INTRODUCTION TO DATA ANALYTICS

Data Processing

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Agenda

- Data Processing
- Data Cleansing
- Data Integration
- Data Transformation
- Feature Engineering

Data Processing

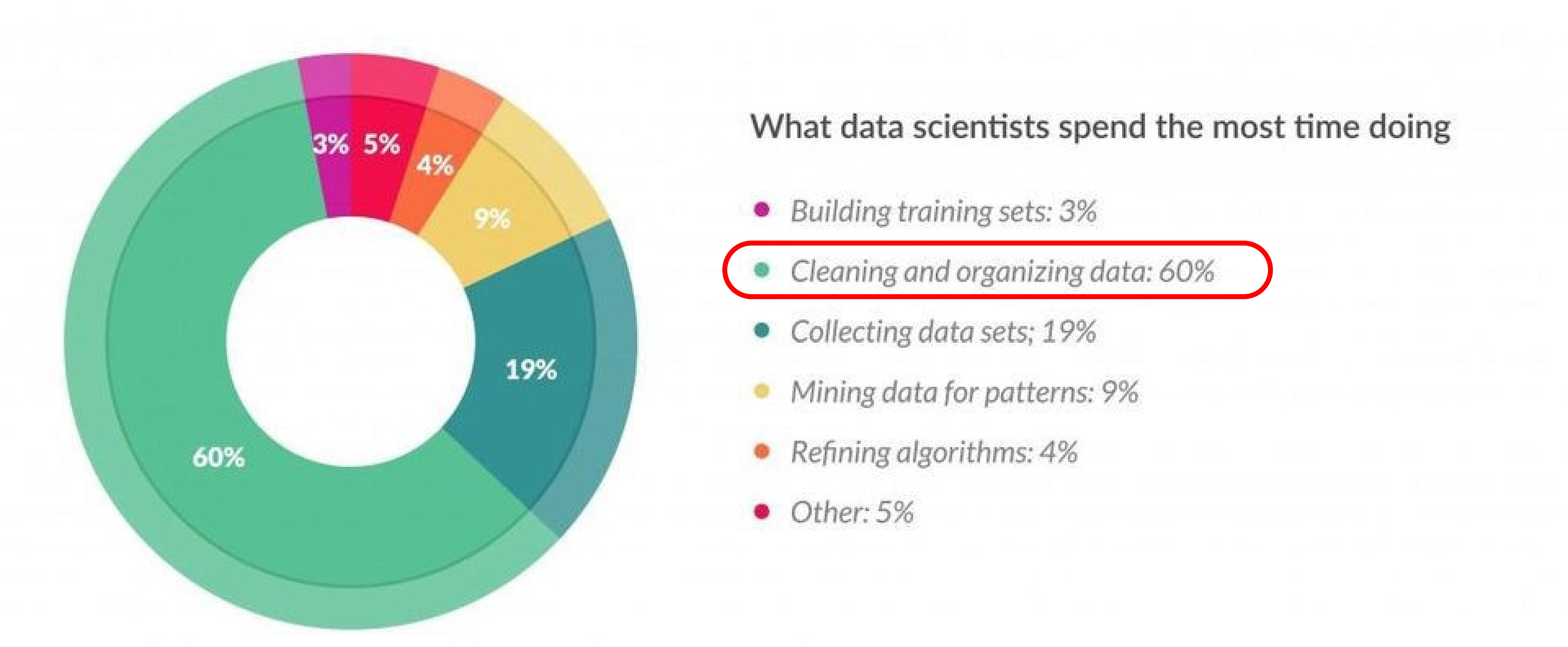
Is Data Beautiful?

Ref: • Brett Romero, “Doing Data Science: A Kaggle Walkthrough – Cleaning Data”

Why Is Data Dirty?

- Incomplete data comes from
  - n/a data value when collected
  - different consideration between the time when the data was collected and when it is analyzed.
  - human/hardware/software problems
- Noisy data comes from the process of data
  - collection
  - entry
  - transmission
- Inconsistent data comes from
  - Different data sources
  - Functional dependency violation

