

# DATA QUALITY AND DATA PROGRAMMING

*"Data cleaning and repairing account for about 60% of the work of data scientists."*

Eunsuk Kang

Required reading:

- Schelter, S., Lange, D., Schmidt, P., Celikel, M., Biessmann, F. and Grafberger, A., 2018. [Automating large-scale data quality verification](#). Proceedings of the VLDB Endowment, 11(12), pp.1781-1794.
- Nick Hynes, D. Sculley, Michael Terry. "[The Data Linter: Lightweight Automated Sanity Checking for ML Data Sets](#)." NIPS Workshop on ML Systems (2017)

# LEARNING GOALS

- Design and implement automated quality assurance steps that check data schema conformance and distributions
- Devise thresholds for detecting data drift and schema violations
- Describe common data cleaning steps and their purpose and risks
- Evaluate the robustness of AI components with regard to noisy or incorrect data
- Understanding the better models vs more data tradeoffs
- Programatically collect, manage, and enhance training data

# DATA-QUALITY CHALLENGES

# CASE STUDY: INVENTORY MANAGEMENT



# INVENTORY DATABASE

Product Database:

ID	Name	Weight	Description	Size	Vendor
...	...	...	...	...	...

Stock:

ProductID	Location	Quantity
...	...	...

Sales history:

UserID	ProductId	DateTime	Quantity	Price
...	...	...	...	...

# WHAT MAKES GOOD QUALITY DATA?

- Accuracy
  - The data was recorded correctly.
- Completeness
  - All relevant data was recorded.
- Uniqueness
  - The entries are recorded once.
- Consistency
  - The data agrees with itself.
- Timeliness
  - The data is kept up to date.

# DATA IS NOISY

- Unreliable sensors or data entry
  - Wrong results and computations, crashes
  - Duplicate data, near-duplicate data
  - Out of order data
  - Data format invalid
- 
- **Examples?**

# DATA CHANGES

- System objective changes over time
- Software components are upgraded or replaced
- Prediction models change
- Quality of supplied data changes
- User behavior changes
- Assumptions about the environment no longer hold
  
- **Examples?**



# USERS MAY DELIBERATELY CHANGE DATA

- Users react to model output
- Users try to game/deceive the model
- **Examples?**

# MANY DATA SOURCES



*sources of different reliability and quality*

# ACCURACY VS PRECISION

- Accuracy: Reported values (on average) represent real value
- Precision: Repeated measurements yield the same result
- Accurate, but imprecise: Average over multiple measurements
- Inaccurate, but precise: Systematic measurement problem, misleading





# DATA QUALITY AND MACHINE LEARNING

- More data -> better models (up to a point, diminishing effects)
- Noisy data (imprecise) -> less confident models, more data needed
  - some ML techniques are more or less robust to noise (more on robustness in a later lecture)
- Inaccurate data -> misleading models, biased models
- Need the "right" data
- Invest in data quality, not just quantity

# DATA CLEANING

*Data cleaning and repairing account for about 60% of the work of data scientists.*

Quote: Gil Press. “[Cleaning Big Data: Most Time-Consuming, Least Enjoyable Data Science Task, Survey Says.](#)”  
Forbes Magazine, 2016.



Source: Rahm, Erhard, and Hong Hai Do. [Data cleaning: Problems and current approaches](#). IEEE Data Eng. Bull. 23.4 (2000): 3-13.

# SINGLE-SOURCE PROBLEM EXAMPLES

Further readings: Rahm, Erhard, and Hong Hai Do. [Data cleaning: Problems and current approaches](#). IEEE Data Eng. Bull. 23.4 (2000): 3-13.





# SINGLE-SOURCE PROBLEM EXAMPLES

- Schema level:
  - Illegal attribute values: `bdate=30.13.70`
  - Violated attribute dependencies: `age=22, bdate=12.02.70`
  - Uniqueness violation: `(name="John Smith", SSN="123456"), (name="Peter Miller", SSN="123456")`
  - Referential integrity violation: `emp=(name="John Smith", deptno=127)` if department 127 not defined



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  - Referential integrity violation: `emp=(name="John Smith", deptno=127)` if department 127 not defined
- Instance level:
  - Missing values: `phone=9999-999999`
  - Misspellings: `city=Pittsburg`
  - Misfielded values: `city=USA`
  - Duplicate records: `name=John Smith, name=J. Smith`
  - Wrong reference: `emp=(name="John Smith", deptno=127)` if department 127 defined but wrong



# DIRTY DATA: EXAMPLE

TABLE: CUSTOMER

ID	Name	Birthday	Age	Sex	Phone	ZIP
3456	Ford, Harrison	18.2.76	43	M	9999999999	15232
3456	Mark Hamil	33.8.81	43	M	6173128718	17121
3457	Kim Kardashian	11.10.56	63	M	4159102371	94016

