

Introduction to Data Analytics

IBM Data Analyst Course: Course One, Week Three

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AGENDA

Gathering Data

Wrangling Data





PROCESS FOR IDENTIFYING DATA

Determine the information you want to collect

Define a plan for collecting data

Determine your data collection methods



Determine the information you want to collect







Define a plan for collecting data

| | | | | Da | ta Coll | ection P | an/Matri | χ | | | | | |
|----|------|-------|-----------|-----|-----------------|----------------------|--|--|---|--|---|------------------|----------|
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| 01 | 1901 | Netic | Data Type | | E. | iš. | and | Sample Size | Реџец | Delverable | | | |
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Establish a timeframe

How much data is sufficient for credible analysis?

Define dependencies, risk and mitigation plan



Determine your data collection methods

The methods of data collection depends upon a number of factors:

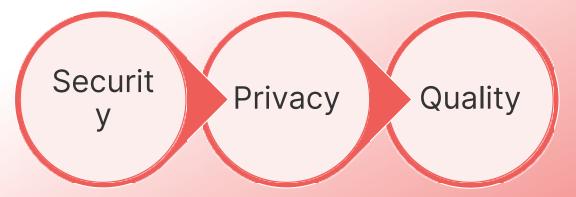
Source of Data
Type of Data
Timeframe over which you need data

- Volume of Data
- Degree of accuracy required
- **Funds**



ey Consideration while collecting data

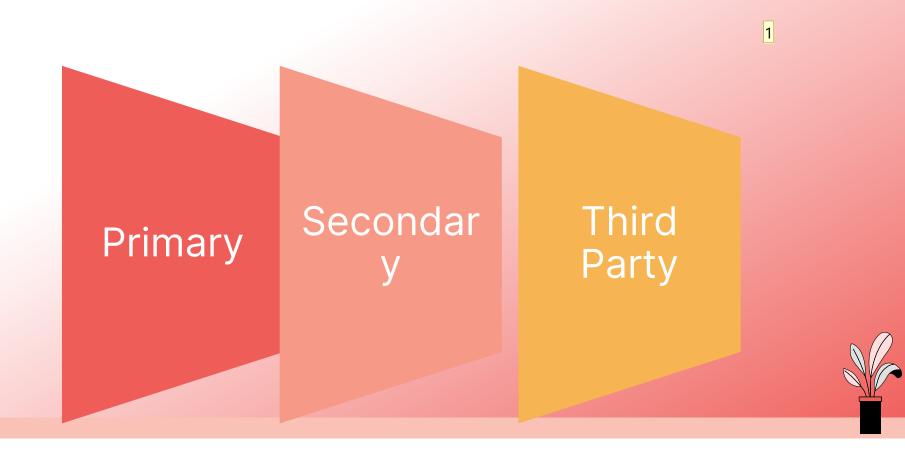
The data you identify, the source of that data and the practices you employ for gathering the data have implications for



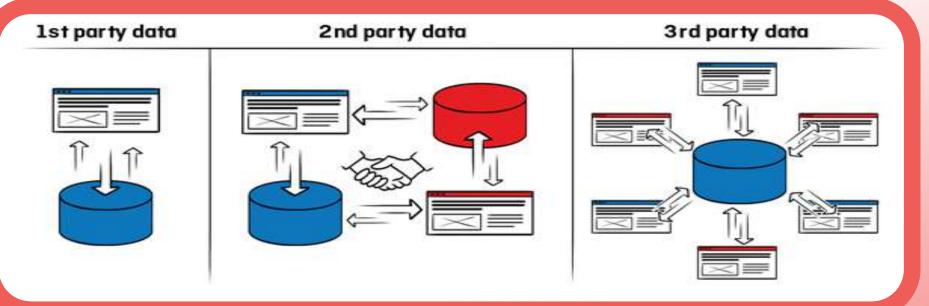
In order for data to be reliable, it should be free of errors, complete, consistent, relevant and accessible.



Data Sources



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Primary data refers to information obtained directly from the source. Data from organization's CRM, HR or workflow applications. This can be obtained directly from surveys, focus groups, interviews or questionnaires

Secondary data refers to the information obtained from existing sources such as external databases, research articles, training material. This can also be obtained directly from surveys, focus groups, interviews or questionnaires.

Third party refers to data which is purchased from aggregators who collect data from various sources and combine it into comprehensive datasets.



Sources for gathering data

Some of the data sources from which you could be gathering data include databases, the web, social media, interactive platforms, sensor devices, data exchanges, surveys and observation studies.





