Spending the most time doing …



What data scientists spend the most time doing

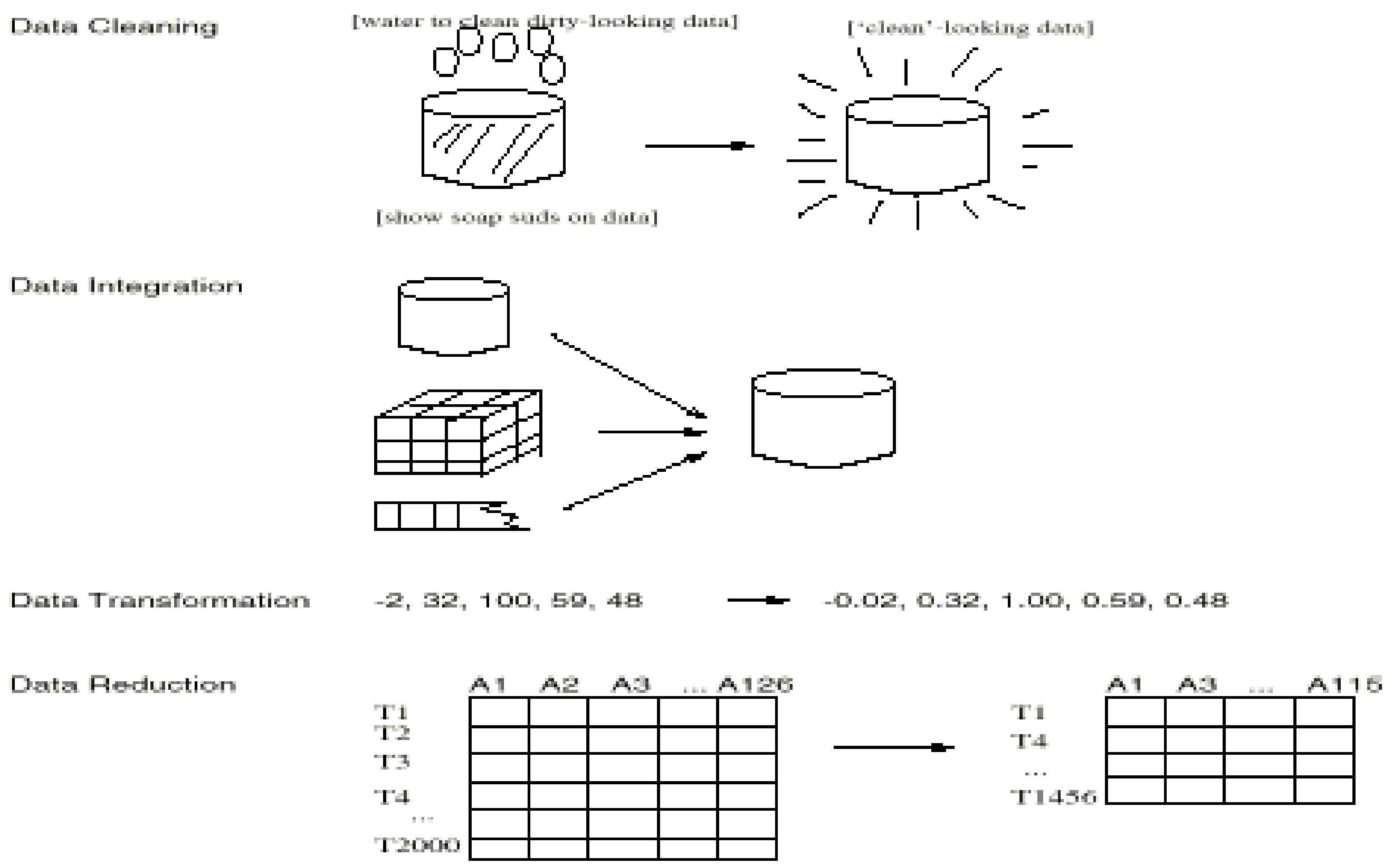
- ● Building training sets: 3%
- ● Cleaning and organizing data: 60%
- ● Collecting data sets; 19%
- ● Mining data for patterns: 9%
- ● Refining algorithms: 4%
- ● Other: 5%

Ref: • (image) https://www.forbes.com/sites/gilpress/2016/03/23/data-preparation-most-time-consuming-least-enjoyable-data-science-task-survey-says/

Tasks

- Data Cleaning
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- Data Integration
  - Integration of multiple databases, data cubes, or files
- Data Transformation
  - Normalization and aggregation
- Data Reduction (NEXT TIME)
  - Obtains reduced representation in volume but produces the same or similar analytical results

Data Processing



Data Cleansing

Data Cleaning

- Importance
  - “Data cleaning is one of the three biggest problems in data warehousing”—Ralph Kimball
  - “Data cleaning is the number one problem in data warehousing”—DCI survey
- Data cleaning tasks
  - Fill in missing values
  - Identify outliers and smooth out noisy data
  - Correct inconsistent data
  - Resolve redundancy caused by data integration

Ref: • Chris Clifton, “Instruction to Data Mining”

Missing Data

- Data is not always available
  - E.g., many tuples have no recorded value for several attributes, such as customer income in sales data
- Missing data may be due to
  - equipment malfunction
  - inconsistent with other recorded data and thus deleted
  - data not entered due to misunderstanding
  - certain data may not be considered important at the time of entry
  - not register history or changes of the data
- Missing data may need to be inferred.

Ref: • Chris Clifton, "Instruction to Data Mining"

How to Handle Missing Data?

- Ignore the tuple: usually done when class label is missing (assuming the tasks in classification—not effective when the percentage of missing values per attribute varies considerably.
- Fill in the missing value manually: tedious + infeasible?
- Fill in it automatically with
  - a global constant : e.g., “unknown”, a new class?!
  - the attribute mean
  - the attribute mean for all samples belonging to the same class: smarter
  - the most probable value: inference-based such as Bayesian formula or decision tree

Options for Dealing With Missing Data

Missing data in general is one of the trickier issues that is dealt with when cleaning data. Broadly there are two solutions:

- **Deleting/Ignoring rows with missing values**
- **Filling in the Values**

Ref: • Brett Romero, "Doing Data Science: A Kaggle Walkthrough – Cleaning Data"

Deleting/Ignoring rows with missing values

- The simplest solution available when faced with missing values is to not use the records with missing values when training your model. However, there are some issues to be aware of before you starting deleting masses of rows from your dataset.
- The first is that this approach only makes sense if the number of rows with missing data is relatively small compared to the dataset. If you are finding that you will be deleting more than around 10% of your dataset due to rows having missing values, you may need to reconsider.

