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1 Data Cleaning with Python

It's commonly said that data scientists spend 80% of their time cleaning and manipulating data and only 20% of their time analyzing it. The time spent cleaning is vital since analyzing dirty data can lead us to draw inaccurate conclusions. Data cleaning is an essential task in data science. Without properly cleaned data, the results of any data analysis or machine learning model could be inaccurate. Here I will work to identify, diagnose, and treat a variety of data cleaning problems in Python, ranging from simple to advanced. I will deal with improper data types, check that the data is in the correct range, handle missing data, perform record linkage, and more!

Common Data Problems

Here I'll learn how to overcome some of the most common dirty data problems. I'll convert data types, apply range constraints to remove future data points, and remove duplicated data points to avoid double-counting.

Common data types

Manipulating and analyzing data with incorrect data types could lead to compromised analysis as you go along the data science workflow.

When working with new data, you should always check the data types of your columns using the .dtypes attribute or the .info() method which I'll work on next. Often times, I'll run into columns that should be converted to different data types before starting any analysis.

Correctly identifying what type your data is is one of the easiest ways to avoid hampering your analysis due to data type constraints in the long run.

Numeric data or … ?

I'll be working with bicycle ride sharing data in San Francisco called ride_sharing. It contains information on the start and end stations, the trip duration, and some user information for a bike sharing service.

The user_type column contains information on whether a user is taking a free ride and takes on the following values:

1 - for free riders.

2 - for pay per ride.

3 - for monthly subscribers.

I will print the information of ride_sharingusing .info() and see a firsthand example of how an incorrect data type can flaw the analysis of the dataset. The pandaspackage is imported as pd.

[1]:
```
import pandas as pd
```

[4]:
```
ride_sharing = pd.read_csv('ride_sharing_new.csv', index_col=0)
```

[7]:
```
# Printing the information of ride_sharing
print(ride_sharing.info())

# Printing summary statistics of user_type column
print(ride_sharing['user_type'].describe())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25760 entries, 0 to 25759
Data columns (total 9 columns):
duration           25760 non-null object
station_A_id       25760 non-null int64
station_A_name     25760 non-null object
station_B_id       25760 non-null int64
station_B_name     25760 non-null object
bike_id            25760 non-null int64
user_type          25760 non-null int64
user_birth_year    25760 non-null int64
user_gender        25760 non-null object
dtypes: int64(5), object(4)
memory usage: 2.0+ MB
None
count    25760.000000
mean         2.008385
std          0.704541
min          1.000000
25%          2.000000
50%          2.000000
75%          3.000000
max          3.000000
Name: user_type, dtype: float64
```

[6]:
```
ride_sharing.head()
```

[6]:
```
     duration  station_A_id  \
0  12 minutes            81
1  24 minutes             3
2   8 minutes            67
3   4 minutes            16
4  11 minutes            22

                                  station_A_name  station_B_id  \
```

```
0                                Berry St at 4th St           323
1       Powell St BART Station (Market St at 4th St)           118
2  San Francisco Caltrain Station 2  (Townsend St…           23
3                           Steuart St at Market St            28
4                             Howard St at Beale St           350

                 station_B_name  bike_id  user_type  user_birth_year  \
0             Broadway at Kearny     5480          2             1959
1  Eureka Valley Recreation Center     5193          2             1965
2    The Embarcadero at Steuart St     3652          3             1993
3     The Embarcadero at Bryant St     1883          1             1979
4            8th St at Brannan St     4626          2             1994

  user_gender
0        Male
1        Male
2        Male
3        Male
4        Male
```

Question

By looking at the summary statistics - they don't really seem to offer much description on how users are distributed along their purchase type, why do you think that is?

Answer:

The user_type column has a finite set of possible values that represent groupings of data, it should be converted to category.

Convert user_type into categorical by assigning it the 'category' data type and store it in the user_type_cat column.

Make sure you converted user_type_cat correctly by using an assert statement.

[8]:

```python
# Printing the information of ride_sharing
print(ride_sharing.info())

# Printing summary statistics of user_type column
print(ride_sharing['user_type'].describe())

# Converting user_type from integer to category
ride_sharing['user_type_cat'] = ride_sharing['user_type'].astype('category')

# Writing an assert statement confirming the change
assert ride_sharing['user_type_cat'].dtype == 'category'

# Printing new summary statistics
print(ride_sharing['user_type_cat'].describe())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25760 entries, 0 to 25759
Data columns (total 9 columns):
duration           25760 non-null object
station_A_id       25760 non-null int64
station_A_name     25760 non-null object
station_B_id       25760 non-null int64
station_B_name     25760 non-null object
bike_id            25760 non-null int64
user_type          25760 non-null int64
user_birth_year    25760 non-null int64
user_gender        25760 non-null object
dtypes: int64(5), object(4)
memory usage: 2.0+ MB
None
count    25760.000000
mean         2.008385
std          0.704541
min          1.000000
25%          2.000000
50%          2.000000
75%          3.000000
max          3.000000
Name: user_type, dtype: float64
count     25760
unique        3
top           2
freq      12972
Name: user_type_cat, dtype: int64
```

