How to deal with data?

IFT6758, Fall 2020; Lecture 1

Data is variable

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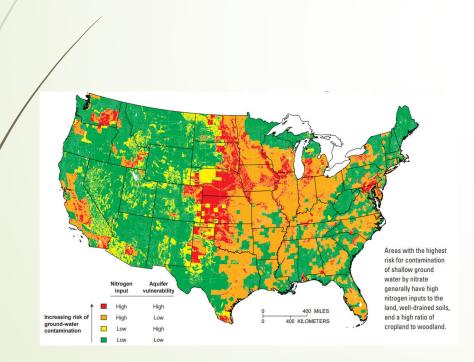


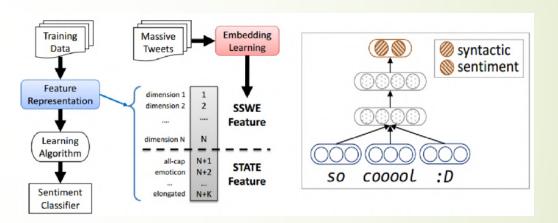




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- Data are the result of deliberate human intervention
- Data is varied across domains and within domains





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Tidy data

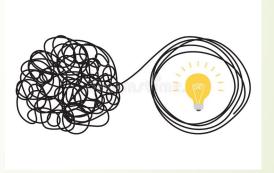
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<u>Tidy data</u>

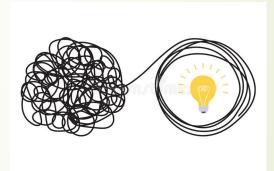
<u>Tidy data in Python</u>



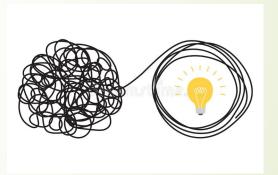
Understand what the variables are



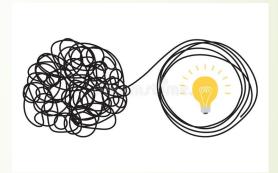
- Understand what the variables are
- Manage column types



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- Handle missing values



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- Manage column types
- Handle missing values
- Join, reorganize, and tidy

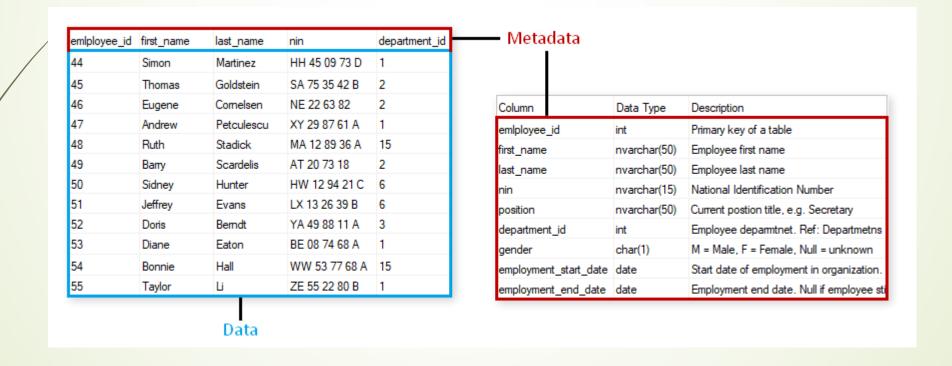


Understand the data: Metadata

- What do the tables mean?
- What do the columns mean?
- How were the data collected?

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 - Chicago Taxi Trips (BigQuery Dataset)
 - includes taxi trips (7000 licensed taxicabs) from 2013 to the present





```
In [6]:
taxi.dtypes
Out [6]:
unique_key
                           object
taxi_id
                           object
trip_start_timestamp
                           object
trip_end_timestamp
                           object
trip_seconds
                          float64
trip_miles
                          float64
pickup_census_tract
                          float64
dropoff_census_tract
                          float64
pickup_community_area
                          float64
dropoff_community_area
                          float64
fare
                          float64
tips
                          float64
tolls
                          float64
                          float64
extras
trip_total
                          float64
                           object
payment_type
                           object
company
pickup_latitude
                          float64
pickup_longitude
                          float64
pickup_location
                          float64
dropoff_latitude
                          float64
dropoff_longitude
                          float64
dropoff_location
                          float64
dtype: object
```

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"22-01-2019T15:00:02" datetime.datetime(2019, 1, 22, 15, 0, 2)

Once it is in datetime format, new attributes can be derived

import datetime

x = datetime.datetime(2018, 6, 1)

print(x.strftime("%B"))

June

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- Lets you convert arbitrary strings into datetime objects

"22-01-2019T15:00:02" datetime.datetime(2019, 1, 22, 15, 0, 2)

Once it is in datetime format, new attributes can be derived

import datetime

x = datetime.datetime.now()

print(x.year)
print(x.strftime("%A"))