Ref: • Brett Romero, “Doing Data Science: A Kaggle Walkthrough – Cleaning Data”

Filling in the Values

- The second broad option for dealing with missing data is to fill the missing values with a value. But what value to use? This depends on a range of factors, including the type of data you are trying to fill.
- If the data is categorical (i.e. countries, device types, etc.), it may make sense to simply create a new category that will represent 'unknown'.
- Another option may be to fill the values with the most common value for that column (the mode). However, because these are broad methods for filling the missing values, this may oversimplify your data and/or make your final model less accurate.

Ref: • Brett Romero, "Doing Data Science: A Kaggle Walkthrough – Cleaning Data"

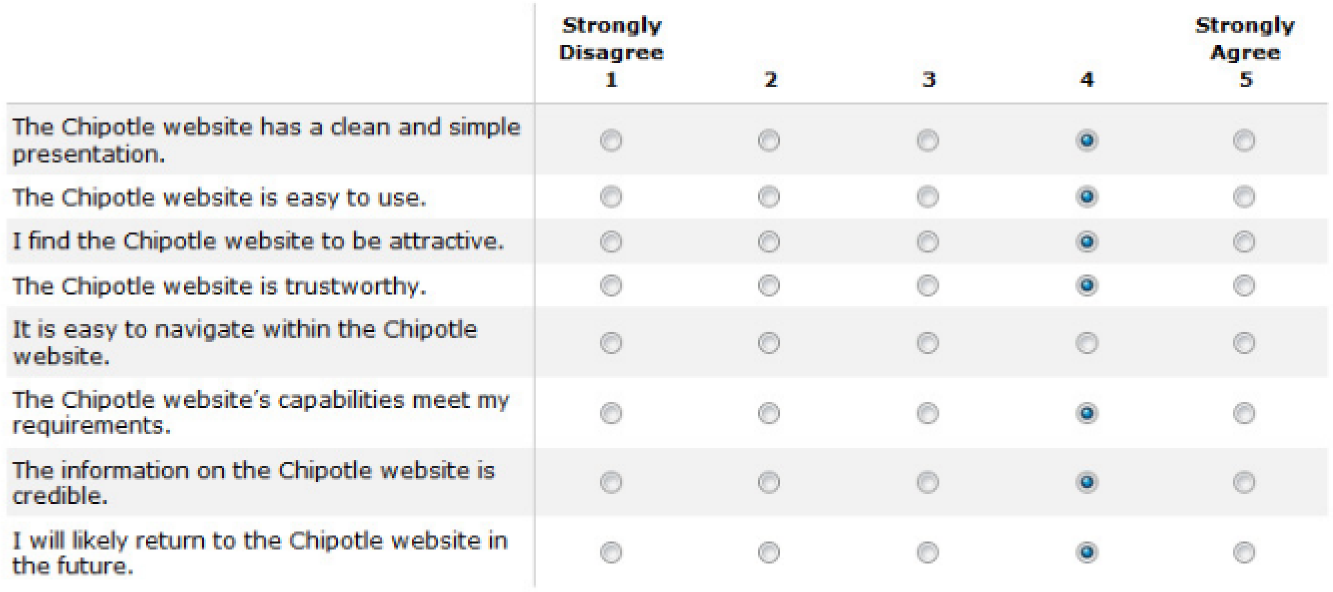
Filling in the Values

- For numerical values (for example the age column) there are some other options. Given that in this case using the mode to fill values makes less sense, we could instead use the mean or median. We could even take an average based on some other criteria – for example filling the missing age values based on an average age for users that selected the same country_destination.
- For both types of data (categorical and numerical), we can also use far more complicated methods to impute the missing values. Effectively, we can use a similar methodology that we are planning to use to predict the country_destination to predict the values in any of the other columns, based on the columns that do have data. And just like with modeling in general, there are an almost endless number of ways this can be done, which won’t be detailed here.

Ref: • Brett Romero, “Doing Data Science: A Kaggle Walkthrough – Cleaning Data”

Educated Guessing

- It sounds arbitrary and isn’t your preferred course of action, but you can often infer a missing value. For related questions, for example, like those often presented in a matrix, if the participant responds with all “4s”, assume that the missing value is a 4.