[9]:

```
ride_sharing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25760 entries, 0 to 25759
Data columns (total 10 columns):
duration           25760 non-null object
station_A_id       25760 non-null int64
station_A_name     25760 non-null object
station_B_id       25760 non-null int64
station_B_name     25760 non-null object
bike_id            25760 non-null int64
user_type          25760 non-null int64
user_birth_year    25760 non-null int64
user_gender        25760 non-null object
user_type_cat      25760 non-null category
dtypes: category(1), int64(5), object(4)
memory usage: 2.0+ MB
```

[ ]:
```
Taking a look at the new summary statistics, it seems that most users are pay␣
↪per ride users!
```

[10]:
```
# Stripping duration of minutes
ride_sharing['duration_trim'] = ride_sharing['duration'].str.strip('minutes')

# Converting duration to integer
ride_sharing['duration_time'] = ride_sharing['duration_trim'].astype('int')

# Writing an assert statement making sure of conversion
assert ride_sharing['duration_time'].dtype == 'int'

# Printing formed columns and calculate average ride duration
print(ride_sharing[['duration','duration_trim','duration_time']])
print(ride_sharing['duration_time'].mean())
```

```
         duration duration_trim  duration_time
0      12 minutes           12             12
1      24 minutes           24             24
2       8 minutes            8              8
3       4 minutes            4              4
4      11 minutes           11             11
…             …            …              …
25755  11 minutes           11             11
25756  10 minutes           10             10
25757  14 minutes           14             14
25758  14 minutes           14             14
25759  29 minutes           29             29

[25760 rows x 3 columns]
11.389052795031056
```

11 minutes is really not bad for an average ride duration in a city like San-Francisco. Next I am going to jump right ahead into sanity checking the range of values in the data.

[11]:
```
ride_sharing.head()
```

[11]:
```
     duration  station_A_id  \
0  12 minutes            81
1  24 minutes             3
2   8 minutes            67
3   4 minutes            16
4  11 minutes            22

                                       station_A_name  station_B_id  \
0                                     Berry St at 4th St           323
1         Powell St BART Station (Market St at 4th St)           118
2   San Francisco Caltrain Station 2  (Townsend St…            23
```

```
3                            Steuart St at Market St            28
4                              Howard St at Beale St           350

                    station_B_name  bike_id  user_type  user_birth_year  \
0                Broadway at Kearny     5480          2             1959
1  Eureka Valley Recreation Center     5193          2             1965
2    The Embarcadero at Steuart St     3652          3             1993
3     The Embarcadero at Bryant St     1883          1             1979
4              8th St at Brannan St     4626          2             1994

  user_gender user_type_cat duration_trim  duration_time
0        Male             2            12             12
1        Male             2            24             24
2        Male             3             8              8
3        Male             1             4              4
4        Male             2            11             11
```

Tire size constraints

Here I am going to build on top of the work you've been doing with the ride_sharing DataFrame. I'll be working with the tire_sizes column which contains data on each bike's tire size.

Bicycle tire sizes could be either 26 , 27 or 29 and are here correctly stored as a categorical value. In an effort to cut maintenance costs, the ride sharing provider decided to set the maximum tire size to be 27 .

I will make sure the tire_sizes column has the correct range by first converting it to an integer, then setting and testing the new upper limit of 27 for tire sizes.

[ ]:
```
# Convert tire_sizes to integer
#ride_sharing['tire_sizes'] = ride_sharing['tire_sizes'].astype('int')

# Set all values above 27 to 27
#ride_sharing.loc[ride_sharing['tire_sizes'] > 27, 'tire_sizes'] = 27

# Reconvert tire_sizes back to categorical
#ride_sharing['tire_sizes'] = ride_sharing['tire_sizes'].astype('category')

# Print tire size description
#print(ride_sharing['tire_sizes'].describe())
```

Now I will work on another arilines dataset and deal with text and categorical data problems

[49]:
```
import datetime as dt
today_date = dt.date.today()
```

[50]:
```
today_date
```

[50]:
```
datetime.date(2020, 7, 5)
```

[17]:
```
airlines = pd.read_csv('airlines_final.csv')
airlines.head()
```

[17]:
```
   Unnamed: 0    id        day      airline        destination    dest_region  \
0           0  1351    Tuesday  UNITED INTL             KANSAI           Asia
1           1   373     Friday       ALASKA  SAN JOSE DEL CABO  Canada/Mexico
2           2  2820   Thursday        DELTA        LOS ANGELES        West US
3           3  1157    Tuesday    SOUTHWEST        LOS ANGELES        West US
4           4  2992  Wednesday     AMERICAN              MIAMI        East US

  dest_size boarding_area   dept_time  wait_min     cleanliness  \
0       Hub  Gates 91-102  2018-12-31     115.0           Clean
1     Small   Gates 50-59  2018-12-31     135.0           Clean
2       Hub   Gates 40-48  2018-12-31      70.0         Average
3       Hub   Gates 20-39  2018-12-31     190.0           Clean
4       Hub   Gates 50-59  2018-12-31     559.0  Somewhat clean

          safety        satisfaction
0        Neutral      Very satisfied
1      Very safe      Very satisfied
2  Somewhat safe             Neutral
3      Very safe  Somewhat satsified
4      Very safe  Somewhat satsified
```

Text and categorical data problems

Categorical and text data can often be some of the messiest parts of a dataset due to their unstructured nature. Here I will work to fix whitespace and capitalization inconsistencies in category labels, collapse multiple categories into one, and reformat strings for consistency.

