# Week 2:
# Data Preparation

Visual Data Analytics

University of Sydney

THE UNIVERSITY OF SYDNEY

# Outline

- Data frames
- Operations on data frames
- Data types
- Data profiling

# Data frames

# What is data?

- Data can be *structured* or *unstructured*
- Structured data has
  - Observations/ cases in rows
  - Variables/ features in columns
- Think of structured data as something that can be put into a spreadsheet.

# Example

| | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | Player | Games Played | Minutes | Points | Birthplace |
| 2 | LeBron James | 1394 | 53142 | 37860 | Akron, USA |
| 3 | Kevin Durant | 974 | 35776 | 26565 | Washington DC, USA |
| 4 | James Harden | 962 | 33378 | 23915 | Los Angeles, USA |
| 5 | Russell Westbrook | 1054 | 36352 | 23781 | Long Beach, USA |
| 6 | Chris Paul | 1178 | 40623 | 21235 | Winston-Salem, USA |
| 7 | Stephen Curry | 852 | 29256 | 20843 | Akron, USA |
| 8 | DeMar DeRozan | 993 | 34087 | 20812 | Compton, USA |
| 9 | Damian Lillard | 734 | 26648 | 18149 | Oakland, USA |
| 10 | Rudy Gay | 1089 | 34135 | 17463 | New York, USA |
| 11 | Paul George | 765 | 25711 | 15713 | Palmdale, USA |
| 12 | Kyle Lowry | 1055 | 33750 | 15556 | Philadelphia, USA |
| 13 | Giannis Antetokounmpo | 686 | 22365 | 15283 | Athens, Greece |
| 14 | Anthony Davis | 629 | 21641 | 15075 | Chicago, USA |
| 15 | Bradley Beal | 668 | 23211 | 14772 | St Louis, USA |
| 16 | Kyrie Irving | 637 | 21756 | 14770 | Melbourne, Australia |

Current as of January 2023

# US Cities and States

| | A | B |
|---|---|---|
| 1 | Akron | Ohio |
| 2 | Los Angeles | California |
| 3 | Long Beach | California |
| 4 | Winston-Salem | North Carolina |
| 5 | Compton | California |
| 6 | Oakland | California |
| 7 | New York | New York |
| 8 | Palmdale | California |
| 9 | Philadelphia | Pennsylvania |
| 10 | Chicago | Illinois |
| 11 | St Louis | Missouri |
| 12 | | |

# Observations and variables

- In the first table:
  - What are the observations?
  - What are the variables?
- How about the second table?

# Pandas

- The Python library *pandas* stores data in a basic object called a *data frame*.
- It also provides functions for reading in and manipulating data frames.

# NBA Data

```
import pandas as pd
NBA = pd.read_csv('../data/NBA1.csv')
NBA
```

```
##                     Player  Games Played  Minutes  Points           Birthpl
## 0             LeBron James          1394    53142   37860            Akron,
## 1             Kevin Durant           974    35776   26565  Washington DC,
## 2             James Harden           962    33378   23915     Los Angeles,
## 3        Russell Westbrook          1054    36352   23781      Long Beach,
## 4               Chris Paul          1178    40623   21235  Winston-Salem,
## 5            Stephen Curry           852    29256   20843            Akron,
## 6            DeMar DeRozan           993    34087   20812          Compton,
## 7           Damian Lillard           734    26648   18149          Oakland,
## 8                 Rudy Gay          1089    34135   17463         New York,
## 9              Paul George           765    25711   15713         Palmdale,
## 10              Kyle Lowry          1055    33750   15556     Philadelphia,
## 11  Giannis Antetokounmpo            686    22365   15283        Athens, Gre
## 12           Anthony Davis           629    21641   15075          Chicago,
## 13            Bradley Beal           668    23211   14772        St Louis,
## 14            Kyrie Irving           637    21756   14770  Melbourne, Austra
```

# Keys

- A key uniquely identifies an entry into the database.
- In the first table the player name can act as a key.
- Player birthplace could not be a key since both James and Curry are born in Akron.
- However, be careful with names as keys, since two players may have the same name.

