>        <dbl>
 1 2013-01-02     28.0
 2 2013-01-03     27.8
 3 2013-01-04     28.8
 4 2013-01-07     29.4
 5 2013-01-08     29.1
 6 2013-01-09     30.6
 7 2013-01-10     31.3
 8 2013-01-11     31.7
 9 2013-01-14     31.0
10 2013-01-15     30.1
# ... with 998 more rows
```

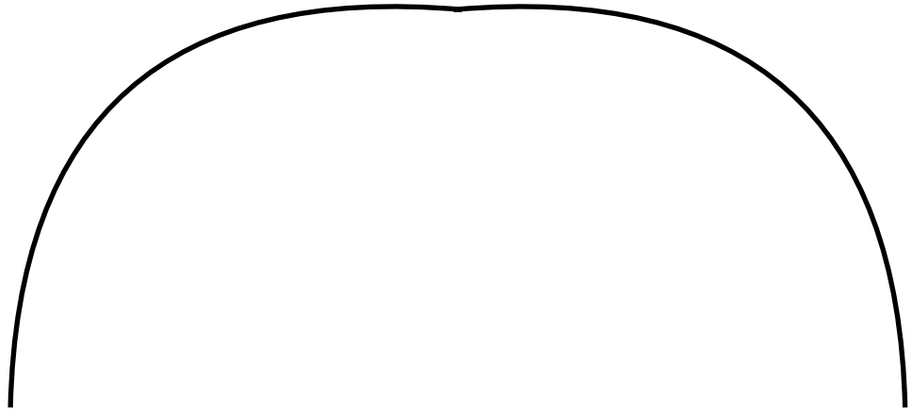
Extracting analysis / assessment sets

```
FB_splits ← rolling_origin(FB_adjusted, initial = 500,
                                        assess = 20, cumulative = FALSE)
```

```
# Rolling origin forecast resampling
# A tibble: 489 x 2
   splits          id
   <list>          <chr>
 1 <S3: rsplit>    Slice001
 2 <S3: rsplit>    Slice002
 3 <S3: rsplit>    Slice003
 4 <S3: rsplit>    Slice004
 5 <S3: rsplit>    Slice005
 6 <S3: rsplit>    Slice006
 7 <S3: rsplit>    Slice007
 8 <S3: rsplit>    Slice008
 9 <S3: rsplit>    Slice009
10 <S3: rsplit>    Slice010
# … with 479 more rows
```

<train/test/total>

<500/20/1008>



analysis()

```
# A tibble: 500 x 2
   date       adjusted
   <date>        <dbl>
 1 2013-01-02     28
 2 2013-01-03     27.8
 3 2013-01-04     28.8
 ...
```

assessment()

```
# A tibble: 20 x 2
   date       adjusted
   <date>        <dbl>
 1 2014-12-26     80.8
 2 2014-12-29     80.0
 3 2014-12-30     79.2
 ...
```

Workflow for fitting many models

```
library(purrr)
library(forecast)

fit_arima ← function(split) {

  # tibble with date and adjusted cols
  analysis_set ← analysis(split)

  # fit arima (really just AR1)
  Arima(
    y = analysis_set$adjusted,
    order = c(1, 0, 0)
  )
}

FB_splits %>%
  mutate(
    model = map(
      .x = splits,
      .f = ~fit_arima(.x)
    )
  )
```

```
# Rolling origin forecast resampling
# A tibble: 489 x 3
   splits         id       model
 * <list>         <chr>    <list>
 1 <S3: rsplit> Slice001 <S3: ARIMA>
 2 <S3: rsplit> Slice002 <S3: ARIMA>
 3 <S3: rsplit> Slice003 <S3: ARIMA>
 4 <S3: rsplit> Slice004 <S3: ARIMA>
 5 <S3: rsplit> Slice005 <S3: ARIMA>
 6 <S3: rsplit> Slice006 <S3: ARIMA>
 7 <S3: rsplit> Slice007 <S3: ARIMA>
 8 <S3: rsplit> Slice008 <S3: ARIMA>
 9 <S3: rsplit> Slice009 <S3: ARIMA>
10 <S3: rsplit> Slice010 <S3: ARIMA>
# … with 479 more rows
```

Then what?

- Predict on the assessment set
- Visualize performance
- Calculate in / out of sample performance metrics
- Calculate confidence intervals around metrics because of the resamples

Problem:

You want to perform **cross-validation** in

R with **time series**

...

faster.

Solution: `furrr`

Apply `purrr`'s mapping

functions **in parallel**

Example

```
library(purrr)
```

```
library(furrr)
plan(multiprocess)
```

Set a parallel "plan"

```
# Sleep 3 times - Sequentially

map(c(2, 2, 2), ~Sys.sleep(.x))
#> 6.08 sec elapsed
```

```
# Sleep 3 times - In parallel!

future_map(c(2, 2, 2), ~Sys.sleep(.x))
#> 2.212 sec elapsed
```

rsample

+

furrr

=

Fit resamples in parallel

```
FB_splits %>%
  mutate(
    model = map(
      .x = splits,
      .f = ~fit_arima(.x)
    )
  )
```

```
#> 8.113 sec elapsed
```

```
FB_splits %>%
  mutate(
    model = future_map(
      .x = splits,
      .f = ~fit_arima(.x)
    )
  )
```

```
#> 4.229 sec elapsed
```

Demo

Thank you!

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