	Strongly Disagree 1	2	3	4	Strongly Agree 5
The Chipotle website has a clean and simple presentation.	○	○	○	●	○
The Chipotle website is easy to use.	○	○	○	●	○
I find the Chipotle website to be attractive.	○	○	○	●	○
The Chipotle website is trustworthy.	○	○	○	●	○
It is easy to navigate within the Chipotle website.	○	○	○	○	○
The Chipotle website’s capabilities meet my requirements.	○	○	○	●	○
The information on the Chipotle website is credible.	○	○	○	●	○
I will likely return to the Chipotle website in the future.	○	○	○	●	○

Ref: • Jeff Sauro: “7 Ways to Handle Missing Data”

Noisy Data

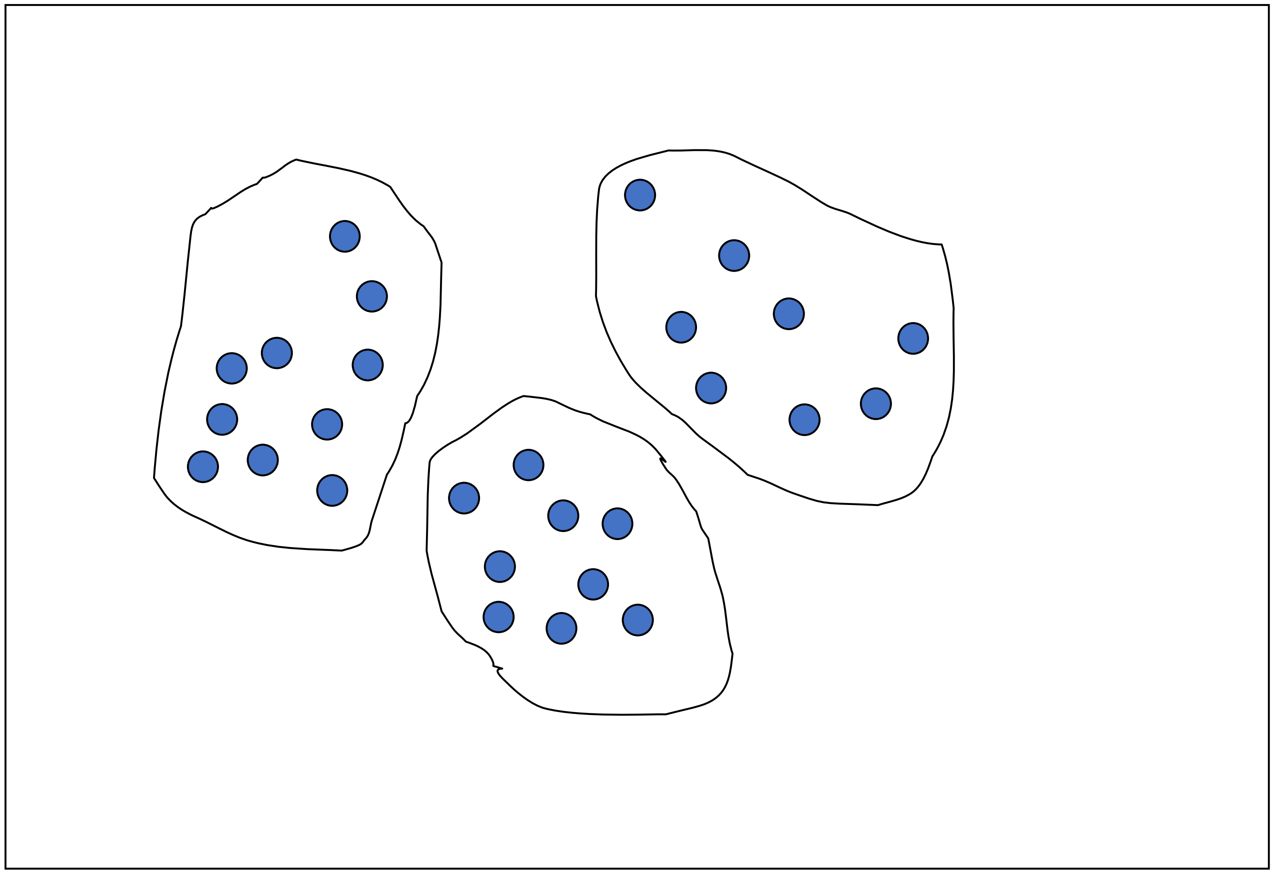
- Noise: random error or variance in a measured variable
- Incorrect attribute values may due to
  - faulty data collection instruments
  - data entry problems
  - data transmission problems
  - technology limitation
  - inconsistency in naming convention
- Other data problems which requires data cleaning
  - duplicate records
  - incomplete data
  - inconsistent data

Ref: • Chris Clifton, “Instruction to Data Mining”

How to Handle Noisy Data?

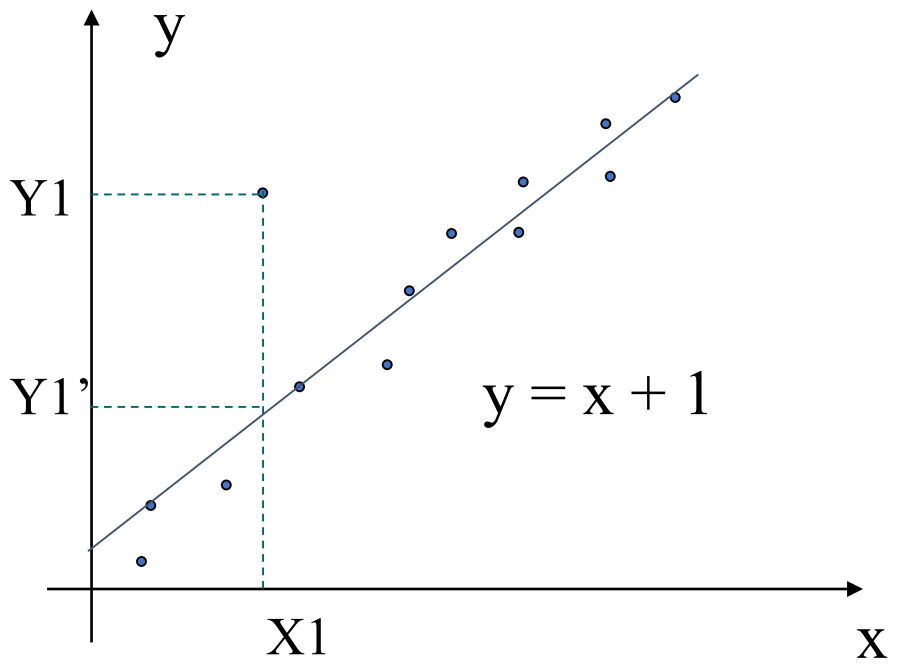
- Clustering
  - detect and remove outliers
- Combined computer and human inspection
  - detect suspicious values and check by human (e.g., deal with possible outliers)
- Regression
  - smooth by fitting the data into regression functions

