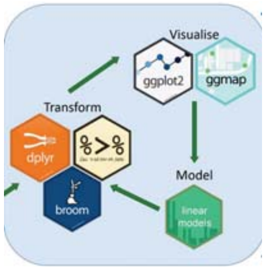
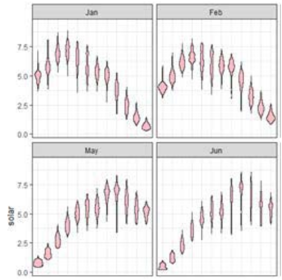
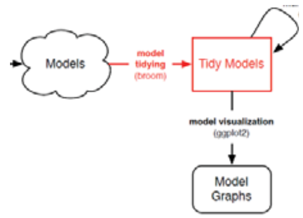






ggplot2: Going further in the tidyverse

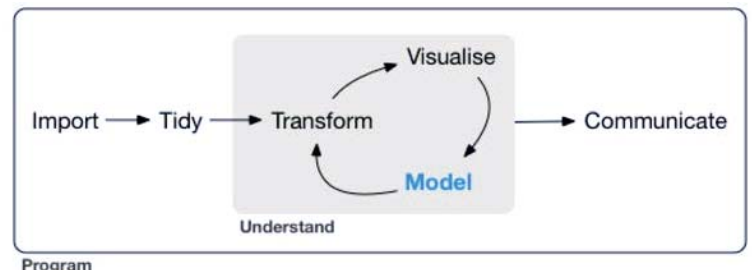
Michael Friendly

Psych 6135

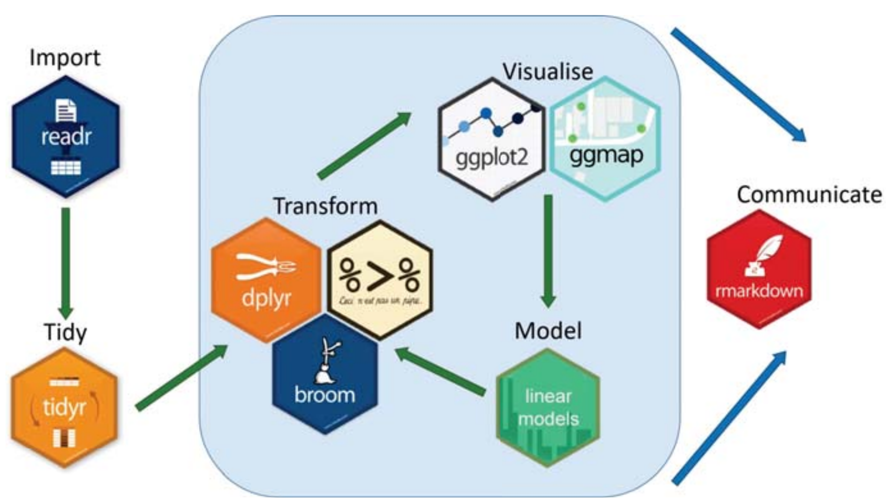
http://euclid.psych.yorku.ca/www/psy6135/

A larger view: Data science

- Data science treats statistics & data visualization as parts of a larger process
  - Data import: text files, data bases, web scraping, …
  - Data cleaning → "tidy data"
  - Model building & visualization
  - Reproducible report writing



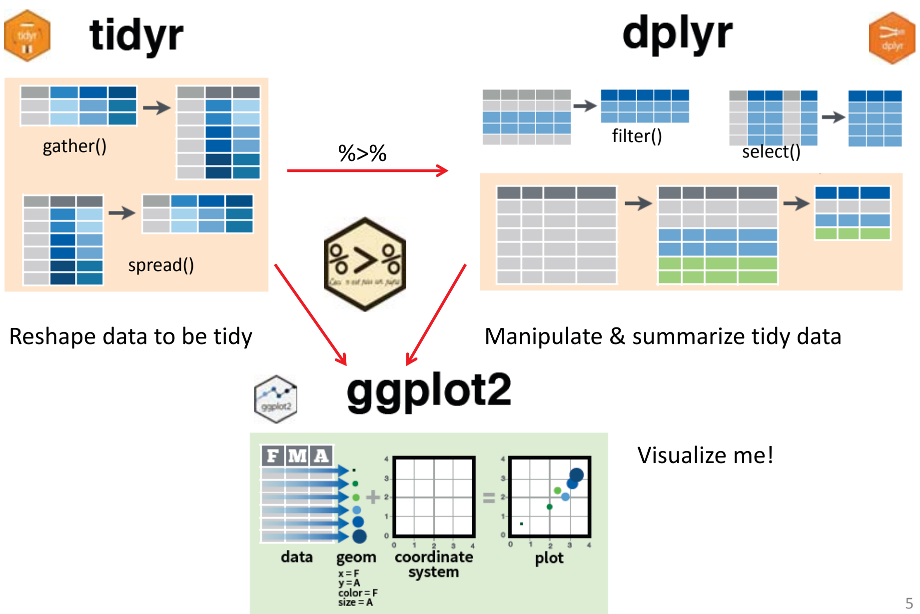
The tidyverse of R packages



Topics

- Data wrangling: getting your data into shape
  - dplyr & tidyr
  - pipes: %>%
  - grouping & sumarising
  - Example: NASA data on solar radiation
- Visualizing models: broom
  - Example: gapminder data
- ggplot2 extensions
- tables in R

Tidy tools: overview

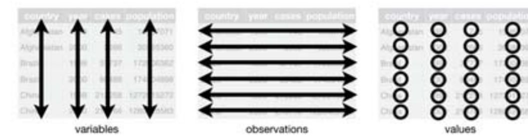


Data wrangling with dplyr & tidyr

What is Tidy Data?