[51]:
```
categories = pd.read_csv('survey.csv')
categories
```

[51]:
```
      cleanliness           safety          satisfaction
0           Clean          neutral        Very satisfied
1         Average        Very safe               Neutral
2  Somewhat clean    Somewhat safe    Somewhat satisfied
3  Somewhat cirty      Very unsafe  Somewhat unsatisfied
4           Dirty  Somewhat unsafe      Very unsatisfied
```

[18]:
```
# Print categories DataFrame
print(categories)

# Print unique values of survey columns in airlines
print('Cleanliness: ', airlines['cleanliness'].unique(), "\n")
print('Safety: ', airlines['safety'].unique(), "\n")
print('Satisfaction: ', airlines['satisfaction'].unique(), "\n")
```

```
      cleanliness           safety          satisfaction
0           Clean          neutral        Very satisfied
1         Average        Very safe               Neutral
2  Somewhat clean    Somewhat safe    Somewhat satisfied
3  Somewhat cirty      Very unsafe  Somewhat unsatisfied
4           Dirty  Somewhat unsafe      Very unsatisfied
Cleanliness:  ['Clean' 'Average' 'Somewhat clean' 'Somewhat dirty' 'Dirty']

Safety:  ['Neutral' 'Very safe' 'Somewhat safe' 'Very unsafe' 'Somewhat unsafe']

Satisfaction:  ['Very satisfied' 'Neutral' 'Somewhat satsified' 'Somewhat
unsatisfied'
 'Very unsatisfied']
```

[19]:

```
# Finding the cleanliness category in airlines not in categories
cat_clean = set(airlines['cleanliness']).difference(categories['cleanliness'])

# Finding rows with that category
cat_clean_rows = airlines['cleanliness'].isin(cat_clean)

# Printing rows with inconsistent category
print(airlines[cat_clean_rows])
```

```
      Unnamed: 0    id       day        airline        destination  \
0              0  1351   Tuesday    UNITED INTL             KANSAI
1              1   373    Friday         ALASKA  SAN JOSE DEL CABO
3              3  1157   Tuesday      SOUTHWEST        LOS ANGELES
6              6  2578  Saturday        JETBLUE         LONG BEACH
10            11  1129   Tuesday      SOUTHWEST          SAN DIEGO
…            …     …         …              …                  …
2470        2802   394    Friday         ALASKA        LOS ANGELES
2473        2805  2222  Thursday      SOUTHWEST            PHOENIX
2474        2806  2684    Friday         UNITED            ORLANDO
2475        2807  2549   Tuesday        JETBLUE         LONG BEACH
2476        2808  2162  Saturday  CHINA EASTERN            QINGDAO

        dest_region dest_size boarding_area   dept_time  wait_min cleanliness  \
0              Asia       Hub  Gates 91-102  2018-12-31     115.0       Clean
1     Canada/Mexico     Small   Gates 50-59  2018-12-31     135.0       Clean
3           West US       Hub   Gates 20-39  2018-12-31     190.0       Clean
6           West US     Small    Gates 1-12  2018-12-31      63.0       Clean
10          West US    Medium   Gates 20-39  2018-12-31     540.0       Clean
…               …         …            …          …         …           …
2470        West US       Hub   Gates 50-59  2018-12-31     115.0       Clean
2473        West US       Hub   Gates 20-39  2018-12-31     165.0       Clean
2474        East US       Hub   Gates 70-90  2018-12-31      92.0       Clean
2475        West US     Small    Gates 1-12  2018-12-31      95.0       Clean
```

```
2476           Asia     Large    Gates 1-12  2018-12-31     220.0       Clean

             safety        satisfaction
0           Neutral      Very satisfied
1         Very safe      Very satisfied
3         Very safe  Somewhat satsified
6         Very safe  Somewhat satsified
10        Very safe  Somewhat satsified
…               …                   …
2470      Very safe      Very satisfied
2473      Very safe      Very satisfied
2474      Very safe      Very satisfied
2475  Somewhat safe      Very satisfied
2476      Very safe  Somewhat satsified

[911 rows x 13 columns]
```