# Atomicity

- Beware of variables that combine multiple pieces of information.
- Birthplace can be broken down into city and country.
- This may be useful if we want to visualise points scored by players born in USA and players born outside USA.
- Variables should be *atomic*
- This is also known as *parsing* the data.

# Split

```
new = NBA.Birthplace.str.split(', ',expand = True)
new
```

```
##                   0          1
## 0             Akron        USA
## 1     Washington DC        USA
## 2       Los Angeles        USA
## 3        Long Beach        USA
## 4     Winston-Salem        USA
## 5             Akron        USA
## 6           Compton        USA
## 7           Oakland        USA
## 8          New York        USA
## 9          Palmdale        USA
## 10     Philadelphia        USA
## 11           Athens     Greece
## 12          Chicago        USA
## 13         St Louis        USA
## 14        Melbourne  Australia
```

# With original table

```
NBA["CityOfBirth"] = new[0]
NBA["CountryOfBirth"] = new[1]
NBA
```

```
##                    Player  Games Played  ...    CityOfBirth  CountryOfBirth
## 0            LeBron James          1394  ...          Akron             USA
## 1            Kevin Durant           974  ...  Washington DC             USA
## 2            James Harden           962  ...    Los Angeles             USA
## 3       Russell Westbrook          1054  ...     Long Beach             USA
## 4              Chris Paul          1178  ...  Winston-Salem             USA
## 5           Stephen Curry           852  ...          Akron             USA
## 6           DeMar DeRozan           993  ...        Compton             USA
## 7          Damian Lillard           734  ...        Oakland             USA
## 8                Rudy Gay          1089  ...       New York             USA
## 9             Paul George           765  ...       Palmdale             USA
## 10             Kyle Lowry          1055  ...   Philadelphia             USA
## 11  Giannis Antetokounmpo           686  ...         Athens          Greece
## 12          Anthony Davis           629  ...        Chicago             USA
## 13           Bradley Beal           668  ...      St Louis              USA
## 14           Kyrie Irving           637  ...      Melbourne       Australia
##
```

# Another example

| Player | Points |
|---|---|
| Steph Curry | 20843 for Warriors |
| Kevin Durant | 17566 for Thunder, 5374 for Warriors, 3625 for Nets |

# Split

| Player | Points for Warriors | Points for Thunder | Points for Nets |
|---|---|---|---|
| Steph Curry | 20843 | | |
| Kevin Durant | 5374 | 17566 | 3625 |

# Problems

- Empty cells for Steph Curry
  - Not such a big issue (see missing data later)
- What if Kevin Durant moves to another team? (He did...)
- What if we want to include Giannis (only played for Bucks)?
  - Would need new columns and code that previously worked may break.

# Solution

| Player | Team | Points |
|---|---|---|
| Steph Curry | Warriors | 20843 |
| Kevin Durant | Thunder | 17566 |
| Kevin Durant | Warriors | 5374 |
| Kevin Durant | Nets | 3625 |

# First Normal Form

- New data entries can be added by adding rows only.
- Now the player and team combined form key.
- Overall the example so far is about getting the data into the *first normal form*.
- For the purposes of visualisation the lesson is to think carefully about how the data is structured.

# Operations on Data Frames

# The simple machines

- Hundreds of years ago, it was believed that all machines were made up of six simple machines
- These include: levers, wheels, pulleys, screws, etc.
- Nowadays machines are more complicated.
- But this is a good metaphor for data frames

# Simple machines of data

- We will consider six "simple machines" of data frames.
  - Transforming
  - Sorting
  - Filtering
  - Group by/ aggregate
  - Reshaping (melting and casting)
  - Joining (merging)
- By some combination of these we can 'munge' data frames into almost any data frame we need.