A dataset is said to be tidy if:

- observations are in rows
- variables are in columns
- each value is in its own cell.



A "messy" dataset: Survey of income by religion from Pew Research

- Values of income are in separate columns
- Column headers are values, not variable names
- Cell values are frequencies--- implicit, not explicit

religion	<$10k	$10-20k	$20-30k	$30-40k	$40-50k	$50-75k
Agnostic	27	34	60	81	76	137
Atheist	12	27	37	52	35	70
Buddhist	27	21	30	34	33	58
Catholic	418	617	732	670	638	1116

This organization is easy in Excel

But, this makes data analysis and graphing hard

Tidying: reshaping wide to long

We can tidy the data by reshaping from wide to long format using tidyr::gather()

```
> pew <- read.delim(
  file = "http://stat405.had.co.nz/data/pew.txt",
  header = TRUE,
  stringsAsFactors = FALSE, check.names = FALSE)

> (pew1 <- pew[1:4, 1:6])  # small subset

  religion <$10k $10-20k $20-30k $30-40k $40-50k
1 Agnostic    27      34      60      81      76
2  Atheist    12      27      37      52      35
3 Buddhist    27      21      30      34      33
4 Catholic   418     617     732     670     638
```

key value columns

```
>library(tidyr)
> gather(pew1, "income", "frequency", 2:6)
   religion  income frequency
1  Agnostic   <$10k        27
2   Atheist   <$10k        12
3  Buddhist   <$10k        27
4  Catholic   <$10k       418
5  Agnostic $10-20k        34
6   Atheist $10-20k        27
7  Buddhist $10-20k        21
8  Catholic $10-20k       617
9  Agnostic $20-30k        60
10  Atheist $20-30k        37
11 Buddhist $20-30k        30
12 Catholic $20-30k       732
13 Agnostic $30-40k        81
14  Atheist $30-40k        52
15 Buddhist $30-40k        34
16 Catholic $30-40k       670
…  …        …              …
```

Another solution, using reshape2::melt()

```
> library(reshape2)
> pew_tidy <- melt(
    data = pew1,
    id = "religion",
    variable.name = "income",
    value.name = "frequency"
)
```

NB: income is a character variable; we might want to create an ordered factor or numeric version

Using pipes: %>%

- R is a functional language
  - This means that f(x) returns a value, as in y <- f(x)
  - That value can be passed to another function: g(f(x))
  - And so on: h(g(f(x)))

```
> x <- c(0.109, 0.359, 0.63, 0.996, 0.515, 0.142)
> exp(diff(log(x)))
[1] 3.29 1.75 1.58 0.52 0.28
```

  - This gets messy and hard to read, unless you break it down step by step

```
> # Compute the logarithm of `x`, calculate lagged differences,
> # return the exponential function of the result
> log(x)
[1] -2.216 -1.024 -0.462 -0.004 -0.664 -1.952
> diff(log(x))
[1]  1.19  0.56  0.46 -0.66 -1.29
> exp(diff(log(x)))
[1] 3.29 1.75 1.58 0.52 0.28
```

Using pipes: %>%

- Pipes (%>%) change the syntax to make this easier

```
> # use pipes
> x %>% log() %>% diff() %>% exp()
[1] 3.29 1.75 1.58 0.52 0.28
```

- Basic rules
  - `x %>% f()` passes object on left hand side as first argument (or . argument) of function on right hand side
    - `x %>% f()` is the same as `f(x)`
    - `x %>% f(y)` is the same as `f(x, y)`
    - `y %>% f(x, ., z)` is the same as `f(x, y, z)`
  - `x %<>% f()` does the same, but assigns the result to x
    - Shortcut for `x <- x %>% f()`

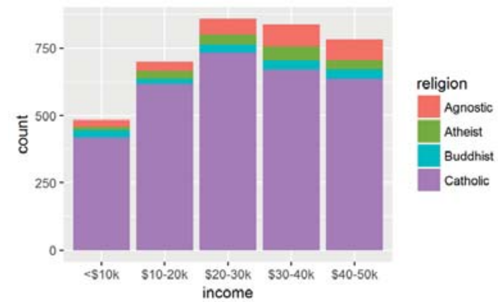
Using pipes: %>% ggplot()

For the Pew data, mutate income into an ordered factor and make a ggplot

```
pew1 %>%
  gather("income", "frequency", 2:6) %>%
  mutate(income = ordered(income, levels=unique(income))) %>%
  ggplot(aes(x=income, fill=religion)) +
    geom_bar(aes(weight=frequency))
```

mutate() calculates new column variables
The levels of income are now ordered appropriately.

The result is piped to ggplot()



Tidying: separate() and unite()

It sometimes happens that several variables are crammed into one column, or parts of one variable are split across multiple columns

tidyr::**separate(storms, date, c("y", "m", "d"))**
Separate one column into several.

tidyr::**unite(data, col, ..., sep)**
Unite several columns into one.