Cluster Analysis



Ref: • Chris Clifton, “Instruction to Data Mining”

Regression



Data Integration

Data Integration

- Data integration:
  - combines data from multiple sources into a coherent store
- Schema integration
  - integrate metadata from different sources
  - Entity identification problem: identify real world entities from multiple data sources, e.g., A.cust-id ≡ B.cust-#
- Detecting and resolving data value conflicts
  - for the same real world entity, attribute values from different sources are different
  - possible reasons: different representations, different scales, e.g., metric vs. British units

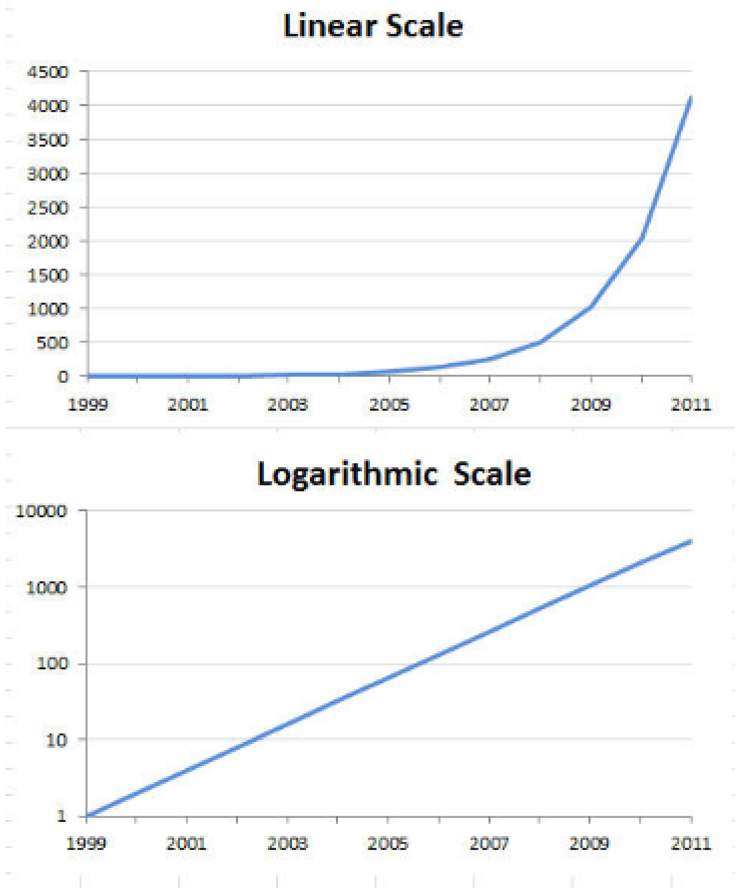
Ref: • Chris Clifton, "Instruction to Data Mining"

Data Integration

Data Transformation

- Smoothing: remove noise from data
- Aggregation: summarization, data cube construction
- Generalization: concept hierarchy climbing
- Normalization: scaled to fall within a small, specified range
  - min-max normalization
  - z-score normalization
  - normalization by decimal scaling
- Attribute/feature construction
  - New attributes constructed from the given ones

Reshape



Ref: • (image) https://www.pinterest.com/pin/413838653229463002/

Sparse Matrix

User	Movie	Rating
u1	m1	3
u1	m2	4
u2	m1	2
u2	m2	4
u2	m3	5
u3	m4	4
u3	m5	2
u4	m4	5
u4	m5	2

$$\Rightarrow$$

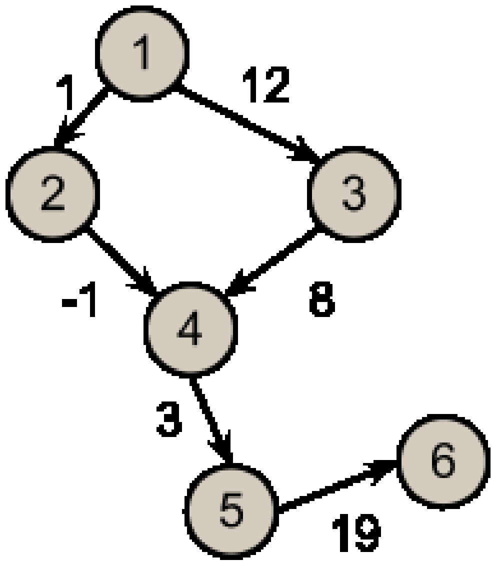
$$\begin{array}{c|c|c|c|c|c|}
 & m1 & m2 & m3 & m4 & m5 \\ \hline
u1 & 3 & 4 & & & \\ \hline
u2 & 2 & 4 & 5 & & \\ \hline
u3 & & & & 4 & 2 \\ \hline
u4 & & & & 5 & 2 \\ \hline
\end{array}$$