[20]:

```
# Finding the cleanliness category in airlines not in categories
cat_clean = set(airlines['cleanliness']).difference(categories['cleanliness'])

# Finding rows with that category
cat_clean_rows = airlines['cleanliness'].isin(cat_clean)

# Printing rows with inconsistent category
print(airlines[cat_clean_rows])

# Printing rows with consistent categories only
print(airlines[~cat_clean_rows])
```

```
      Unnamed: 0    id       day        airline        destination  \
0              0  1351   Tuesday    UNITED INTL             KANSAI
1              1   373    Friday         ALASKA  SAN JOSE DEL CABO
3              3  1157   Tuesday      SOUTHWEST        LOS ANGELES
6              6  2578  Saturday        JETBLUE         LONG BEACH
10            11  1129   Tuesday      SOUTHWEST          SAN DIEGO
…            …    …       …              …                 …
2470        2802   394    Friday         ALASKA        LOS ANGELES
2473        2805  2222  Thursday      SOUTHWEST            PHOENIX
2474        2806  2684    Friday         UNITED            ORLANDO
2475        2807  2549   Tuesday        JETBLUE         LONG BEACH
2476        2808  2162  Saturday  CHINA EASTERN            QINGDAO

        dest_region dest_size boarding_area   dept_time  wait_min cleanliness  \
0              Asia       Hub  Gates 91-102  2018-12-31     115.0       Clean
1     Canada/Mexico     Small   Gates 50-59  2018-12-31     135.0       Clean
3           West US       Hub   Gates 20-39  2018-12-31     190.0       Clean
6           West US     Small    Gates 1-12  2018-12-31      63.0       Clean
10          West US    Medium   Gates 20-39  2018-12-31     540.0       Clean
```

```
…            …      …           …          …       …         …
2470         West US       Hub   Gates 50-59  2018-12-31     115.0       Clean
2473         West US       Hub   Gates 20-39  2018-12-31     165.0       Clean
2474         East US       Hub   Gates 70-90  2018-12-31      92.0       Clean
2475         West US     Small    Gates 1-12  2018-12-31      95.0       Clean
2476            Asia     Large    Gates 1-12  2018-12-31     220.0       Clean

             safety        satisfaction
0           Neutral      Very satisfied
1         Very safe      Very satisfied
3         Very safe  Somewhat satsified
6         Very safe  Somewhat satsified
10        Very safe  Somewhat satsified
…             …                 …
2470      Very safe      Very satisfied
2473      Very safe      Very satisfied
2474      Very safe      Very satisfied
2475  Somewhat safe      Very satisfied
2476      Very safe  Somewhat satsified

[911 rows x 13 columns]
      Unnamed: 0    id        day         airline   destination  \
2              2  2820   Thursday           DELTA   LOS ANGELES
4              4  2992  Wednesday        AMERICAN         MIAMI
5              5   634   Thursday          ALASKA        NEWARK
7              8  2592   Saturday      AEROMEXICO   MEXICO CITY
8              9   919     Friday      AIR CANADA       TORONTO
…          …    …         …             …            …
2466        2798  3099     Sunday          ALASKA        NEWARK
2468        2800  1942    Tuesday          UNITED        BOSTON
2469        2801  2130   Thursday  CATHAY PACIFIC     HONG KONG
2471        2803  2888  Wednesday          UNITED        AUSTIN
2472        2804  1475    Tuesday          ALASKA  NEW YORK-JFK

        dest_region  dest_size boarding_area   dept_time  wait_min  \
2           West US        Hub   Gates 40-48  2018-12-31      70.0
4           East US        Hub   Gates 50-59  2018-12-31     559.0
5           East US        Hub   Gates 50-59  2018-12-31     140.0
7     Canada/Mexico        Hub    Gates 1-12  2018-12-31     215.0
8     Canada/Mexico        Hub  Gates 91-102  2018-12-31      70.0
…             …          …           …          …       …
2466        East US        Hub   Gates 50-59  2018-12-31     105.0
2468        EAST US      Large   Gates 70-90  2018-12-31     145.0
2469           Asia        Hub    Gates 1-12  2018-12-31     380.0
2471     Midwest US     Medium   Gates 70-90  2018-12-31      60.0
2472        East US        Hub   Gates 50-59  2018-12-31     280.0

         cleanliness           safety        satisfaction
```

```
2            Average    Somewhat safe             Neutral
4     Somewhat clean        Very safe  Somewhat satsified
5     Somewhat clean        Very safe      Very satisfied
7     Somewhat clean        Very safe             Neutral
8     Somewhat clean    Somewhat safe  Somewhat satsified
…                …                …                  …
2466  Somewhat clean        Very safe  Somewhat satsified
2468  Somewhat clean    Somewhat safe  Somewhat satsified
2469  Somewhat clean    Somewhat safe  Somewhat satsified
2471  Somewhat clean  Somewhat unsafe  Somewhat satsified
2472  Somewhat clean          Neutral  Somewhat satsified

[1566 rows x 13 columns]
```

Inconsistent categories

I wil be revisiting the airlines DataFrame from above.

As a reminder, the DataFrame contains flight metadata such as the airline, the destination, waiting times as well as answers to key questions regarding cleanliness, safety, and satisfaction on the San Francisco Airport.

I will examine two categorical columns from this DataFrame, dest_region and dest_size respectively, assess how to address them and make sure that they are cleaned and ready for analysis. The pandas package has been imported as pd, and the airlines DataFrame is in the environment.