ACTIVITY

Suggest a correct source of gathering data for below specified scenarios:

Scenario 1:

A marketing company is interested in the proportion of people who will buy a particular product.

Scenario 2:

A Community College instructor is interested in the mean number of days math students are absent from class during a quarter.

Scenario 3:

John requires an information about mechanical, orderly tasks, like checking the number of manual interventions required in a day to keep an assembly line functioning smoothly.

Scenario 4:

Sneha wants to launch her online store. She wants to run a quick analysis through which she can decide on the type of online purchases made by users frequently.

How to gather and import data?

SQL Queries

API

Web Scraping / Web Harvesting

Data Streams

Data exchanges

Other



Unstructured vs Structured Data Structured Data Semi-unstructured Data Unstructured Data Often numbers or labels, stored Loosely organized into Text-heavy information that's in a structured framework of categories using meta tags not organized in a clearly defined framework or model. columns and rows relating to pre-set parameters. D CODES IN DATABASES THREE BY HOLDE, SERT, DRAFT MEDICPOSTS EMPLS ONLINE REVIEWS NUMERICAL DATA GOOGLE SHEETS TWEETS ORGANIZED BY HAZHTAGS. WOEDS, MASSES w stop patrick #DLDERS DEGANGED BY TOPIC SPEECH SOUNDS

Import Data

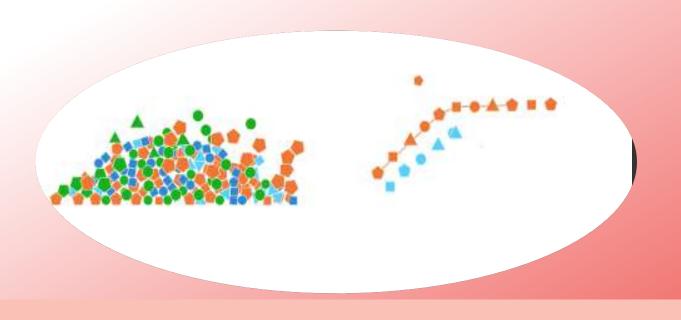
Structured data can be stored in relational databases with well defines schemas

Semi Structured data can be stored in noSQL clusters

Unstructured data can be stored in noSQL databases or datalakes.



DATA WRANGLING





What is Data Wrangling?

Data wrangling, sometimes referred to as data munging, is the process of transforming and mapping data from one "raw" data form into another format with the intent of making it more appropriate and valuable for a variety of downstream purposes such as analytics. The goal of data wrangling is to assure quality and useful data.

It is a 4-step process that involves—Discovery, Transformation, Validation, and Publishing.



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The Data Wrangling Process

Discovery

Transformation

Validation

Publishing







The **Discovery phase**, also known as the **Exploration phase**, is about understanding your **data** better with respect to your use case.

Creating a plan for cleaning, structuring, organizing and mapping your data.



Transformation

Transformation phase, forms the bulk of the **data** wrangling process. It involves the task to **transform** the data, such as

structuring, normalizing, de normalizing, cleaning, and enriching data.





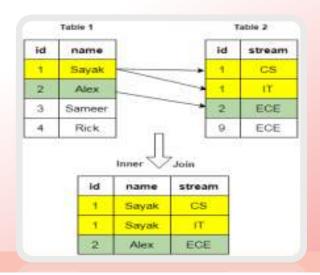
Structuring the data

Structuring refers to actions that change the form or schema of your data. Splitting columns, pivoting rows and deleting fields are all forms of structuring.

Join and Union are most common structural transformation to combine data from one or more tables.

JOIN

UNION







Normalizing and De normalizing Data

Normalization, from a statistical view, often has to do with calculating new values from a dataset to standardize the **data** on a particular scale.

It can also imply how well the transaction data is handled for reducing redundancy and inconsistency.





DENORMALI EATION

Combining data from multiple tables for faster querying of data for reports and analysis

Consider the relations **Client**, **PropertyForRent** and **Viewing**.