# Transform

- Create a new variable based on values of existing variables.
- For example, in the NBA data frame we have games played and points.
- Suppose we want to create a variable of points per game (PPG)

# Transform in Python

```
NBA["PPG"]=NBA["Points"]/ NBA["Games Played"]
NBA
```

```
##                   Player  Games Played  ...  CountryOfBirth        PPG
## 0           LeBron James          1394  ...             USA  27.159254
## 1           Kevin Durant           974  ...             USA  27.274127
## 2           James Harden           962  ...             USA  24.859667
## 3      Russell Westbrook          1054  ...             USA  22.562619
## 4             Chris Paul          1178  ...             USA  18.026316
## 5          Stephen Curry           852  ...             USA  24.463615
## 6          DeMar DeRozan           993  ...             USA  20.958711
## 7         Damian Lillard           734  ...             USA  24.726158
## 8               Rudy Gay          1089  ...             USA  16.035813
## 9            Paul George           765  ...             USA  20.539869
## 10            Kyle Lowry          1055  ...             USA  14.745024
## 11 Giannis Antetokounmpo           686  ...          Greece  22.278426
## 12         Anthony Davis           629  ...             USA  23.966614
## 13          Bradley Beal           668  ...             USA  22.113772
## 14          Kyrie Irving           637  ...       Australia  23.186813
##
```

# Sort

- Suppose we want to sort the data according to one of the variables.
- We can use the `sort_values` function.
- Consider that we want to sort by minutes played from smallest to largest.

# Players by minutes

```
NBAbymin = NBA.sort_values(by = 'Minutes')
NBAbymin
```

```
##                     Player  Games Played  ...  CountryOfBirth        PPG
## 12           Anthony Davis           629  ...             USA  23.966614
## 14            Kyrie Irving           637  ...       Australia  23.186813
## 11   Giannis Antetokounmpo           686  ...          Greece  22.278426
## 13            Bradley Beal           668  ...             USA  22.113772
## 9              Paul George           765  ...             USA  20.539869
## 7           Damian Lillard           734  ...             USA  24.726158
## 5            Stephen Curry           852  ...             USA  24.463615
## 2             James Harden           962  ...             USA  24.859667
## 10              Kyle Lowry          1055  ...             USA  14.745024
## 6            DeMar DeRozan           993  ...             USA  20.958711
## 8                 Rudy Gay          1089  ...             USA  16.035813
## 1             Kevin Durant           974  ...             USA  27.274127
## 3        Russell Westbrook          1054  ...             USA  22.562619
## 4               Chris Paul          1178  ...             USA  18.026316
## 0             LeBron James          1394  ...             USA  27.159254
##
```

# Filter

- Filtering involves selecting only some subset of the data.
- There are many ways to do this
  - Select rows
  - Select columns
- Select by a logical condition

# Example

- Suppose we only want to consider
  - Players with points per game greater than 20
  - Players born in Akron
  - Players not born in the United States
- These are all examples of logical conditions (either true or false).

# Players with PPG above 20

```
NBAppg20 = NBA.loc[NBA["PPG"]>20]
NBAppg20
```

```
##                     Player  Games Played  ...  CountryOfBirth        PPG
## 0             LeBron James          1394  ...             USA  27.159254
## 1             Kevin Durant           974  ...             USA  27.274127
## 2             James Harden           962  ...             USA  24.859667
## 3        Russell Westbrook          1054  ...             USA  22.562619
## 5            Stephen Curry           852  ...             USA  24.463615
## 6            DeMar DeRozan           993  ...             USA  20.958711
## 7           Damian Lillard           734  ...             USA  24.726158
## 9              Paul George           765  ...             USA  20.539869
## 11   Giannis Antetokounmpo           686  ...          Greece  22.278426
## 12           Anthony Davis           629  ...             USA  23.966614
## 13            Bradley Beal           668  ...             USA  22.113772
## 14            Kyrie Irving           637  ...       Australia  23.186813
##
## [12 rows x 8 columns]
```

# Players born in Akron

```
NBAAkr = NBA.loc[NBA["CityOfBirth"] == 'Akron']
NBAAkr
```

```
##            Player  Games Played  Minutes  ...  CityOfBirth CountryOfBirth
## 0    LeBron James          1394    53142  ...        Akron            USA  2
## 5   Stephen Curry           852    29256  ...        Akron            USA  2
##
## [2 rows x 8 columns]
```

Note that a single = denotes assignment, a double == denotes 'equals' in a logical statement.