For example, for the pew data, we might want separate income into low & high

```
pew_long %>%
  mutate(inc = gsub("[\\$k]", "", income)) %>%
  mutate(inc = gsub("<", "0-", inc)) %>%
  separate(inc, c("low", "high"), "-") %>%
  head()
```

```
  religion  income frequency low high
1 Agnostic   <$10k        27   0   10
2  Atheist   <$10k        12   0   10
3 Buddhist   <$10k        27   0   10
4 Catholic   <$10k       418   0   10
5 Agnostic $10-20k        34  10   20
6  Atheist $10-20k        27  10   20
```


dplyr: Subset observations (rows)

dplyr implements a variety of verbs to select a subset of observations from a dataset

dplyr::**filter(iris, Sepal.Length > 7)**
Extract rows that meet logical criteria.

dplyr::**distinct(iris)**
Remove duplicate rows.

dplyr::**sample_frac(iris, 0.5, replace = TRUE)**
Randomly select fraction of rows.

dplyr::**sample_n(iris, 10, replace = TRUE)**
Randomly select n rows.

dplyr::**slice(iris, 10:15)**
Select rows by position.

dplyr::**top_n(storms, 2, date)**
Select and order top n entries (by group if grouped data).

In a pipe expression, omit the dataset name

```
iris %>% filter(Sepal.Length >7)
iris %>% filter(Species=="setosa")

iris %>% sample_n(10)
iris %>% slice(1:50)   # setosa
```

dplyr: Subset variables (columns)

dplyr::**select(iris, Sepal.Width, Petal.Length, Species)**

Select columns by name or helper function.

Many helper functions in dplyr allow selection by a function of variable names:

select(iris, **contains**("."))
Select columns whose name contains a character string.

select(iris, **ends_with**("Length"))
Select columns whose name ends with a character string.

select(iris, **everything**())
Select every column.

select(iris, **matches**(".t."))
Select columns whose name matches a regular expression.

select(iris, **num_range**("x", 1:5))
Select columns named x1, x2, x3, x4, x5.

select(iris, **one_of**(c("Species", "Genus")))
Select columns whose names are in a group of names.

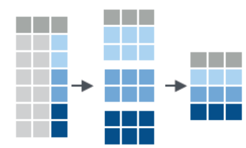
select(iris, **starts_with**("Sepal"))
Select columns whose name starts with a character string.

select(iris, Sepal.Length**:**Petal.Width)
Select all columns between Sepal.Length and Petal.Width (inclusive).

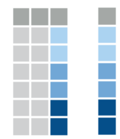
select(iris, **-**Species)
Select all columns except Species.

dplyr: group_by() and summarise()

- Fundamental operations in data munging are:
  - grouping a dataset by one or more variables
  - calculating one or more summary measures
  - ungrouping: expand to an ungrouped copy, if needed




```
mtcars %>%
  group_by(cyl) %>%
  summarise(avg=mean(mpg))
```




```
mtcars %>%
  group_by(cyl) %>%
  summarise(avg=mean(mpg)) %>%
  ungroup()
```

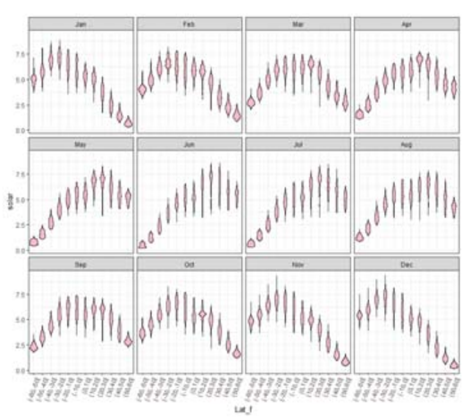

Example: NASA data on solar radiation

Surface meteorology and Solar Energy
A renewable energy resource web site (release 6.0)
sponsored by NASA's Applied Science Program in the Science Mission Directorate
developed by POWER: Prediction of Worldwide Energy Resource Project

- over 200 satellite-derived meteorology and solar energy parameters
- monthly averaged from 22 years of data
- data tables for a particular location
- GIS Web Mapping Application & Services

How does solar radiation vary with latitude, over months of the year?

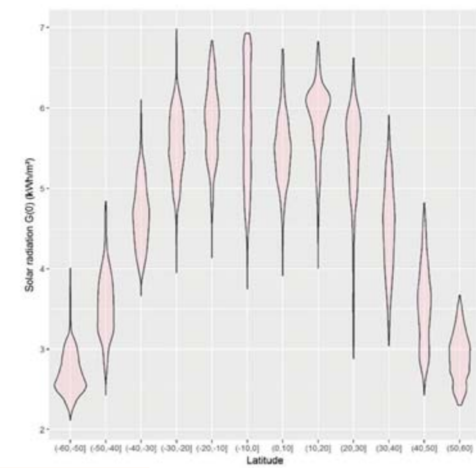
How to make this plot?