Client

| clientNo | fName | Name | teľNo | prefType | maxRent |
|----------|-------|---------|---------------|----------|---------|
| CR76 | John | Kay | 0207-774-5632 | Flat | 425 |
| CR56 | Aline | Stewart | 0141-848-1825 | Flat | 350 |
| CR74 | Mike | Ritchie | 01475-392178 | House | 790 |
| CR62 | Mary | Tregear | 01224-196720 | Flat | 600 |

PropertyForRent

| propertyNo | street | city | postcode | type | rooms | rent | ownerNo | staffNo | branchNo |
|------------|----------------|----------|----------|-------|-------|------|---------|---------|----------|
| PA14 | 16 Holhesd | Aberdeen | A87 55U | House | 6 | 650 | CD46 | SA9 | B007 |
| PL94 | 6 Argyll St | London | NW3 | Hat | 4 | 400 | CON7 | \$1.41 | B005 |
| PG4 | 6 Lewrence St. | Glugow | G11.9QX | Hat | 3 | 350 | CO40 | esemes. | B003 |
| PG36 | 2 Manor Rd | Glasgow | G32 4QX | Plat | 5 | 375 | CO95 | 5G37 | 19003 |
| PGZI | 18 Dair Rd | Glasgow | G12 | House | 5 | 600 | CO87 | SG37 | B003 |
| PG16 | 5 Nover Dr | Clargow | G12 9AX | Plat | 4 | 450 | CO93 | \$014 | B003 |

Viewing

| clientNo | propertyNo | viewDate | comment |
|----------|------------|-----------|----------------|
| CR56 | PA14 | 24-May-04 | too small |
| CR76 | PG4 | 20-Apr-04 | too remote |
| CR56 | PG4 | 26-May-04 | |
| CR62 | PA14 | 14-May-04 | |
| CR56 | PG56 | 28-Apr-04 | no dining room |



Cleaning data

During the cleaning stage, users identify data quality issues, such as missing or mismatched values, and apply the appropriate transformation to correct or delete these values from the dataset.

Example: In this dataset, if the data has also some negative values in time column, Given that it's impossible for a time to be negative, we will simply remove those rows since they seem to represent errors in the dataset and might throw off our analysis.





Data Cleaning

Data cleaning is the process of ensuring data is correct, consistent and usable

Missing data can reduce statistical power

Data inconsistency creates unreliable dat

Removing duplicate and inaccurate data from databases can help business save valuable resources

Incorrect data may lead to bad decisions



Data cleaning Workflow

The workflow is a sequence of three steps aiming at producing highquality data and taking into account all the criteria we've talked about.

- **Inspection:** Detect unexpected, incorrect, and inconsistent data. Fix or remove the anomalies discovered. Verifying: After **cleaning**, the results are inspected to verify correctness
- **Data profiling** is the process of reviewing source data, understanding structure, content and interrelationships, and identifying potential for data projects..
- Verification: After cleaning, the results are inspected to verify correctness.



Data Enrichment

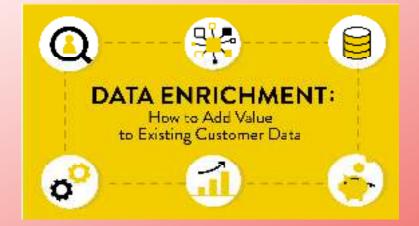
Lets take an example here:

Weather can be an important factor in outdoor trips, as it is much less appealing to ride a bicycle on a particularly rainy or windy day.

An analyst might be able to get further insights and draw more well-informed conclusions if you added weather data to the Trip dataset.

To accomplish this, you can use the join function to bring these two datasets together. After loading the Weather data you can see that it is already quite clean and standardized. Next, hitting the join function will allow you to select the Trip dataset that you've already cleaned.

You want to join the two datasets using the date value as your join key so that the rows and columns match--however only one date column needs to be incorporated into the output dataset to avoid a duplicate. Once the join is created, this transformed dataset will have both trip and weather data within it







Checking the quality of data after cleansing, normalizing, denormal zing and enriching the data

Verifying consistency, quality and security of data

Once the transformations are complete, you can view the Results Summary, which displays detailed statistics of the transformations applied over the entire dataset. You can then export the results of this transformation into the appropriate output format best-fit for your visualization or analytics tool of choice,





When your data has been successfully structured, cleaned, enriched and validated, it's time to publish your wrangled output for use in downstream analytics processes. Through the wrangling process, a wider variety of data sources can be used in different statistics, analytics and data visualization applications. This broadens the usage of data throughout the organization and enhances the potential value of data to the business.

Now you're ready to deliver the output of your data wrangling efforts into the appropriate format for downstream analytic uses. You can publish and save your results as a CSV, JSON, or any other format of your choice.



Tools for Data Wrangling

















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Any Questions?



Activity

Use Case

Maria is a 25-year-old US Army veteran, newly returned to the civilian workforce. She has recently completed a six-year commitment with the Army. During her time in the Army, she worked in supply management and logistics. She has decided to pursue a degree in Management Systems and Information Technology.