Document to Vector

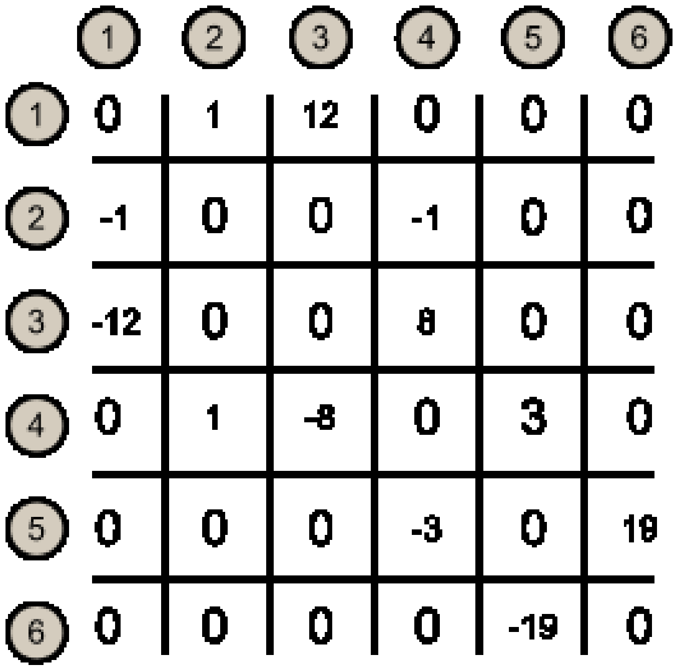
$$\begin{array}{r|cccccc|}
 & D1 & D2 & D3 & D4 & D5 & \ldots \\
\hline
a & 145 & 223 & 346 & 78 & 89 & \cdots \\
abandon & 4 & 0 & 0 & 5 & 3 & \cdots \\
ability & 5 & 10 & 0 & 4 & 7 & \cdots \\
able & 31 & 35 & 64 & 3 & 5 & \cdots \\
about & 64 & 68 & 89 & 24 & 9 & \cdots \\
above & 4 & 5 & 8 & 0 & 0 & \cdots \\
abroad & 0 & 0 & 1 & 0 & 0 & \cdots \\
absence & 2 & 4 & 0 & 0 & 0 & \cdots \\
absent & 0 & 0 & 1 & 0 & 0 & \cdots \\
absolute & 3 & 1 & 5 & 0 & 1 & \cdots \\
abstract & 5 & 1 & 2 & 1 & 0 & \cdots \\
abuse & 0 & 1 & 0 & 0 & 0 & \cdots \\
academic & 1 & 3 & 0 & 0 & 0 & \cdots \\
\ldots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots
\end{array}$$

Ref: • (image) https://lmu-pms.github.io/irom-blog/posts/Doc2Vec.html

Adjacency Matrix



Weighted Directed Graph



	1	2	3	4	5	6
1	0	1	12	0	0	0
2	-1	0	0	-1	0	0
3	-12	0	0	8	0	0
4	0	1	-8	0	3	0
5	0	0	0	-3	0	19
6	0	0	0	0	-19	0

Adjacency Matrix

Ref: • (image) https://www.quora.com/How-can-I-find-the-correct-adjacency-matrix-given-a-particular-graph

Feature Engineering

Feature Engineering

- Imputation
- Handling Outliers
- Binning
- Log Transform
- One-Hot Encoding
- Grouping Operations
- Feature Split
- Scaling
- Extracting Date

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Imputation

- Filling missing values
- **Numerical Imputation**
    - Replace with 0 is not a good solution
    - Mean may be better
    - Mean of the group
    - Same in cluster
    - Regression
- **Categorical Imputation**
    - Replacing the missing values with the maximum occurred value.
    - If values are distributed uniformly and there is not a dominant value, imputing a category like "Other" might be more sensible, because in such a case, your imputation is likely to converge a random selection.