NASA data: solar radiation

This is easy to do for the total Annual solar radiation, a column in the data

```
> str(nasa)
'data.frame':   64800 obs. of  15 variables:
 $ Lat: int  -90 -90 -90 -90 -90 -90 -90 -90 -90 -90 ...
 $ Lon: int  -180 -179 -178 -177 -176 -175 -174 -173 -172 -171 ...
 $ Jan: num  9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 ...
 $ Feb: num  5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 ...
 $ Mar: num  0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 ...
 $ Apr: num  0 0 0 0 0 0 0 0 0 0 ...
 $ May: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jun: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jul: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Aug: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Sep: num  0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 ...
 $ Oct: num  3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 ...
 $ Nov: num  8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 ...
 $ Dec: num  11 11 11 11 11 ...
 $ Ann: num  3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 ...
```

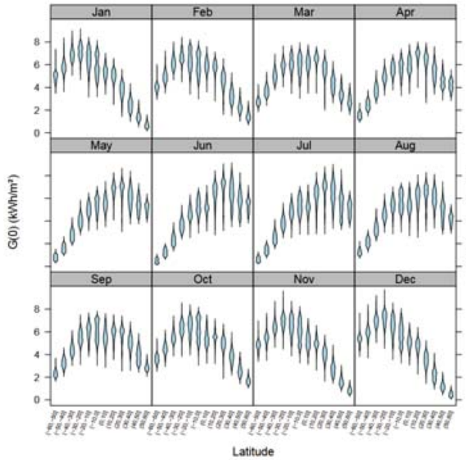



```
nasa %>%
  filter(abs(Lat) < 60) %>%
  mutate(Latf = cut(Lat, pretty(Lat, n=10))) %>%
  ggplot(aes(x=Latf, y=Ann)) +
    geom_violin(fill="pink", alpha=0.3) +
    labs(x="Latitude", y="Solar radiation G(0) (kWh/m²)")
```

Faceting & tidy data

This is complicated to do for the separate months, because the data structure is **untidy**--- months were in separate variables (wide format)

```
> str(nasa)
'data.frame':   64800 obs. of  15 variables:
 $ Lat: int  -90 -90 -90 -90 -90 -90 -90 -90 -90 -90 ...
 $ Lon: int  -180 -179 -178 -177 -176 -175 -174 -173 -172 -171 ...
 $ Jan: num  9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 ...
 $ Feb: num  5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 ...
 $ Mar: num  0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 ...
 $ Apr: num  0 0 0 0 0 0 0 0 0 0 ...
 $ May: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jun: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jul: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Aug: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Sep: num  0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 ...
 $ Oct: num  3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 ...
 $ Nov: num  8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 ...
 $ Dec: num  11 11 11 11 11 ...
 $ Ann: num  3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 ...
```



tidying the data

In wide format (with lattice), one has to construct a plot formula to plot those columns

```
> x <- paste(names(nasa)[3:14], collapse='+')
> (formula <- as.formula(paste(x, '~cut(Lat, pretty(Lat, 20))', sep='')))
Jan + Feb + Mar + Apr + May + Jun + Jul + Aug + Sep + Oct + Nov +
   Dec ~ cut(Lat, pretty(Lat, 20))
```

It is much easier to reshape the data to long format, so solar is all in one column

```
library(tidyr)
library(dplyr)
library(ggplot2)

nasa_long <- nasa %>%
   select(-Ann) %>%
   gather(month, solar, Jan:Dec, factor_key=TRUE) %>%
   filter( abs(Lat) < 60 ) %>%
   mutate( Lat_f = cut(Lat, pretty(Lat, 12)))
```

%>% "pipes" data to the next stage

select() extracts or drops columns

gather() collapses columns into key-value pairs

filter() subsets observations

mutate() creates new variables

tidying the data

```
> str(nasa_long)
'data.frame':   514080 obs. of  5 variables:
 $ Lat  : int  -59 -59 -59 -59 -59 -59 -59 -59 -59 -59 ...
 $ Lon  : int  -180 -179 -178 -177 -176 -175 -174 -173 -172 -171 ...
 $ month: Factor w/ 12 levels "Jan","Feb","Mar",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ solar: num  5.19 5.19 5.25 5.25 5.17 5.17 5.15 5.15 5.15 5.15 ...
 $ Lat_f: Factor w/ 12 levels "(-60,-50]","(-50,-40]",..: 1 1 1 1 1 1 1 1 1 1 ...

> head(nasa_long)
  Lat  Lon month solar     Lat_f
1 -59 -180   Jan  5.19 (-60,-50]
2 -59 -179   Jan  5.19 (-60,-50]
3 -59 -178   Jan  5.25 (-60,-50]
4 -59 -177   Jan  5.25 (-60,-50]
5 -59 -176   Jan  5.17 (-60,-50]
6 -59 -175   Jan  5.17 (-60,-50]
```

For ease of plotting, I created a factor version of Lat with 12 levels

The data are now in a form where I can plot solar against Lat or Lat_f and facet by month

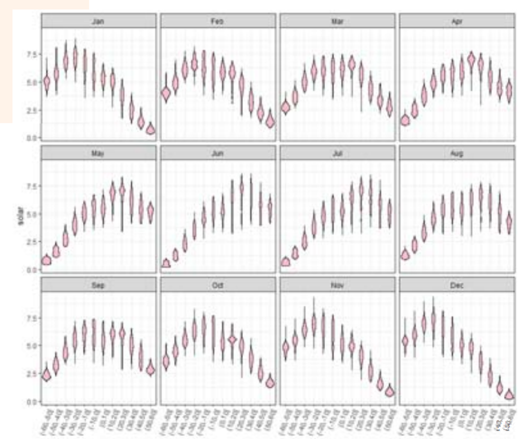
plotting the tidy data

Using geom_violin() shows the shapes of the distributions for levels of Lat_f

```
ggplot(nasa_long, aes(x=Lat_f, y=solar)) +
   geom_violin(fill="pink") +
   facet_wrap(~ month) +
   theme_bw() +
   theme(axis.text.x =
         element_text(angle = 70,
                      hjust = 1))
```