# Players born outside USA

```
NBAnonUS = NBA.loc[NBA["CountryOfBirth"] != 'USA']
NBAnonUS
```

```
##                      Player  Games Played  ...  CountryOfBirth        PPG
## 11  Giannis Antetokounmpo           686  ...          Greece  22.278426
## 14            Kyrie Irving           637  ...       Australia  23.186813
##
## [2 rows x 8 columns]
```

In general we can read ! as 'not' in Python

# Group by / aggregate

- Suppose we want to compare total points scored by players country of birth.
- This requires two functions
  - The `groupby` function tells us the variable to group on (in this case Country of Birth).
  - The `agg` function tells us which variable to aggregate (in this case points)

# Groupby/aggregate in Python

```
NBAg = NBA.groupby('CountryOfBirth').agg({'Points': 'sum'})
NBAg
```

```
##                    Points
## CountryOfBirth
## Australia           14770
## Greece              15283
## USA                271739
```

Other ways to aggregate include mean, min and max.

# Reshape

- Often in order to produce the visualisation we want we need to reshape the data.
- This is done using two functions
  - The function `melt` converts the data from wide to long.
  - The function `pivot` converts the data from long to wide.

# Melting

```
NBAlong = NBA.melt(id_vars=['Player'],value_vars=['Games Played', 'Minu
NBAlong
```

```
##                     Player      variable  value
## 0             LeBron James  Games Played   1394
## 1             Kevin Durant  Games Played    974
## 2             James Harden  Games Played    962
## 3        Russell Westbrook  Games Played   1054
## 4               Chris Paul  Games Played   1178
## 5            Stephen Curry  Games Played    852
## 6            DeMar DeRozan  Games Played    993
## 7           Damian Lillard  Games Played    734
## 8                 Rudy Gay  Games Played   1089
## 9              Paul George  Games Played    765
## 10              Kyle Lowry  Games Played   1055
## 11   Giannis Antetokounmpo  Games Played    686
## 12           Anthony Davis  Games Played    629
## 13            Bradley Beal  Games Played    668
## 14            Kyrie Irving  Games Played    637
## 15            LeBron James       Minutes  53142
```

# Pivoting

```
NBAwide = NBAlong.pivot(index='Player', columns = 'variable')
NBAwide
```

```
##                                    value
## variable                     Games Played Minutes Points
## Player
## Anthony Davis                         629   21641  15075
## Bradley Beal                          668   23211  14772
## Chris Paul                           1178   40623  21235
## Damian Lillard                        734   26648  18149
## DeMar DeRozan                         993   34087  20812
## Giannis Antetokounmpo                 686   22365  15283
## James Harden                          962   33378  23915
## Kevin Durant                          974   35776  26565
## Kyle Lowry                           1055   33750  15556
## Kyrie Irving                          637   21756  14770
## LeBron James                         1394   53142  37860
## Paul George                           765   25711  15713
## Rudy Gay                             1089   34135  17463
## Russell Westbrook                    1054   36352  23781
```

# A better example

```
Sydney = pd.read_csv('../data/SydneyClimate.csv')
Sydney
```

```
##    Year   M01   M02   M03   M04   M05   M06   M07   M08   M09   M10   M11
## 0  2017   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN  24.9  24.8
## 1  2018  28.5  28.1  27.4  26.7  22.2  17.7  19.9  19.3  21.0  21.9  25.0
## 2  2019  29.6  27.7  26.9  25.1  22.7  18.6  19.8  19.5  22.0  24.7  27.0
## 3  2020  29.0  27.5  25.6  24.5  20.3  18.7  18.2  19.5  22.7  24.2  26.1
## 4  2021  27.4  26.7  25.5  24.3  20.9  18.1  18.2  20.7  22.5  24.2  23.2
## 5  2022  27.7  26.7  24.8  23.7  20.8  18.3  17.0  19.8  20.6  22.6  24.3
```