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Handling Outliers

- These will detect them using standard deviation, and percentiles.
- **Outlier Detection with Standard Deviation**
  - If a value has a distance to the average higher than *x* * standard deviation, it can be assumed as an outlier. Then what x should be?
- **Outlier Detection with Percentiles**
  - To assume a certain percent of the value from the top or the bottom as an outlier. The key point is here to set the percentage value once again, and this depends on the distribution of your data.
  - Detect data between 5th and 95th percentiles.
  - An Outlier Dilemma: Drop or Cap

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Binning

- The main motivation of binning is to make the model more robust and prevent overfitting, however, it has a cost to the performance. Every time you bin something, you sacrifice information and make your data more regularized.
- **Numerical Binning Example**

Value	Bin
0-30 ->	Low
31-70 ->	Mid
71-100 ->	High

- **Categorical Binning Example**

Value	Bin
Spain ->	Europe
Italy ->	Europe
Chile ->	South America
Brazil ->	South America

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Log Transform

- Logarithm transformation (or log transform) is one of the most commonly used mathematical transformations in feature engineering. What are the benefits of log transform:
  - It helps to handle skewed data and after transformation, the distribution becomes more approximate to normal.
  - In most of the cases the magnitude order of the data changes within the range of the data. For instance, the difference between ages 15 and 20 is not equal to the ages 65 and 70. In terms of years, 5 years of difference in young ages mean a higher magnitude difference. This type of data comes from a multiplicative process and log transform normalizes the magnitude differences like that.
  - It also decreases the effect of the outliers, due to the normalization of magnitude differences and the model become more robust.

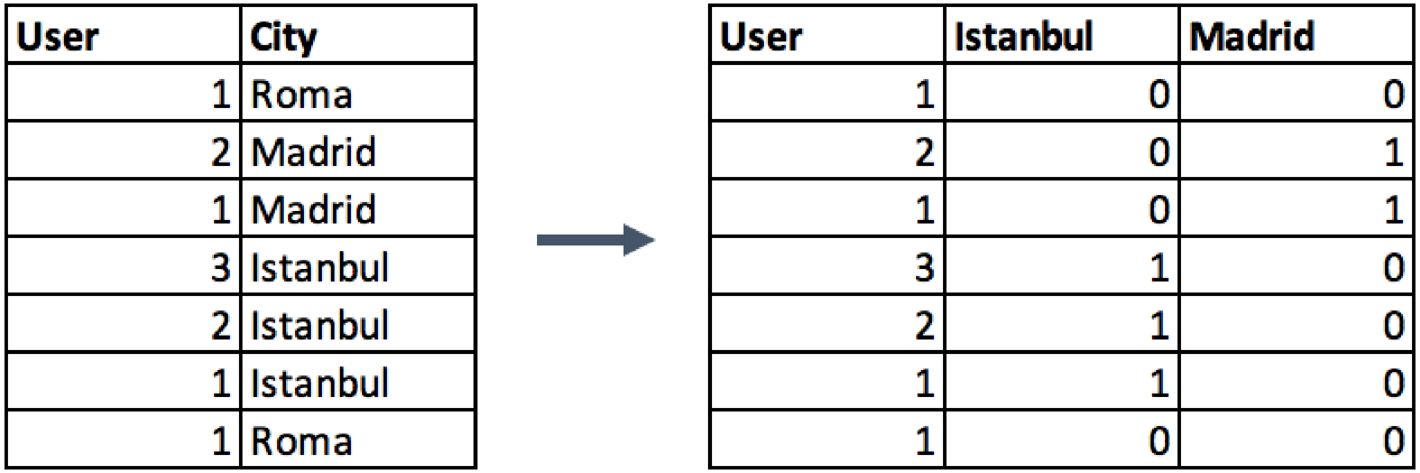
Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

One-Hot Encoding

- One-hot encoding is one of the most common encoding methods in machine learning. This method spreads the values in a column to multiple flag columns and assigns 0 or 1 to them. These binary values express the relationship between grouped and encoded column.
- This method changes your categorical data, which is challenging to understand for algorithms, to a numerical format and enables you to group your categorical data without losing any information. (For details please see the last part of Categorical Column Grouping)

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

One-Hot Encoding



User	City
1	Roma
2	Madrid
1	Madrid
3	Istanbul
2	Istanbul
1	Istanbul
1	Roma

User	Istanbul	Madrid
1	0	0
2	0	1
1	0	1
3	1	0
2	1	0
1	1	0
1	0	0

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

One-Hot Encoding

User	Social Network
A	Facebook, Twitter
B	Instagram
C	Instagram, Facebook

User	Facebook	Instagram	Twitter
A	1	0	1
B	0	1	0
C	1	1	0

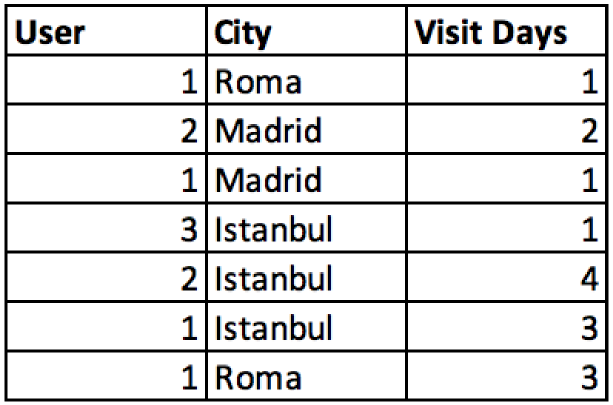
```
encoded_columns = pd.get_dummies(data['column'])
data = data.join(encoded_columns).drop('column', axis=1)
```

Grouping Operations

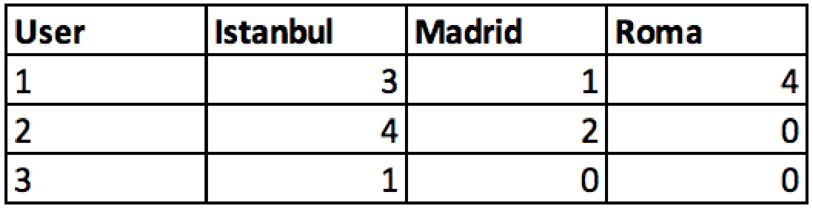
- In most machine learning algorithms, every instance is represented by a row in the training dataset, where every column show a different feature of the instance. This kind of data called "**Tidy**".
- Datasets such as transactions rarely fit the definition of tidy data above, because of the multiple rows of an instance. In such a case, we group the data by the instances and then every instance is represented by only one row.