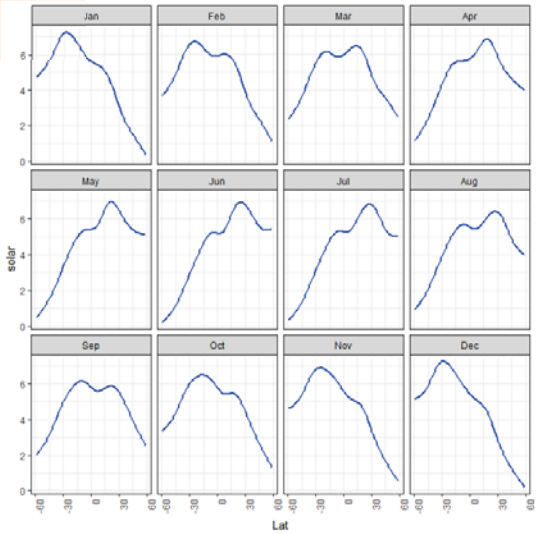
facet_wrap(~month) does the right thing

I had to adjust the x-axis labels for Lat_f to avoid overplotting



plotting the tidy data: smoothing

```
ggplot(nasa_long, aes(x=Lat, y=solar)) +
  geom_smooth(color="blue" ) +
  facet_wrap(~ month) +
  theme_bw()
```



Here we treat Lat as quantitative. geom_smooth() uses method = “gam” here because of large *n*

The variation in the smoothed trends over the year suggest quite lawful behavior

build a model

What we saw in the plot suggests a generalized additive model, with a smooth, s(Lat)

```
library(mgcv)
nasa.gam <- gam(solar ~ Lon + month + s(Lat), data=nasa_long)
summary(nasa.gam)
```

```
Family: gaussian
Link function: identity

Formula:
solar ~ Lon + month + s(Lat)

Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.691e+00  6.833e-03 686.409  < 2e-16 ***
Lon        -1.713e-04  1.898e-05  -9.022  < 2e-16 ***
monthFeb    1.195e-01  9.664e-03  12.364  < 2e-16 ***
  ...          ...
monthDec   -8.046e-02  9.664e-03  -8.326  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
         edf Ref.df     F p-value
s(Lat) 8.997      9 37285  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.398   Deviance explained = 39.8%
GCV = 2.0006  Scale est. = 2.0005    n = 514080
```

The violin plots suggest that variance is not constant. I’m ignoring this here by using the default gaussian model.

Model terms:

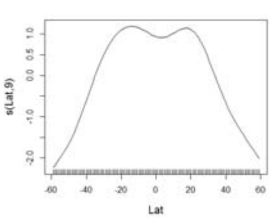
- Lon wasn’t included before
- month is a factor, for the plots
- s(Lat) fits a smoothed term in latitude, averaged over other factors

There are other model choices, but it is useful to visualize what we have done so far

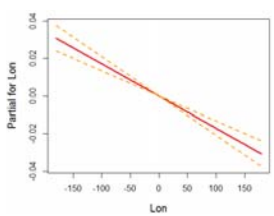
visualize the model

Effect plots show the fitted relationship between the response and model terms, averaged over other predictors.
The mgcv package has its own versions of these.

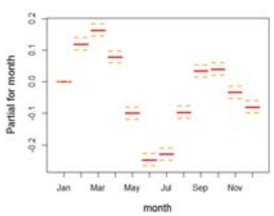
```
plot(nasa.gam, cex.lab=1.25)
termplot(nasa.gam, terms="month", se=TRUE, lwd.term=3, lwd.se=2, cex.lab=1.25)
termplot(nasa.gam, terms="Lon", se=TRUE, lwd.term=3, lwd.se=2, cex.lab=1.25)
```



why the dip at the equator?



effect of longitude is very small, but maybe interpretable



month should be modeled as a time variable

Visualizing models

- R modeling functions [lm(), glm(), …] return model objects, but these are “messy”
  - extracting coefficients takes several steps: data.frame(coef(mymod))
  - some info (R^2, F, p.value) is computed in print() method, not stored
  - can’t easily combine models
- Some have associated plotting functions
  - plot(model): diagnostic plots
  - car package: many model plot methods
  - effects package: plot effects for model terms
- But what if you want to:
  - make a table of model summary statistics
  - fit a collection of models, compare, summarize or visualize them?

broom: visualizing models

- The broom package turns model objects into tidy data frames
  - **glance**(models) extracts model-level summary statistics (R^2, df, AIC, BIC)
  - **tidy**(models) extracts coefficients, SE, p-values
  - **augment**(models) extracts observation-level info (residuals, …)