TABLE: ADDRESS

ZIP	City	State
15232	Pittsburgh	PA
94016	Sam Francisco	CA
73301	Austin	Texas

*Problems with the data?*

# DISCUSSION: POTENTIAL DATA QUALITY PROBLEMS?



# DATA CLEANING OVERVIEW

- Data analysis / Error detection
  - Error types: e.g. schema constraints, referential integrity, duplication
  - Single-source vs multi-source problems
  - Detection in input data vs detection in later stages (more context)
- Error repair
  - Repair data vs repair rules, one at a time or holistic
  - Data transformation or mapping
  - Automated vs human guided



# ERROR DETECTION

- Illegal values: min, max, variance, deviations, cardinality
- Misspelling: sorting + manual inspection, dictionary lookup
- Missing values: null values, default values
- Duplication: sorting, edit distance, normalization

# ERROR DETECTION: EXAMPLE

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Q. Can we (automatically) detect errors? Which errors are problem-dependent?

# COMMON STRATEGIES FOR CLEANING

- Enforce schema constraints
  - e.g., delete rows with missing data or use defaults
- Explore sources of errors
  - e.g., debugging missing values, outliers
- Remove outliers
  - e.g., Testing for normal distribution, remove  $> 2\sigma$
- Normalization
  - e.g., range  $[0, 1]$ , power transform
- Fill in missing values

# DATA CLEANING TOOLS

The screenshot shows the Google Refine interface for a dataset of government IT contracts. The top bar includes the Google Refine logo, the search query 'government IT contracts', and a 'Permalink' link. Below the search bar, there are controls for 'Facet / Filter' and 'Undo / Redo 5'. A 'Refresh' button is also present. The main area is divided into two panels. The left panel shows a facet for 'Type of Contract' with 783 choices. The facet is sorted by 'name' and 'count'. A list of contract types is shown, including 'Firm Fixed Price' (836), 'FFP: Firm Fixed Price' (619), 'T&M: Time & Materials' (361), 'Time and Materials' (232), 'Time & Materials' (189), 'CPFF: Cost Plus Fixed Fee' (183), 'CPAF: Cost Plus Award Fee' (130), 'Task Based Indefinite Delivery/Indefinite Quantity (ID/IQ) Time & Materials (T&M) Task Order' (115), 'Firm-Fixed-Price' (112), and 'Fixed Price' (105). A black arrow points to the 'Firm Fixed Price' entry. The right panel shows a table of 5200 rows. The table has columns for 'Contract ID', 'Contractor Name', 'Type of Contract', and 'Date of Award'. The first 8 rows are displayed, showing various contractors and their contract details.

	Contract ID	Contractor Name	Type of Contract	Date of Award
1.	1939	ASAP SOFTWARE EXPRESS INC DELL MARKETING L.P.	Microsoft Enterprise Agreement	04/01/2009
2.	1940	BMC SOFTWARE DISTRIBUTION INCORPORATED	Remedy Service Desk Maintenance	04/01/2009
3.	1941	GOVCONNECTION INCORPORATED	Cisco SmartNet	05/01/2009
4.	1942	ITS CORPORATION	Time & Materials	12/31/2008
5.	7490	SENET INTERNATIONAL CORPORATIO	Firm Fixed Price C&A	05/04/2009
6.	1945		firm fixed price	01/26/2009
7.	1946	IT FEDERAL SALES LIMITED LIABILITY COMPANY	firm fixed price	10/01/2009
8.	1947		firm fixed price	09/30/2009

OpenRefine (formerly Google Refine), Trifacta Wrangler, Drake, etc.,

# DIFFERENT CLEANING TOOLS

- Outlier detection
- Data deduplication
- Data transformation
- Rule-based data cleaning and rule discovery
  - (conditional) functional dependencies and other constraints
- Probabilistic data cleaning

Further reading: Ilyas, Ihab F., and Xu Chu. [Data cleaning](#). Morgan & Claypool, 2019.