Grouping Operations

- Categorical Column Grouping



User	City	Visit Days
1	Roma	1
2	Madrid	2
1	Madrid	1
3	Istanbul	1
2	Istanbul	4
1	Istanbul	3
1	Roma	3



User	Istanbul	Madrid	Roma
1	3	1	4
2	4	2	0
3	1	0	0

- Numerical Column Grouping
  - Numerical columns are **grouped** using **sum** and **mean** functions in most of the cases. Both can be preferable according to the meaning of the feature.

Feature Split

- Splitting features is a good way to make them useful in terms of machine learning. Most of the time the dataset contains string columns that violates tidy data principles. By extracting the utilizable parts of a column into new features:
  - We enable machine learning algorithms to comprehend them.
  - Make possible to bin and group them.
  - Improve model performance by uncovering potential information.
- Split function is a good option, however, there is no one way of splitting features. It depends on the characteristics of the column, how to split it. Let’s introduce it with two examples. First, a simple split function for an ordinary name column:

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Feature Split

user	name
1	John Doe
2	Peter Smith
3	Tony Brown

$\rightarrow$

user	first_name	last_name
1	John	Doe
2	Peter	Smith
3	Tony	Brown

Movie
Toy Story (1995)
Jumanji (1995)
Grumpier Old Men (1995)

$\rightarrow$

Year
1995
1995
1995

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Scaling

- In most cases, the numerical features of the dataset do not have a certain range and they differ from each other. In real life, it is nonsense to expect age and income columns to have the same range. But from the machine learning point of view, how these two columns can be compared?
- Scaling solves this problem. The continuous features become identical in terms of the range, after a scaling process. This process is not mandatory for many algorithms, but it might be still nice to apply. However, the algorithms based on distance calculations such as k-NN or k-Means need to have scaled continuous features as model input.

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Scaling

- **Normalization** (or min-max normalization) scale all values in a fixed range between 0 and 1. This transformation does not change the distribution of the feature and due to the decreased standard deviations, the effects of the outliers increases. Therefore, before normalization, it is recommended to handle the outliers.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

value	normalized
2	0.23
45	0.63
-23	0.00
85	1.00
28	0.47
2	0.23
35	0.54
-12	0.10

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Scaling

- Standardization (or z-score normalization) scales the values while taking into account standard deviation. If the standard deviation of features is different, their range also would differ from each other. This reduces the effect of the outliers in the features.
- In the following formula of standardization,
  - the mean is shown as μ
  - the standard deviation is shown as σ.

$$z = \frac{x - \mu}{\sigma}$$

value	normalized
2	-0.52
45	0.70
-23	-1.23
85	1.84
28	0.22
2	-0.52
35	-0.42
-12	-0.92

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Extracting Date

- It might be the reason for this, that dates can be present in numerous formats, which make it hard to understand by algorithms, even they are simplified to a format like "01–01–2017".
- Building an ordinal relationship between the values is very challenging for a machine learning algorithm if you leave the date columns without manipulation. Here, three types of preprocessing for dates are suggested:
  - Extracting the parts of the date into different columns: Year, month, day, etc.
  - Extracting the time period between the current date and columns in terms of years, months, days, etc.
  - Extracting some specific features from the date: Name of the weekday, Weekend or not, holiday or not, etc.

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Extracting Date

- If you transform the date column into the extracted columns, the information of them become disclosed and machine learning algorithms can easily understand them.

```
from datetime import date

data = pd.DataFrame({'date':
['01-01-2017',
'04-12-2008',
'23-06-1988',
'25-08-1999',
'20-02-1993',
]})
```

Extracting Date

```
#Transform string to date
data['date'] = pd.to_datetime(data.date, format="%d-%m-%Y")

#Extracting Year
data['year'] = data['date'].dt.year

#Extracting Month
data['month'] = data['date'].dt.month

#Extracting passed years since the date
data['diff_years'] = date.today().year - data['date'].dt.year

#Extracting passed months since the date
data['diff_months'] = (date.today().year - data['date'].dt.year) *
12 + date.today().month - data['date'].dt.month

#Extracting the weekday name of the date
data['day_name'] = data['date'].dt.day_name()
```

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

Extracting Date

```
      date  year  month  diff_years  diff_months   day_name
2017-01-01  2017      1           2           26     Sunday
2008-12-04  2008     12          11          123   Thursday
1988-06-23  1988      6          31          369   Thursday
1999-08-25  1999      8          20          235  Wednesday
1993-02-20  1993      2          26          313   Saturday
```

Ref: • https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

We're entering a new world
in which data may be
more important than software.

Tim O’Reilly

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