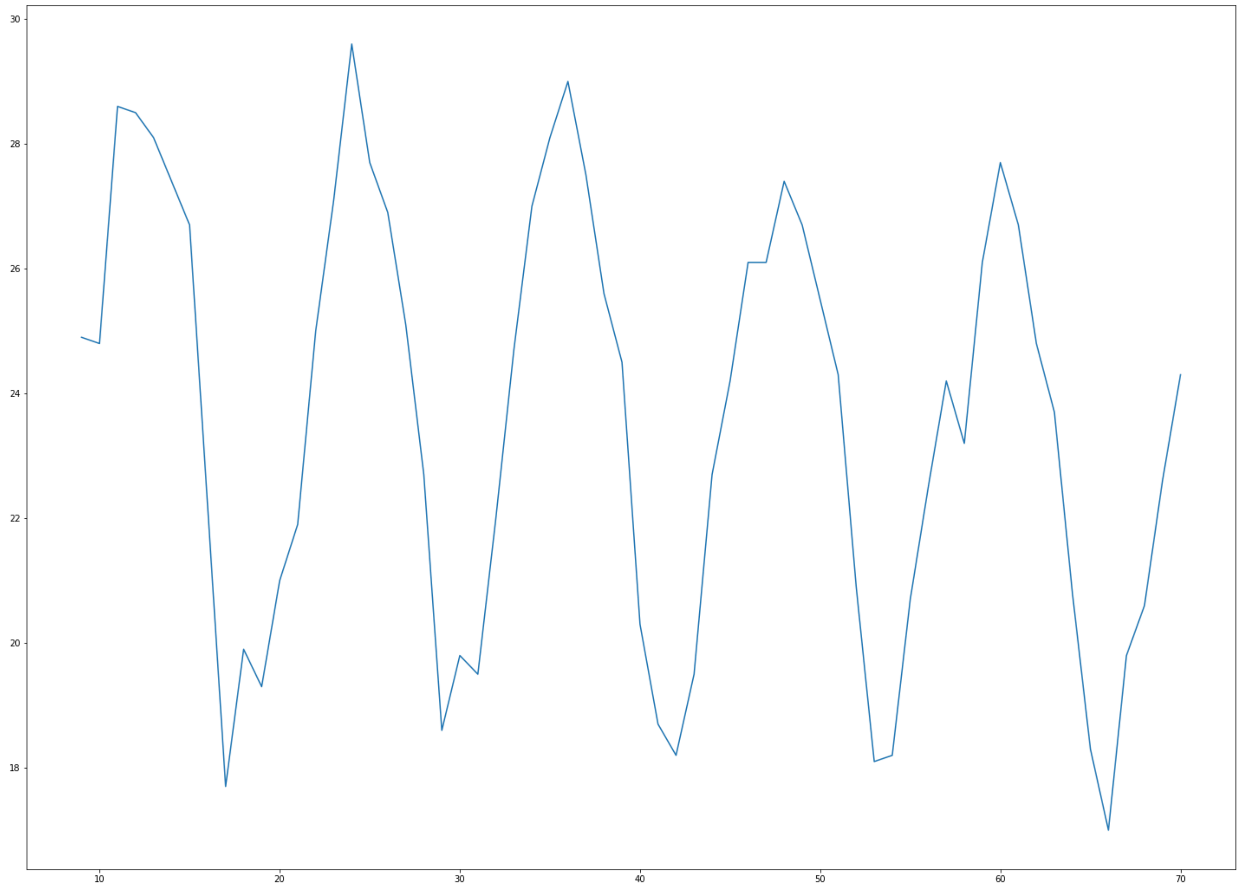
Retrieved from Bureau of Meteorology

# Melting

```
Sydlong = Sydney.melt(id_vars='Year').sort_values(by = ['Year','variabl
Sydlong
```

```
##      Year variable  value
## 0    2017      M01    NaN
## 6    2017      M02    NaN
## 12   2017      M03    NaN
## 18   2017      M04    NaN
## 24   2017      M05    NaN
## ..    ...      ...    ...
## 47   2022      M08   19.8
## 53   2022      M09   20.6
## 59   2022      M10   22.6
## 65   2022      M11   24.3
## 71   2022      M12    NaN
##
## [72 rows x 3 columns]
```

# Plot



# Merge

- Bring two data frames together
- Similar to a VLOOKUP type function in spreadsheet programs such as Excel.
- We can use `merge` to add information about State of birth for NBA players.