[21]:
```python
# Printing the unique values in dest_region and dest_size respectively.
# Printing unique values of both columns
print(airlines['dest_region'].unique())
print(airlines['dest_size'].unique())
```

```
['Asia' 'Canada/Mexico' 'West US' 'East US' 'Midwest US' 'EAST US'
 'Middle East' 'Europe' 'eur' 'Central/South America'
 'Australia/New Zealand' 'middle east']
['Hub' 'Small' '    Hub' 'Medium' 'Large' 'Hub     ' '    Small'
 'Medium     ' '    Medium' 'Small     ' '    Large' 'Large     ']
```

[23]:
```python
# Changing the capitalization of all values of dest_region to lowercase.
# Replacing the 'eur' with 'europe' in dest_region using the .replace() method.
# Printing unique values of both columns
print(airlines['dest_region'].unique())
print(airlines['dest_size'].unique())

# Lowering dest_region column and then replace "eur" with "europe"
airlines['dest_region'] = airlines['dest_region'].str.lower()
airlines['dest_region'] = airlines['dest_region'].replace({'eur':'europe'})
```

```
['asia' 'canada/mexico' 'west us' 'east us' 'midwest us' 'middle east'
 'europe' 'central/south america' 'australia/new zealand']
['Hub' 'Small' 'Medium' 'Large']
```

Stripping white spaces from the dest_size column using the .strip() method.

Verifying that the changes have been into effect by printing the unique values of the columns using .unique() .

[ ]:
```python
# Printing unique values of both columns
print(airlines['dest_region'].unique())
print(airlines['dest_size'].unique())

# Lowering dest_region column and then replace "eur" with "europe"
airlines['dest_region'] = airlines['dest_region'].str.lower()
airlines['dest_region'] = airlines['dest_region'].replace({'eur':'europe'})

# Removing white spaces from `dest_size`
airlines['dest_size'] = airlines['dest_size'].str.strip()

# Verifying changes have been effected
print(airlines['dest_region'].unique())
print(airlines['dest_size'].unique())
```

Remapping categories

To better understand survey respondents from airlines, I want to find out if there is a relationship between certain responses and the day of the week and wait time at the gate.

The airlines DataFrame contains the day and wait_min columns, which are categorical and numerical respectively. The day column contains the exact day a flight took place, and wait_min contains the amount of minutes it took travelers to wait at the gate. To make the analysis easier, I will create two new categorical variables:

wait_type: 'short' for 0-60 min, 'medium' for 60-180 and long for 180+

day_week: 'weekday' if day is in the weekday, 'weekend' if day is in the weekend.

[25]:
```python
# Creating ranges for categories
import numpy as np
label_ranges = [0, 60, 180, np.inf]
label_names = ['short', 'medium', 'long']

# Creating wait_type column
airlines['wait_type'] = pd.cut(airlines['wait_min'], bins = label_ranges,
                                labels = label_names)

# Creating mappings and replace
mappings = {'Monday':'weekday', 'Tuesday':'weekday', 'Wednesday': 'weekday',
            'Thursday': 'weekday', 'Friday': 'weekday',
            'Saturday': 'weekend', 'Sunday': 'weekend'}

airlines['day_week'] = airlines['day'].replace(mappings)
```

[26]:
```
airlines.head()
```

[26]:
```
   Unnamed: 0    id        day      airline        destination    dest_region  \
0           0  1351    Tuesday  UNITED INTL             KANSAI           asia
1           1   373     Friday       ALASKA  SAN JOSE DEL CABO  canada/mexico
2           2  2820   Thursday        DELTA        LOS ANGELES        west us
3           3  1157    Tuesday    SOUTHWEST        LOS ANGELES        west us
4           4  2992  Wednesday     AMERICAN              MIAMI        east us

  dest_size boarding_area   dept_time  wait_min     cleanliness  \
0       Hub  Gates 91-102  2018-12-31     115.0           Clean
1     Small   Gates 50-59  2018-12-31     135.0           Clean
2       Hub   Gates 40-48  2018-12-31      70.0         Average
3       Hub   Gates 20-39  2018-12-31     190.0           Clean
4       Hub   Gates 50-59  2018-12-31     559.0  Somewhat clean

          safety        satisfaction wait_type day_week
0        Neutral      Very satisfied    medium  weekday
1      Very safe      Very satisfied    medium  weekday
2  Somewhat safe             Neutral    medium  weekday
3      Very safe  Somewhat satsified      long  weekday
4      Very safe  Somewhat satsified      long  weekday
```

Advanced data problems

I will dive into more advanced data cleaning problems, such as ensuring that weights are all written in kilograms instead of pounds. This analysis will help us to verify that values have been added correctly and that missing values don't negatively impact the analyses.

Ambiguous dates

I have a DataFrame containing a subscription_date column that was collected from various sources with different Date formats such as YYYY-mm-dd and YYYY-dd-mm. What is the best way to unify the formats for ambiguous values such as 2019-04-07?

- Set them to NA and drop them.
- Infer the format of the data in question by checking the format of subsequent and previous values.
- Infer the format from the original data source.
- All of the above are possible, as long as we investigate where our data comes from, and understand the dynamics affecting it before cleaning it.