Maria has asked you to use your skill with data to help her search for the best school for her. She is willing to relocate anywhere in the continental United States, but she has a few criteria that her ideal schools must satisfy:

Safety of the city

- School should be offering a degree in IT
- Ranking of school.

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CRIME DATA

| 4 | A | В | С | D | E | F | G | н |
|----|----------------|--------------|--------|---------|---------------|----------|----------|-------------------|
| 1 | CITY | ViolentCrime | Murder | Robbery | PropertyCrime | Burglary | Theft | MotorVehicleTheft |
| 2 | Ithaca | 1,160.00 | 15.1 | 122.2 | 4,701.90 | 1,179.50 | 3,356.00 | 166.3 |
| 3 | Seattle | 1,070.10 | 7.6 | 126.6 | 4,233.90 | 801.2 | 2,937.70 | 495.1 |
| 4 | New York City | 936.4 | 4.5 | 120.1 | 4,565.90 | 1,167.00 | 3,083.70 | 315.2 |
| 5 | Minneapolis | 901.5 | 19.3 | 247 | 2,935.80 | 700.9 | 1,769.30 | 465.7 |
| 6 | Philadelphia | 825.4 | 5.5 | 147.8 | 4,529.40 | 966.8 | 3,223.10 | 339.6 |
| 7 | Los Angeles | 818.8 | 6.8 | 170.9 | 2,650.90 | 625.5 | 1,834.10 | 191.2 |
| 8 | North Chicago | 815 | 6.9 | 273 | 2,817.80 | 868.9 | 1,499.10 | 449.7 |
| 9 | Madison | 797.1 | 8.9 | 213.2 | 3,466.10 | 727.1 | 2,180.00 | 559 |
| 10 | New York City | 792.6 | 6.1 | 206.7 | 4,607.80 | 883.4 | 3,047.60 | 676.9 |
| 11 | Princeton | 767.1 | 6.6 | 122.3 | 3,756.30 | 832.7 | 2,602.30 | 321.3 |
| 12 | Los Angeles | 744.2 | 7.6 | 163.2 | 3,636.90 | 1,008.70 | 2,422.30 | 205.9 |
| 13 | Pittsburgh | 734.5 | 6.9 | 112.8 | 3,067.10 | 848.1 | 2,064.70 | 154.3 |
| 14 | East Lansing | 720.2 | 5.2 | 131.1 | 3,075.50 | 669.1 | 2,286.60 | 119.7 |
| 15 | San Diego | 667.9 | 7.8 | 157.9 | 3,894.10 | 1,099.60 | 2,652.80 | 141.7 |
| 16 | Gainesville | 650.6 | 6.9 | 99.3 | 3,464.00 | 627.8 | 2,466.40 | 369.8 |
| 17 | Irvine | 621.6 | 6.5 | 88.7 | 3,469.10 | 1,151.70 | 2,089.20 | 228.1 |
| 18 | North Chicago | 615.7 | 8 | 114.7 | 5,190.60 | 1,392.10 | 3,174.80 | 623.7 |
| 19 | Durham | 612.7 | 5.5 | 128.8 | 2,580.20 | 506.7 | 1,929.50 | 144 |
| 20 | Evanston | 610.3 | 8 | 197.5 | 3,670.50 | 534.9 | 2,811.80 | 323.9 |
| 21 | New Brunswick | 605.4 | 5.1 | 95.5 | 3,370.50 | 697.4 | 2,521.40 | 151.7 |
| 22 | Salt Lake City | 579.7 | 7.9 | 129.7 | 3,596.70 | 787.9 | 2,601.20 | 207.6 |
| 23 | Raleigh | 577.3 | 7.3 | 152.5 | 3,692.20 | 725.5 | 2,274.20 | 692.4 |
| 24 | Pittsburgh | 566.6 | 6.9 | 228.9 | | 596.8 | | 367.2 |
| 25 | Pasadena | 409.3 | 3 | 60.9 | 2,838.60 | 744.2 | 2,000.80 | 93.6 |
| 26 | Santa Barbara | 556.3 | 7.3 | 130.2 | 3,439.30 | 954.3 | 1,881.10 | 603.9 |
| 27 | Lincoln | 537.3 | 6.1 | 136.9 | 3,439.40 | 751.3 | 2,196.60 | 491.5 |