# Merge

```
CitiesStates = pd.read_csv('../data/UScitiesstates.csv')
NBAmerge = pd.merge(NBA,CitiesStates, left_on = 'CityOfBirth', right_on
NBAmerge
```

```
##                 Player  Games Played  ...            City           State
## 0         LeBron James          1394  ...           Akron            Ohio
## 1        Stephen Curry           852  ...           Akron            Ohio
## 2         James Harden           962  ...     Los Angeles      California
## 3    Russell Westbrook          1054  ...      Long Beach      California
## 4           Chris Paul          1178  ...  Winston-Salem  North Carolina
## 5        DeMar DeRozan           993  ...         Compton      California
## 6       Damian Lillard           734  ...         Oakland      California
## 7             Rudy Gay          1089  ...        New York        New York
## 8          Paul George           765  ...        Palmdale      California
## 9           Kyle Lowry          1055  ...    Philadelphia    Pennsylvania
## 10       Anthony Davis           629  ...         Chicago        Illinois
## 11        Bradley Beal           668  ...        St Louis        Missouri
##
## [12 rows x 10 columns]
```

# Different type of merge

- Left: Keep all entries from first data frame
- Right: Keep all entries from second data frame
- Inner: Keep all entries that appear in both data frames
- Outer: Keep all entries that appear in either data frame

# Merge

```
CitiesStates = pd.read_csv('../data/UScitiesstates.csv')
NBAmerge = pd.merge(NBA,CitiesStates, how = 'outer', left_on = 'CityOfB
NBAmerge
```

```
##                       Player  Games Played  ...            City          State
## 0               LeBron James          1394  ...           Akron           Ohio
## 1              Stephen Curry           852  ...           Akron           Ohio
## 2               Kevin Durant           974  ...             NaN            NaN
## 3               James Harden           962  ...     Los Angeles     California
## 4          Russell Westbrook          1054  ...      Long Beach     California
## 5                 Chris Paul          1178  ...   Winston-Salem North Carolina
## 6              DeMar DeRozan           993  ...         Compton     California
## 7             Damian Lillard           734  ...         Oakland     California
## 8                   Rudy Gay          1089  ...        New York       New York
## 9                Paul George           765  ...        Palmdale     California
## 10                Kyle Lowry          1055  ...    Philadelphia   Pennsylvania
## 11     Giannis Antetokounmpo           686  ...             NaN            NaN
## 12             Anthony Davis           629  ...         Chicago       Illinois
## 13              Bradley Beal           668  ...        St Louis       Missouri
## 14              Kyrie Irving           637  ...             NaN            NaN
```

# Putting them together

- In your own time, construct data frames for the following:
  - Each observation is a state and with the maximum points per minute (PPM) by a player from each state.
  - The same as above with states ranked from highest to lowest according to the maximum PPM.
  - The same as above but with an extra column with the player name of the player with the highest PPM in each state.
- There may be more than one correct answer.

# Data types

# Data Types

- Each variable measures a certain characteristic.
- Characteristics can be measured in different ways
- This leads to *data type* which are important for understanding
  - How we can transform data.
  - The correct visualisation to use.

# Scales of measurement

- Any old (or new) statistics textbook will introduce four scales of measurement
  - Nominal
  - Ordinal
  - Interval
  - Ratio
- These are still useful (with some caveats).

# Nominal data

- Tells us something about a characteristic but there is no notion of having more or less of a characteristic.
- Example: Country of birth.
- Can you think of other examples?
- Even if we assign numbers to nominal categories, it does not make sense to find means medians etc.
- The mode still makes sense.

# Ordinal data

- Tells us whether we have more or less of a characteristic, but not how much more or less.
- Example: rate players as good, very good, excellent.
- If we assign numbers to nominal categories it still does not make sense to add or subtract these numbers.
- However the median (and the mode) still make sense.

# Interval/Ratio data

- All numerical data is either interval or ratio data.
- The differences between the two concern whether the zero point of the scale truly represents an absence of the characteristic being measured.
- Best understood with an example.