Like most cleaning data tasks, ambiguous dates require a thorough understanding of where the data comes from. Diagnosing problems is the first step in finding the best solution!

Uniform currencies

I will now be working with a retail banking dataset stored in the banking DataFrame. The dataset contains data on the amount of money stored in accounts, their currency, amount invested, account opening date and last transaction date that were consolidated from American and European branches.

Here I will be working with understanding the average account size and how investments vary by the size of account, however in order to produce this analysis accurately, we first need to unify the currency amount into dollars.

[27]:
```
banking = pd.read_csv('banking_dirty.csv')
```

[28]:
```
banking.head()
```

[28]:
```
   Unnamed: 0   cust_id  birth_date  Age  acct_amount  inv_amount   fund_A  \
0           0  870A9281  1962-06-09   58     63523.31       51295  30105.0
1           1  166B05B0  1962-12-16   58     38175.46       15050   4995.0
2           2  BFC13E88  1990-09-12   34     59863.77       24567  10323.0
3           3  F2158F66  1985-11-03   35     84132.10       23712   3908.0
4           4  7A73F334  1990-05-17   30    120512.00       93230  12158.4

    fund_B   fund_C   fund_D account_opened last_transaction
0   4138.0   1420.0  15632.0       02-09-18         22-02-19
1    938.0   6696.0   2421.0       28-02-19         31-10-18
2   4590.0   8469.0   1185.0       25-04-18         02-04-18
3    492.0   6482.0  12830.0       07-11-17         08-11-18
4  51281.0  13434.0  18383.0       14-05-18         19-07-18
```

[38]:
```
banking.dtypes
```

[38]:
```
Unnamed: 0                    int64
cust_id                      object
birth_date                   object
Age                           int64
acct_amount                 float64
inv_amount                    int64
fund_A                      float64
fund_B                      float64
fund_C                      float64
fund_D                      float64
account_opened       datetime64[ns]
last_transaction             object
acct_year                    object
dtype: object
```

[ ]:
```
###### Uniform dates

After having unified the currencies of different account amounts, I want to add␣
 ↪a temporal dimension to the analysis and see how customers have been␣
 ↪investing their money given the size of their account over each year. The␣
 ↪account_opened column represents when customers opened their accounts and is␣
 ↪a good proxy for segmenting customer activity and investment over time.
```

```
However, since this data was consolidated from multiple sources, I need to make
↪sure that all dates are of the same format. I will do so by converting this
↪column into a datetime object, while making sure that the format is inferred
↪and potentially incorrect formats are set to missing.

• Printing the header of account_opened from the banking DataFrame and taking a
↪look at the different results.
```

[30]:
```python
# Print the header of account_opened
print(banking['account_opened'].head())
```

```
0    02-09-18
1    28-02-19
2    25-04-18
3    07-11-17
4    14-05-18
Name: account_opened, dtype: object
```

Question

Take a look at the output. You tried converting the values to datetime using the default to_datetime() function without changing any argument, however received the following error:

ValueError: month must be in 1..12

Why do you think that is?

Possible Answers

The to_datetime() function needs to be explicitly told which date format each row is in.

The to_datetime() function can only be applied on YY-mm-dd date formats. (correct)

The 21-14-17 entry is erroneous and leads to an error.

- Converting the account_opened column to datetime, while making sure the date format is inferred and that erroneous formats that raise error return a missing value.

[31]:
```python
# Printing the header of account_opened
print(banking['account_opened'].head())

# Converting account_opened to datetime
banking['account_opened'] = pd.to_datetime(banking['account_opened'],
                                           # Inferring datetime format
                                           infer_datetime_format = True,
                                           # Returning missing value for error
                                           errors = 'coerce')
```

```
0    02-09-18
1    28-02-19
2    25-04-18
```

```
3    07-11-17
4    14-05-18
Name: account_opened, dtype: object
```

- Extracting the year from the amended account_opened column and assign it to the acct_year column.
- Printing the newly created acct_year column.

[32]:
```
# Printing the header of account_opend
print(banking['account_opened'].head())

# Converting account_opened to datetime
banking['account_opened'] = pd.to_datetime(banking['account_opened'],
                                            # Infer datetime format
                                            infer_datetime_format = True,
                                            # Return missing value for error
                                            errors = 'coerce')

# Getting year of account opened
banking['acct_year'] = banking['account_opened'].dt.strftime('%Y')

# Printing acct_year
print(banking['acct_year'])
```

```
0   2018-02-09
1   2019-02-28
2   2018-04-25
3   2017-07-11
4   2018-05-14
Name: account_opened, dtype: datetime64[ns]
0     2018
1     2019
2     2018
3     2017
4     2018
      …
95    2018
96    2017
97    2017
98    2017
99    2017
Name: acct_year, Length: 100, dtype: object
```

How's our data integrity?

New data has been merged into the banking DataFrame that contains details on how investments in the inv_amount column are allocated across four different funds A, B, C and D.

Furthermore, the age and birthdays of customers are now stored in the age and birth_date columns respectively.