# DATA SCHEMA

# DATA SCHEMA

- Define expected format of data
  - expected fields and their types
  - expected ranges for values
  - constraints among values (within and across sources)
- Data can be automatically checked against schema
- Protects against change; explicit interface between components

# SCHEMA IN RELATIONAL DATABASES

```
CREATE TABLE employees (  
    emp_no      INT                NOT NULL,  
    birth_date  DATE               NOT NULL,  
    name        VARCHAR(30)        NOT NULL,  
    PRIMARY KEY (emp_no));  
CREATE TABLE departments (  
    dept_no     CHAR(4)            NOT NULL,  
    dept_name   VARCHAR(40)        NOT NULL,  
    PRIMARY KEY (dept_no), UNIQUE KEY (dept_name));  
CREATE TABLE dept_manager (  
    dept_no     CHAR(4)            NOT NULL,  
    emp_no      INT                NOT NULL,  
    FOREIGN KEY (emp_no) REFERENCES employees (emp_no),  
    FOREIGN KEY (dept_no) REFERENCES departments (dept_no),  
    PRIMARY KEY (emp_no, dept_no));
```



# SCHEMA-LESS DATA EXCHANGE

- CSV files
- Key-value stores (JSoN, XML, Nosql databases)
- Message brokers
- REST API calls
- R/Pandas Dataframes

```
1::Toy Story (1995)::Animation|Children's|Comedy  
2::Jumanji (1995)::Adventure|Children's|Fantasy  
3::Grumpier Old Men (1995)::Comedy|Romance
```

```
10|53|M|lawyer|90703  
11|39|F|other|30329  
12|28|F|other|06405  
13|47|M|educator|29206
```

# EXAMPLE: APACHE AVRO

```
{  "type": "record",
  "namespace": "com.example",
  "name": "Customer",
  "fields": [{
    "name": "first_name",
    "type": "string",
    "doc": "First Name of Customer"
  },
  {
    "name": "age",
    "type": "int",
    "doc": "Age at the time of registration"
  }
]
}
```

# EXAMPLE: APACHE AVRO

- Schema specification in JSON format
- Serialization and deserialization with automated checking
- Native support in Kafka
- Benefits
  - Serialization in space efficient format
  - APIs for most languages (ORM-like)
  - Versioning constraints on schemas
- Drawbacks
  - Reading/writing overhead
  - Binary data format, extra tools needed for reading
  - Requires external schema and maintenance
  - Learning overhead

## Speaker notes

Further readings eg <https://medium.com/@stephane.maarek/introduction-to-schemas-in-apache-kafka-with-the-confluent-schema-registry-3bf55e401321>, <https://www.confluent.io/blog/avro-kafka-data/>,  
<https://avro.apache.org/docs/current/>

# MANY SCHEMA FORMATS

## Examples

- Avro
- XML Schema
- Protobuf
- Thrift
- Parquet
- ORC

# DISCUSSION: DATA SCHEMA FOR INVENTORY SYSTEM?

Product Database:

ID	Name	Weight	Description	Size	Vendor
...	...	...	...	...	...

Stock:

ProductID	Location	Quantity
...	...	...

Sales history:

UserID	ProductId	DateTime	Quantity	Price
...	...	...	...	...

# DETECTING INCONSISTENCIES

	DBAName	AKAName	Address	City	State	Zip	
t1	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	<b>Chicago</b>	IL	<b>60608</b>	Conflicts
t2	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	<b>60609</b>	
t3	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	<b>60609</b>	
t4	<b>Johnnyo's</b>	Johnnyo's	3465 S Morgan ST	<b>Cicago</b>	IL	60608	

Does not obey data distribution

Conflict





# DATA QUALITY RULES

- Invariants on data that must hold
- Typically about relationships of multiple attributes or data sources, eg.
  - ZIP code and city name should correspond
  - User ID should refer to existing user
  - SSN should be unique
  - For two people in the same state, the person with the lower income should not have the higher tax rate
- Classic integrity constraints in databases or conditional constraints
- Rules can be used to reject data or repair it

# EXMAPLE: HOLOCLEAN



- User provides rules as integrity constraints (e.g., "two entries with the same name can't have different city")
- Detect violations of the rules in the data; also detect statistical outliers
- Automatically generate repair candidates (with probabilities)

Image source: Theo Rekatsinas, Ihab Ilyas, and Chris Ré, “[HoloClean - Weakly Supervised Data Repairing](#).” Blog, 2017.

# DISCOVERY OF DATA QUALITY RULES

- Rules directly taken from external databases
  - e.g. zip code directory
- Given clean data,
  - several algorithms that find functional relationships ( $X \Rightarrow Y$ ) among columns
  - algorithms that find conditional relationships (if  $Z$  then  $X \Rightarrow Y$ )
  - algorithms that find denial constraints ( $X$  and  $Y$  cannot cooccur in a row)
- Given mostly clean data (probabilistic view),
  - algorithms to find likely rules (e.g., association rule mining)
  - outlier and anomaly detection
- Given labeled dirty data or user feedback,
  - supervised and active learning to learn and revise rules
  - supervised learning to learn repairs (e.g., spell checking)

Further reading: Ilyas, Ihab F., and Xu Chu. [Data cleaning](#). Morgan & Claypool, 2019.