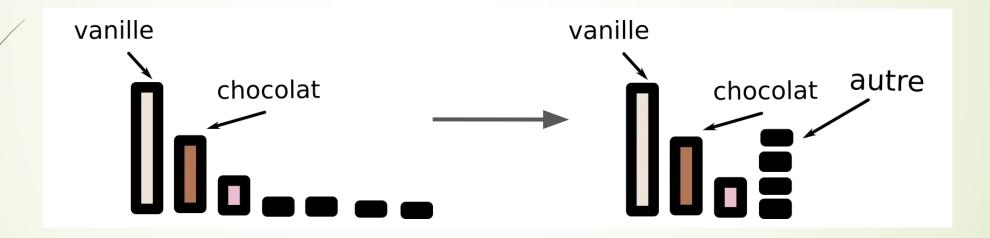
2020 Friday

Common issues

Overwhelming number of levels

Common issues

Overwhelming number of levels

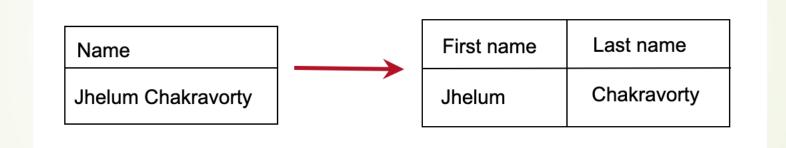


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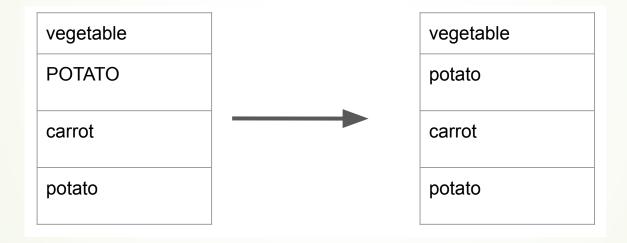


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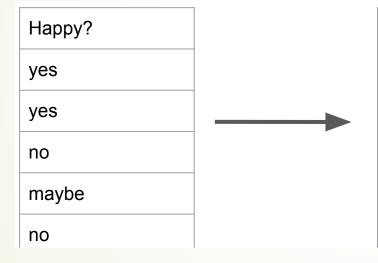


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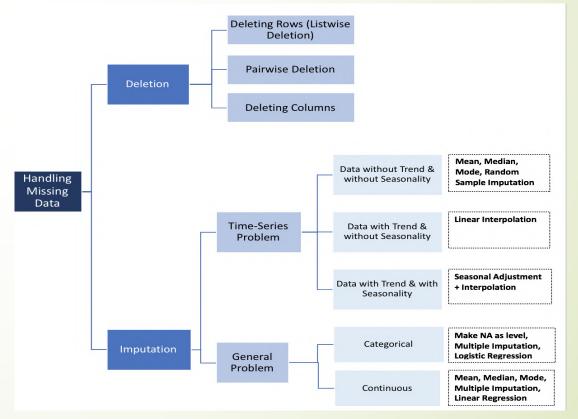


yes	no	maybe
1	0	0
1	0	0
0	1	0
0	0	1
0	1	0

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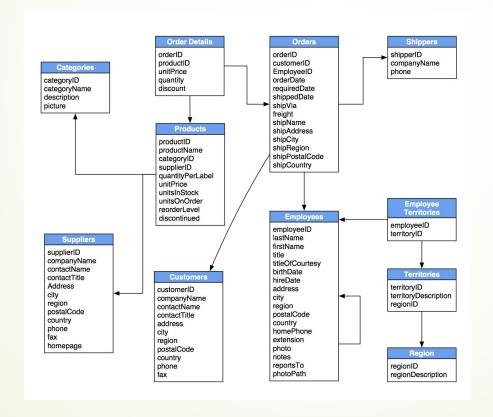


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- Many ways.
 - Imputation and deletion
 - A useful tutorial

Data might be available in messy forms

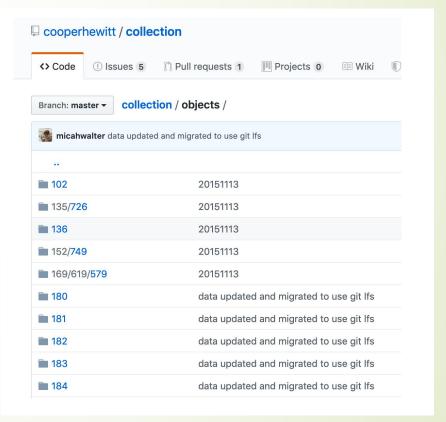
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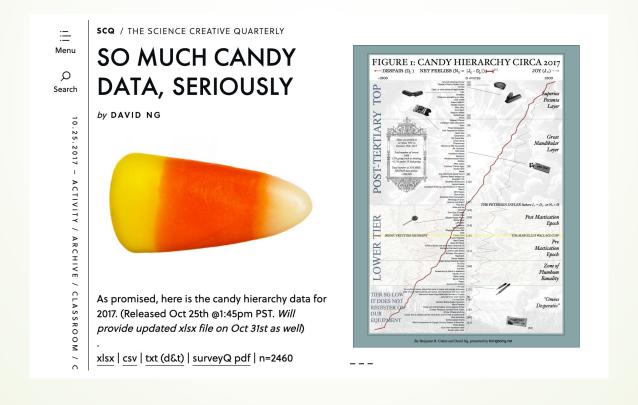


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Painful? Intriguing?

- Persist. There are so many datesets to have fun with.
- Embrace complexity and move forward