I want to understand how customers of different age groups invest. I want to first make sure the data I am analyzing is correct. I will do so by cross field checking values of inv_amount and age against the amount invested in different funds and customers' birthdays.

[33]:
```
# Storing fund columns to sum against
fund_columns = ['fund_A', 'fund_B', 'fund_C', 'fund_D']

# Finding rows where fund_columns row sum == inv_amount
inv_equ = banking[fund_columns].sum(axis = 1) == banking['inv_amount']

# Storing consistent and inconsistent data
consistent_inv = banking[inv_equ]
inconsistent_inv = banking[~inv_equ]

# Storing consistent and inconsistent data
print("Number of inconsistent investments: ", inconsistent_inv.shape[0])
```

```
Number of inconsistent investments:  8
```

Storing today's date into today, and manually calculate customers' ages and storing them in ages_manual.

Finding all rows of banking where the age column is equal to ages_manual and then filtering banking into consistent_ages and inconsistent_ages.

[39]:
```
# Converting birth_date to datetime
banking['birth_date'] = pd.to_datetime(banking['birth_date'],
                                       # Infer datetime format
                                       infer_datetime_format = True,
                                       # Return missing value for error
                                       errors = 'coerce')
```

[41]:
```
# Storing today's date and find ages
today = dt.date.today()
ages_manual = today.year - banking['birth_date'].dt.year

# Finding rows where age column == ages_manual
age_equ = banking['Age'] == ages_manual

# Storing consistent and inconsistent data
consistent_ages = banking[age_equ]
inconsistent_ages = banking[~age_equ]

# Storing consistent and inconsistent data
print("Number of inconsistent ages: ", inconsistent_ages.shape[0])
```

```
Number of inconsistent ages:  8
```

Awesome work! There are only 8 and 8 rows affected by inconsistent inv_amount and age values respectively. In this case, it's best to investigate the underlying data sources before deciding on a course of action!

Is this missing at random?

There are a variety of missingness types when observing missing data. As a reminder, missingness types can be described as the following:

- Missing Completely at Random: No systematic relationship between a column's missing values and other or own values.

- Missing at Random: There is a systematic relationship between a column's missing values and other observed values.

- Missing not at Random: There is a systematic relationship between a column's missing values and unobserved values.

You have a DataFrame containing customer satisfaction scores for a service. What type of missingness is the following?

A customer satisfaction_score column with missing values for highly dissatisfied customers.

Missing completely at random

There's obviously an underlying mechanism behind the missingness of the data.

Missing at Random

This would be more applicable if missing satisfaction_score values were due to values in another column of the DataFrame.

Missing not at random

Awesome work! This is a clear example of missing not at random, where low values of satisfaction_score are missing because of inherently low satisfaction!

[45]:
```
pip install missingno
```

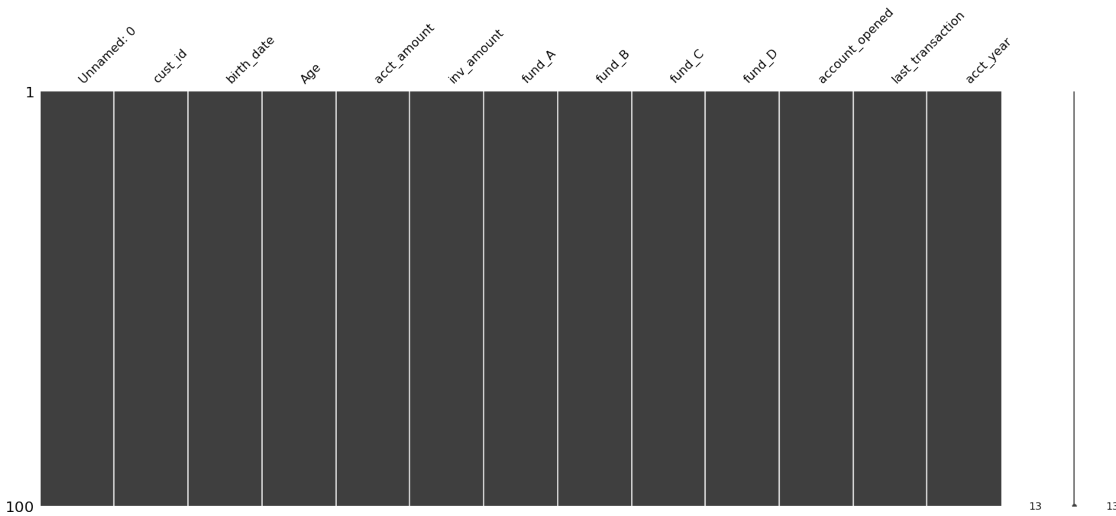
```
Collecting missingno
  Downloading https://files.pythonhosted.org/packages/2b/de/6e4dd6d720c499395443
52155dc06a08c9f7e4271aa631a559dfbeaaf9d4/missingno-0.4.2-py3-none-any.whl
Requirement already satisfied: scipy in /opt/anaconda3/lib/python3.7/site-
packages (from missingno) (1.3.1)
Requirement already satisfied: seaborn in /opt/anaconda3/lib/python3.7/site-
packages (from missingno) (0.9.0)
Requirement already satisfied: matplotlib in /opt/anaconda3/lib/python3.7/site-
packages (from missingno) (3.1.1)
Requirement already satisfied: numpy in /opt/anaconda3/lib/python3.7/site-
packages (from missingno) (1.17.2)
Requirement already satisfied: pandas>=0.15.2 in
/opt/anaconda3/lib/python3.7/site-packages (from seaborn->missingno) (0.25.1)
Requirement already satisfied: cycler>=0.10 in
/opt/anaconda3/lib/python3.7/site-packages (from matplotlib->missingno) (0.10.0)
```

```
Requirement already satisfied: kiwisolver>=1.0.1 in
/opt/anaconda3/lib/python3.7/site-packages (from matplotlib->missingno) (1.1.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/opt/anaconda3/lib/python3.7/site-packages (from matplotlib->missingno) (2.4.2)
Requirement already satisfied: python-dateutil>=2.1 in
/opt/anaconda3/lib/python3.7/site-packages (from matplotlib->missingno) (2.8.0)
Requirement already satisfied: pytz>=2017.2 in
/opt/anaconda3/lib/python3.7/site-packages (from
pandas>=0.15.2->seaborn->missingno) (2019.3)
Requirement already satisfied: six in /opt/anaconda3/lib/python3.7/site-packages
(from cycler>=0.10->matplotlib->missingno) (1.12.0)
Requirement already satisfied: setuptools in /opt/anaconda3/lib/python3.7/site-
packages (from kiwisolver>=1.0.1->matplotlib->missingno) (41.4.0)
Installing collected packages: missingno
Successfully installed missingno-0.4.2
Note: you may need to restart the kernel to use updated packages.
```