COLLEGE SCORE

| 4 | A | В | С | D | E | F | G | н | I I | J |
|----|-------|------|--|----------------|--------------------------|-------|------------|-------|--|----|
| | | | | | | | Staff/Teac | | and the | |
| | uid | RANK | Cornell University | CITY | Courses 117 Managemen | Score | herRatio | Index | NPCURL | |
| 2 | 10023 | 5 | | Ithaca | t | 7 | 8 | 5 | galileo.aamu.edu/netpricecalculator/npcalc.htm | |
| 3 | 10034 | 6 | University of Washington Columbia University in the City | Seattle | IT | 9 | 8 | 9 | www.collegeportraits.org/AL/UAB/estimator/agree | |
| 4 | 10294 | 7 | of New York | New York City | Management | 6 | 7 | 1 | ridge%20University/Freshman-Students | |
| 5 | 10388 | 10 | University of Minnesota-Twin Cities | Minneapolis | Medical | 5 | 6 | 7 | finaid.uah.edu/ | |
| 6 | 10524 | 12 | University of Pennsylvania | Philadelphia | Architecture | 6 | 4 | 6 | aid/forms/calculator/index.aspx/ | |
| 7 | 10659 | 13 | University of California, Los Angeles | Los Angeles | TS/IT | 4 | 5 | | oira.ua.edu | |
| 8 | 10795 | 14 | Yale University | New Haven | Management | 4 | 7 | -4 | m | |
| 9 | 10930 | 16 | University of Wisconsin- Madison | Madison | Management | 4 | -6 | 0 | 491 | |
| 10 | 11066 | 18 | New York University | New York City | rr/wetarcar/Art s | 4 | 7 | 9 | information/price-estimator-calculator | |
| 11 | 11201 | 19 | Princeton University | Princeton | Medical | 9 | 7 | 9 | www.auburn.edu/admissions/money-matters.html | |
| 12 | 11337 | 20 | <u>University of Southern</u> California | Los Angeles | s0 | 6 | -6 | 7 | www.bsc.edu/fp/np-calculator.cfm | |
| 13 | 11472 | 22 | Carnegie Mellon University | Pittsburgh | Architecture | 5 | 6 | | external.cv.edu/npc/npcalc.htm | |
| 14 | 11608 | 23 | Michigan State University | East Lansing | 0 | 6 | 6 | 8 | www.ccal.edu/netprice/netprice/ | |
| 15 | 11743 | 24 | University of California, San Diego | San Diego | IT | 4 | 6 | 8 | Students?iframe=true&width=600&height=1000 | |
| 16 | 11879 | 26 | University of Florida | Gainesville | Architecture | 8 | -7 | 5 | www.escc.edu/NetPrice/npcalc.htm | |
| 17 | 12014 | 29 | University of California, Irvine | Irvine | IT | 8 | 5 | -7 | www.faulknerstate.edu | |
| 18 | 84321 | 1083 | Rosalind Franklin University of Medicine and Science | North Chicago | IT/Architecture | | | | www.faulkner.edu/netprice/ | |
| 19 | 12285 | 31 | Duke University | Durham | Biomedical | 9 | 9 | 9 | www.gadsdenstate.edu/netpricecalculator/ | |
| 20 | 12421 | 34 | Northwestern University | Evanston | 0 | 6 | 8 | 7 | www.nbccosmetology.com/npcalc.htm | |
| 21 | 12556 | 36 | Rutgers, The State University of New Jersev | New Brunswick | Arts | 6 | 6 | 8 | www.wallace.edu/net_price_calculator.aspx | (· |
| 22 | 12692 | 40 | The University of Utah | Salt Lake City | | 4 | 6 | 8 | Calculator/index | |
| 23 | 12827 | 42 | North Carolina State University | Raleigh | t t | 8 | -7 | 5 | www.wccs.edu/index.php?page=npc.html | |
| 24 | 12963 | 43 | University of Pittsburgh | Pittsburgh | ecture | 8 | 5 | -7 | www.herzing.edu/financial-aid/net-price-calculator | |
| 25 | 13098 | 46 | California Institute of Technology | Pasadena | 0 | | | | htm | |
| 26 | 13234 | 47 | University of California, Santa Barbara | Santa Barbara | t t | 4 | 6 | 7 | www.hcu.edu/share/news/npcalc.htm | |



Your Task

1) Clean the data:

Remove any duplicates

Missing Values

Inconsistent values

2) Data Enrichment:

Calculate School Ranking

Calculate overall crime rate

- 3) Structure the data: Merge the tables and produce the dataset which must have :
- Top 5 schools on rankings for It college
- Be in a city that is below 50th percentile in overall crime
- 3. Remove unnecessary columns







Thank You