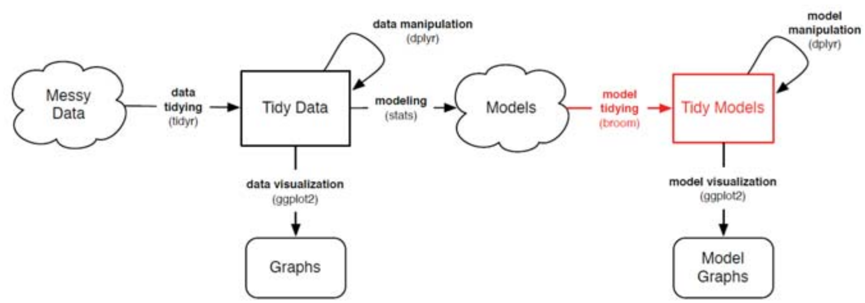


Image from: https://opr.princeton.edu/workshops/Downloads/2016Jan_BroomRobinson.pdf

Example: gapminder data

Predict life expectancy from year, population, GDP and continent:

```
gapmod <- lm(lifeExp ~ year + pop + log(gdpPercap) + continent, data=gapminder)
summary(gapmod)
```

```
Call:
lm(formula = lifeExp ~ year + pop + log(gdpPercap) + continent, data = gapminder)

Residuals:
    Min      1Q  Median      3Q     Max
-24.928  -3.285   0.314   3.699  15.221

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       -4.58e+02   1.67e+01  -27.43  < 2e-16 ***
year               2.38e-01   8.61e-03   27.58  < 2e-16 ***
pop                5.40e-09   1.38e-09    3.91  9.5e-05 ***
log(gdpPercap)     5.10e+00   1.60e-01   31.88  < 2e-16 ***
continentAmericas  8.74e+00   4.63e-01   18.86  < 2e-16 ***
continentAsia      6.64e+00   4.09e-01   16.22  < 2e-16 ***
continentEurope    1.23e+01   5.10e-01   24.11  < 2e-16 ***
continentOceania   1.26e+01   1.27e+00    9.88  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.79 on 1696 degrees of freedom
Multiple R-squared:    0.8,      Adjusted R-squared:  0.799
F-statistic:  969 on 7 and 1696 DF,  p-value: <2e-16
```

observation level

component level (coefficients)

model level

glance() gives the model level summary statistics

```
> glance(gapmod)
  r.squared adj.r.squared sigma statistic p.value df logLik   AIC   BIC deviance df.residual
1       0.8        0.7992 5.789       969       0  8  -5406 10830 10879    56835        1696
```

tidy() gives the model term statistics

```
> tidy(gapmod)
               term   estimate std.error statistic    p.value
1       (Intercept) -4.585e+02 1.671e+01   -27.433 1.982e-137
2              year  2.376e-01 8.613e-03    27.584 1.122e-138
3               pop  5.403e-09 1.381e-09     3.912  9.496e-05
4    log(gdpPercap)  5.103e+00 1.601e-01    31.876 4.096e-175
5 continentAmericas  8.739e+00 4.635e-01    18.856  3.758e-72
6     continentAsia  6.635e+00 4.091e-01    16.219  4.167e-55
7   continentEurope  1.230e+01 5.102e-01    24.113 1.044e-110
8  continentOceania  1.256e+01 1.270e+00     9.884  1.943e-22
```

augment() gives the observation level statistics

```
> augment(gapmod) %>% slice(1:5)
# A tibble: 5 x 12
  lifeExp  year      pop log.gdpPercap. continent .fitted .se.fit .resid    .hat .sigma
    <dbl> <int>    <int>          <dbl> <fct>       <dbl>   <dbl>  <dbl>   <dbl>  <dbl>
1    28.8  1952  8425333           6.66 Asia         46.0   0.408  -17.1 0.00496   5.78
2    30.3  1957  9240934           6.71 Asia         47.4   0.390  -17.1 0.00454   5.78
3    32.0  1962 10267083           6.75 Asia         48.8   0.376  -16.8 0.00423   5.78
4    34.0  1967 11537966           6.73 Asia         49.9   0.372  -15.9 0.00413   5.78
5    36.1  1972 13079460           6.61 Asia         50.5   0.382  -14.4 0.00435   5.78
# ... with 2 more variables: .cooksd <dbl>, .std.resid <dbl>
```


Going further: fitting multiple models

There may be different relations by continent (interactions)
- What if want to fit (and visualize) a separate model for each continent?
- dplyr::do() allows us to store the result of an arbitrary computation in a tidy column

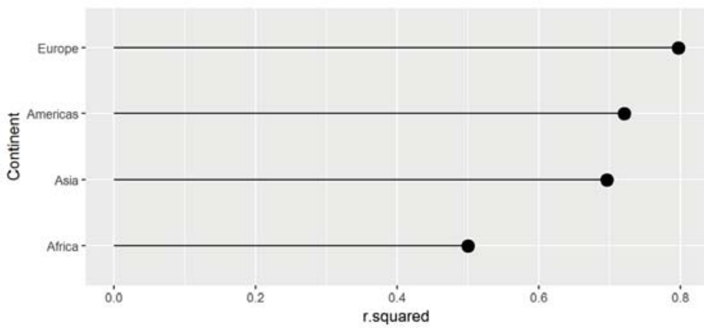
```
# separate models for continents
models <- gapminder %>%
          filter(continent != "Oceania") %>%   # only two countries
          group_by(continent) %>%
          do(mod = lm(lifeExp ~ year + pop + log(gdpPercap),  data=.))
# view model summaries
models %>% glance(mod)
```

```
# A tibble: 4 x 12
# Groups:   continent [4]
  continent r.squared adj.r.squared sigma statistic   p.value    df logLik
  <fct>         <dbl>         <dbl> <dbl>     <dbl>     <dbl> <int>  <dbl>
1 Africa        0.500         0.498  6.48      207. 5.90e- 93     4 -2050.
2 Americas      0.720         0.718  4.97      254. 1.39e- 81     4  -904.
3 Asia          0.696         0.694  6.56      299. 5.27e-101     4 -1305.
4 Europe        0.797         0.795  2.46      466. 7.42e-123     4  -833.
# ... with 4 more variables: AIC <dbl>, BIC <dbl>, deviance <dbl>,
#   df.residual <int>
```