# Points per game

- Suppose I constructed a new index for points per game (PPG) where a PPG of 20 now becomes a PPG of 0.
  - Paul George (PPG: 20.5) would have a "new" PPG of 0.5.
  - Steph Curry (PPG: 24.5) would have a "new" PPG of 4.5.
- Does this mean that Curry is scoring 9 times as much as George? No.

# The textbook example

- The famous example is temperature.
- The Celsius scale attaches 0 and 100 to the freezing and boiling point of water.
  - This is arbitrary
- For the Kelvin scale, zero is true zero since it is a temperature where atoms have no energy (loosely speaking).

# Does it matter?

- Not that much (outside of science).
- Most data we see in business are ratio data.
- In general, I will use *numeric data* and *ratio data* interchangeably.
- Just think carefully when dividing with numerical variables.

# Summary

| Operation | Nominal | Ordinal | Interval | Ratio |
|---|---|---|---|---|
| Equality | ✔ | ✔ | ✔ | ✔ |
| Order | | ✔ | ✔ | ✔ |
| Add / subtract | | | ✔ | ✔ |
| Multiply / divide | | | | ✔ |
| Mode | ✔ | ✔ | ✔ | ✔ |
| Median | | ✔ | ✔ | ✔ |
| Arithmetic mean | | | ✔ | ✔ |
| Geometric mean | | | | ✔ |

# Some exceptions

- Nominal data with two categories.
  - Born in US assigned 1, born outside US assigned 0.
  - Arithmetic mean is then the *proportion* born in US.
- Likert (customer satisfaction) scales:
  - Strongly disagree = 1, Disagree = 2, etc.
  - Using an arithmetic mean is controversial but common in practice.
- Time is very unusual since calendar effects are important in business.

# Types in Pandas

```
NBA.dtypes
```

```
## Player                  object
## Games Played             int64
## Minutes                  int64
## Points                   int64
## Birthplace              object
## CityOfBirth             object
## CountryOfBirth          object
## PPG                    float64
## dtype: object
```

Object is text, int64 is an integer and float64 is a real number.

# Data Profiling

# Some issues

- Duplicated entries
  - Can be removed using `drop_duplicates` function in pandas.
- Data entry errors
  - For example, one cannot score 20000 points in 3 minutes.
  - Requires domain knowledge.
  - These issues can be discovered during visualisation.

# Standardisations

- Steph Curry may appear elsewhere in the data as
  - "Stephen Curry"
  - "Wardell Stephen Curry II" (his full name).
- Similar things happen with company names Facebook/ Meta, General Motors/ GM etc.
- Requires domain knowledge and some extra coding.

# Missing Data

- There are often missing data
- Need to think of a good strategy to encode missing data.
- In Python there is `NaN` for this.
- Often will replace with a number but this is a bad strategy