[46]:
```
importing matplotlib.pyplot as plt
import missingno as msno
# Print number of missing values in banking
print(banking.isna().sum())

# Visualizing missingness matrix
msno.matrix(banking)
plt.show()
```

```
Unnamed: 0          0
cust_id             0
birth_date          0
Age                 0
acct_amount         0
inv_amount          0
fund_A              0
fund_B              0
fund_C              0
fund_D              0
account_opened      0
last_transaction    0
acct_year           0
dtype: int64
```



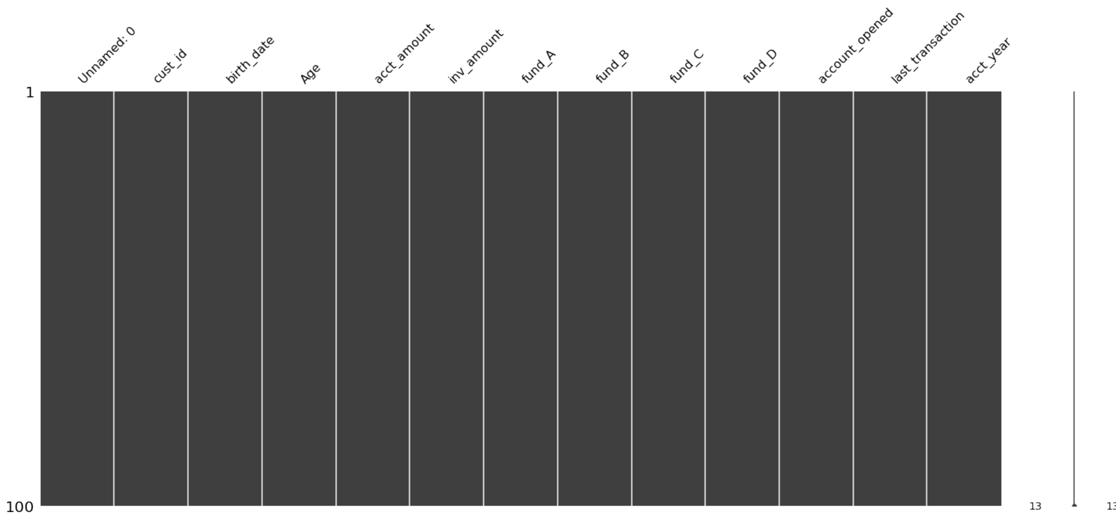
[47]:
```
# Isolating the values of banking missing values of inv_amount into␣
↪missing_investors and with non-missing inv_amount values into investors.

# Printing number of missing values in banking
print(banking.isna().sum())

# Visualizing missingness matrix
msno.matrix(banking)
plt.show()

# Isolating missing and non missing values of inv_amount
missing_investors = banking[banking['inv_amount'].isna()]
investors = banking[~banking['inv_amount'].isna()]
```

```
Unnamed: 0          0
cust_id             0
birth_date          0
Age                 0
acct_amount         0
inv_amount          0
fund_A              0
fund_B              0
fund_C              0
fund_D              0
account_opened      0
last_transaction    0
acct_year           0
dtype: int64
```



That's all for now. I have used many other techniques for data cleaning in my other projects available on my Github page.

Thanks a lot for your attention.

[ ]:

```

```