Going further: plotting multiple models

One visual summary might be a plot of R^2 values, ordered by continent

```
models %>%
   glance(mod) %>%
   ggplot(aes(r.squared, reorder(continent, r.squared))) +
      geom_point(size=4) +
      geom_segment(aes(xend = 0, yend = ..y..)) +
      ylab("Continent")
```



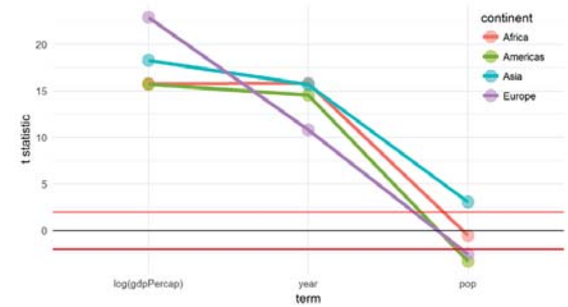
Visualizing coefficients

Coefficient plots are often useful, but these are on different scales.

```
models %>% tidy(mod) %>%                                                         # get model stats
  filter(term != "(Intercept)") %>%                                              # ignore the intercept
  mutate(term=factor(term, levels=c("log(gdpPercap)", "year", "pop"))) %>%       #  reorder terms sensibly
  ggplot(aes(x=term, y=statistic, color=continent, group=continent)) +
    geom_point(size=5, alpha=0.5) +
    geom_line(size=1.5) +
    geom_hline(yintercept=c(-2, 0, 2),  color = c("red", "black", "red")) +      # hlines for non-significance
    ylab("t statistic") +
    theme_minimal() + theme(legend.position=c(0.9, 0.8))
```

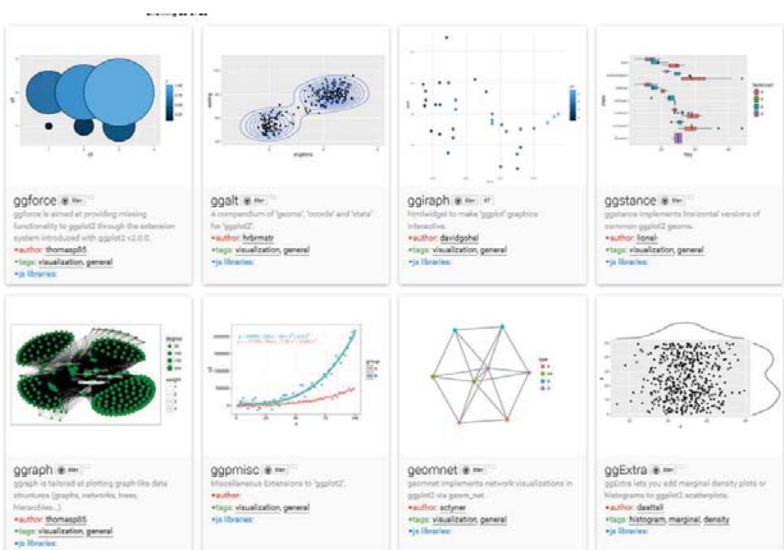
Here, I plot the *t*-statistics, $t=b_{ij}/se(b_{ij})$ for all terms in all models.

Any values outside ~ ±2 are significant, p < 0.5!



ggplot extensions

There are a large number of ggplot extensions. See: http://www.ggplot2-exts.org/

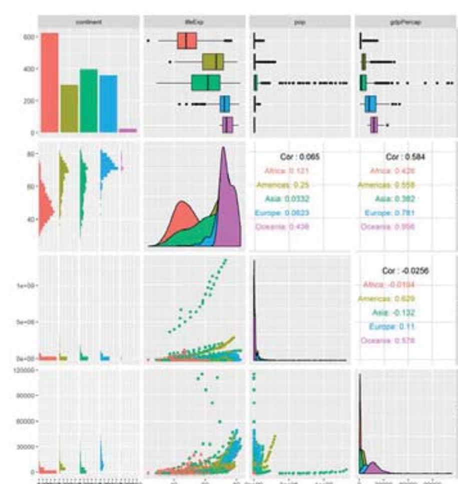


ggplot extensions: GGally

GGally contains a large number of functions that extend ggplot2 to multivariate data

ggpairs() produces generalized scatterplot matrices, with lots of options

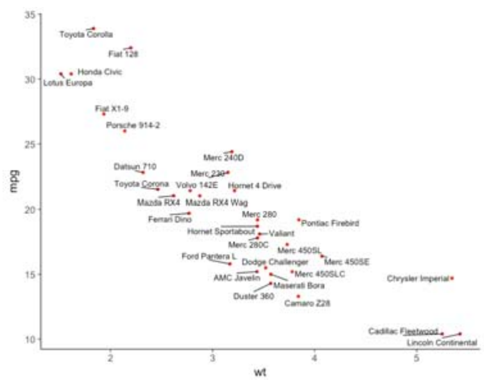
```
library(GGally)
library(dplyr)
library(ggplot2)
library(gapminder)

gapminder %>%
   select(-country, -year) %>%
   ggpairs(aes(color=continent))
```



ggplot extensions: ggrepel

```
devtools::install_github("slowkow/ggrepel")
library(ggplot2)
library(ggrepel)
ggplot(mtcars, aes(wt, mpg)) +
   geom_point(color = 'red') +
   geom_text_repel(aes(label = rownames(mtcars))) +
   theme_classic(base_size = 16)
```

Plotting text labels is often difficult
ggrepel provides geoms for ggplot2 to repel overlapping text labels.