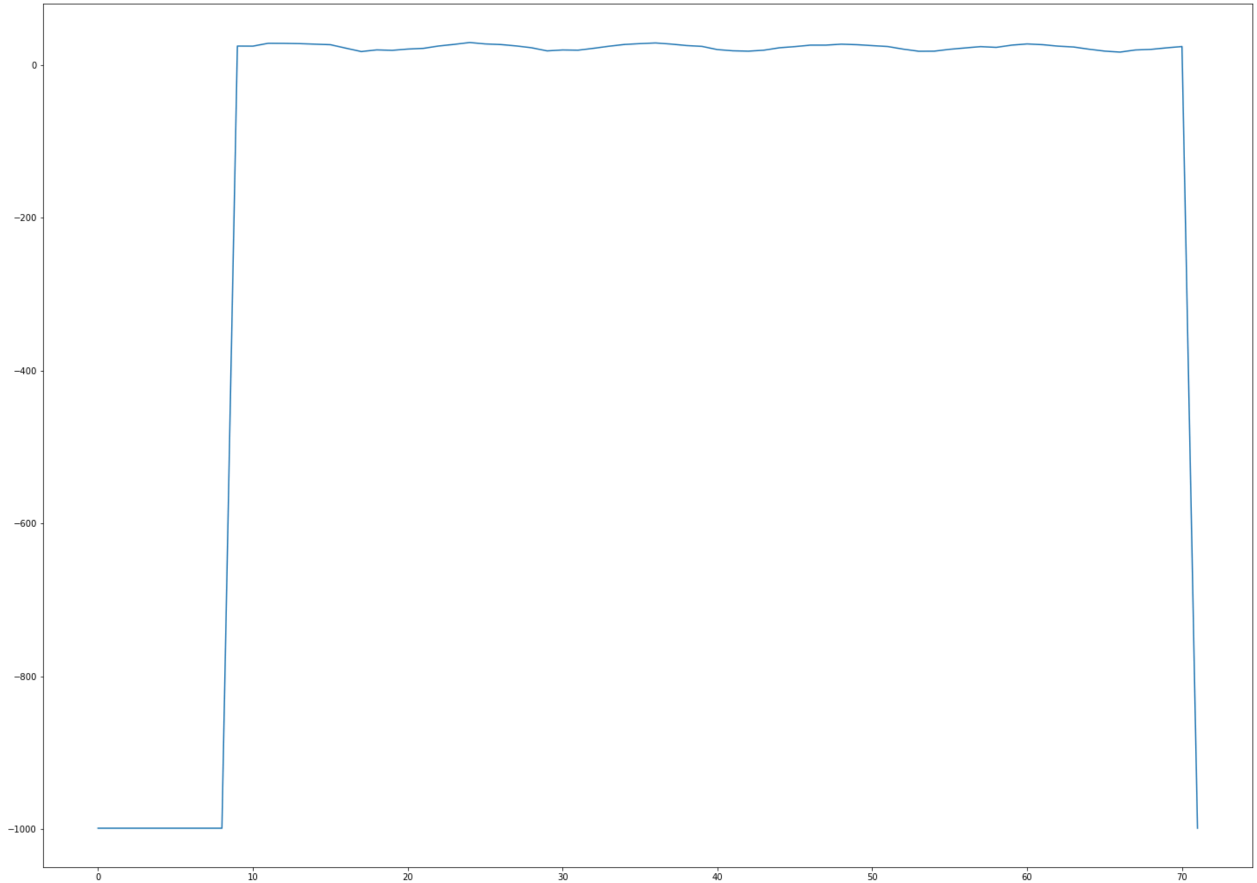
# Do not use "0" for "missing"

- Suppose if games played is missing and we replace with zero.
- The zeros will distort the mean.
- If we compute points per game there will be division by zero.
- Do not replace missing values by zeros.

# Do not use "-999" for "missing"

- Sometimes a completely implausible number such as -999 is used to denote missing.
- This can lead to strange visualisations
- The following example is for the Sydney temperature data

# Temperature



# Dealing with missing data

- Only use complete cases
- Impute missing values
  - With a random value
  - With mean/median or mode
  - More complicated models
- Report/Visualise missing data
  - By reporting missing data this gives a better idea of uncertainty.

# Report missing

**Do you approve or disapprove of the job Anthony Albanese is doing as Prime Minister?**

| | TOTAL | Labor | TOTAL: Coalition | Greens | Minor parties/ Independents |
|---|---|---|---|---|---|
| Strongly approve | 18% | 30% | 10% | 22% | 9% |
| Approve | 42% | 58% | 31% | 49% | 29% |
| Disapprove | 16% | 5% | 26% | 13% | 23% |
| Strongly disapprove | 12% | 0% | 22% | 2% | 26% |
| Don't know | 13% | 7% | 11% | 14% | 13% |
| TOTAL: Approve | 60% | 88% | 41% | 71% | 39% |
| TOTAL: Disapprove | 28% | 5% | 48% | 15% | 49% |

Source: Guardian

# Wrap-up

# Conclusions

- Our focus from now on will be visualisation.
- Writing code to visualise messy data is hard.
- Spend the time to clean your data.
- Focus on the *principles* since these work for Excel, Tableau, R, Python, etc.
- After you appreciate the principles, practice your coding.

Questions