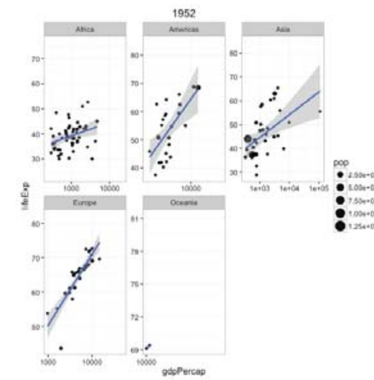


ggplot extensions: gganimate

gganimate is a wrapper for the animation package with ggplot2.

It adds a frame= aesthetic, and animates the image as the frame variable changes

Install from github:
devtools::install_github("dgrtwo/gganimate")



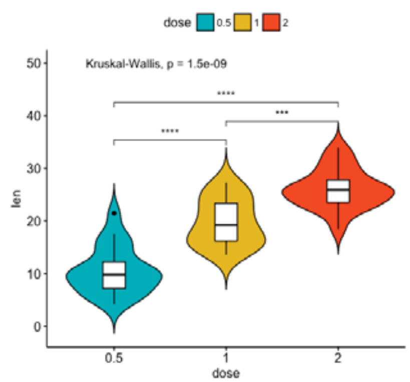

```
p5 <- ggplot(gapminder, aes(gdpPercap, lifeExp, size = pop, frame = year)) +
  geom_point() +
  geom_smooth(aes(group = year), method = "lm", show.legend = FALSE) +
  facet_wrap(~continent, scales = "free") +
  scale_x_log10()

gganimate(p5)
```


ggpubr

The ggpubr package provides some easy-to-use functions for creating and customizing publication ready plots.

```
ggviolin(df, x = "dose", y = "len", fill = "dose",
        palette = c("#00AFBB", "#E7B800", "#FC4E07"),
        add = "boxplot", add.params = list(fill = "white")) +
  stat_compare_means(comparisons = my_comparisons, label = "p.signif") +
  stat_compare_means(label.y = 50)
```

see the examples at
http://www.sthda.com/english/rpkgs/ggpubr/

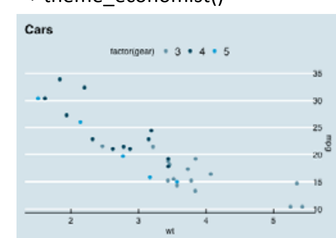


ggthemes

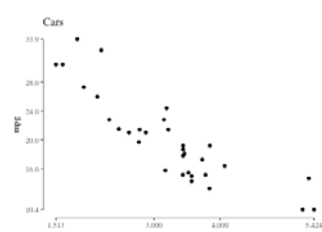
ggthemes provides a large number of extra geoms, scales, and themes for ggplot

```
install.packages('ggthemes', dependencies = TRUE)
```

\+ theme_economist()



\+ theme_tufte()



\+ theme_fivethirtyeight()

Tables in R

- Not a ggplot topic, but it is useful to know that you can also produce beautiful tables in R
- There are many packages for this: See the CRAN Task View on Reproducible Research, https://cran.r-project.org/web/views/ReproducibleResearch.html
  - xtable: Exports tables to LaTeX or HTML, with lots of control
  - stargazer: Well-formatted model summary tables, side-by-side
  - apaStyle: Generate APA Tables for MS Word

Tables in R: xtable

Just a few examples, stolen from xtable: vignette("xtableGallery.pdf")

```
fm1 <- aov(tlimth ~ sex + ethnicty + grade + disadvg, data = tli)
xtable(fm1)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
sex	1	75.37	75.37	0.38	0.5417
ethnicty	3	2572.15	857.38	4.27	0.0072
grade	1	36.31	36.31	0.18	0.6717
disadvg	1	59.30	59.30	0.30	0.5882
Residuals	93	18682.87	200.89		

```
fm3 <- glm(disadvg ~ ethnicty*grade, data = tli, family = binomial)
xtable(fm3)
```

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	3.1888	1.5966	2.00	0.0458
ethnictyHISPANIC	-0.2848	2.4808	-0.11	0.9086
ethnictyOTHER	212.1701	22122.7093	0.01	0.9923
ethnictyWHITE	-8.8150	3.3355	-2.64	0.0082
grade	-0.5308	0.2892	-1.84	0.0665
ethnictyHISPANIC:grade	0.2448	0.4357	0.56	0.5742
ethnictyOTHER:grade	-32.6014	3393.4687	-0.01	0.9923
ethnictyWHITE:grade	1.0171	0.5185	1.96	0.0498

Too many decimals are used here, but you can control all that