# ASSOCIATION RULE MINING

- Sale 1: Bread, Milk
- Sale 2: Bread, Diaper, Beer, Eggs
- Sale 3: Milk, Diaper, Beer, Coke
- Sale 4: Bread, Milk, Diaper, Beer
- Sale 5: Bread, Milk, Diaper, Coke

## Rules

- {Diaper, Beer} -> Milk (40% support, 66% confidence)
- Milk -> {Diaper, Beer} (40% support, 50% confidence)
- {Diaper, Beer} -> Bread (40% support, 66% confidence)

*(also useful tool for exploratory data analysis)*

Further readings: Standard algorithms and many variations, see [Wikipedia](#)

# DISCUSSION: DATA QUALITY RULES IN INVENTORY SYSTEM



# DATA LINTER

Further readings: Nick Hynes, D. Sculley, Michael Terry. "[The Data Linter: Lightweight Automated Sanity Checking for ML Data Sets](#)." NIPS Workshop on ML Systems (2017)

# EXCURSION: STATIC ANALYSIS AND CODE LINTERS

*Automate routine inspection tasks*

```
if (user.jobTitle = "manager") {  
    ...  
}
```

```
function fn() {  
    x = 1;  
    return x;  
    x = 3; // dead code  
}
```

```
PrintWriter log = null;  
if (anyLogging) log = new PrintWriter(...);  
if (detailedLogging) log.println("Log started");
```

# STATIC ANALYSIS

- Analyzes the structure/possible executions of the code, without running it
- Different levels of sophistication
  - Simple heuristic and code patterns (linters)
  - Sound reasoning about all possible program executions
- Tradeoff between false positives and false negatives
- Often supporting annotations needed (e.g., @Nullable)
- Tools widely available, open source and commercial



The screenshot shows a code editor with two tabs: 'index.js' and '.eslintrc'. The 'index.js' tab is active, displaying the following JavaScript code:

```
1
2
3   for (i = 0; i <= 10; i++)
4   {
5       if (i == 3)
6
7
8   }
9   var out = "The value is now " + i;
10  document.write(out);
11  document.write(text: "<br/>");
12 }
```

An ESLint error message is displayed in a tooltip over the opening curly brace on line 4:

ESLint: Opening curly brace does not appear on the same line as controlling statement. (brace-style)





# A LINTER FOR DATA?



# DATA LINTER AT GOOGLE

- Miscoding
  - Number, date, time as string
  - Enum as real
  - Tokenizable string (long strings, all unique)
  - Zip code as number
- Outliers and scaling
  - Unnormalized feature (varies widely)
  - Tailed distributions
  - Uncommon sign
- Packaging
  - Duplicate rows
  - Empty/missing data

Further readings: Hynes, Nick, D. Sculley, and Michael Terry. [The data linter: Lightweight, automated sanity checking for ML data sets](#). NIPS MLSys Workshop. 2017.

# DETECTING DRIFT

# DRIFT & MODEL DECAY

*in all cases, models are less effective over time*

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- Concept drift
  - properties to predict change over time (e.g., what is credit card fraud)
  - over time: different expected outputs for same inputs
  - model has not learned the relevant concepts

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  - input data differs from training data
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- Upstream data changes
  - external changes in data pipeline (e.g., format changes in weather service)
  - model interprets input data incorrectly
  - over time: abrupt changes due to faulty inputs



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## Speaker notes

- fix1: retrain with new training data or relabeled old training data
  - fix2: retrain with new data
  - fix3: fix pipeline, retrain entirely

# ON TERMINOLOGY

- Concept and data drift are separate concepts
- In practice and literature not always clearly distinguished
- Colloquially encompasses all forms of model degradations and environment changes
- Define term for target audience

# WATCH FOR DEGRADATION IN PREDICTION ACCURACY



Image source: Joel Thomas and Clemens Mewald. [Productionizing Machine Learning: From Deployment to Drift Detection](#). Databricks Blog, 2019

# INDICATORS OF CONCEPT DRIFT

*How to detect concept drift in production?*



# INDICATORS OF CONCEPT DRIFT

- Model degradations observed with telemetry
- Telemetry indicates different outputs over time for similar inputs
- Relabeling training data changes labels
- Interpretable ML models indicate rules that no longer fit

*(many papers on this topic, typically on statistical detection)*

# DEALING WITH DRIFT

- Regularly retrain model on recent data
  - Use evaluation in production to detect decaying model performance
- Involve humans when increasing inconsistencies detected
  - Monitoring thresholds, automation
- Monitoring, monitoring, monitoring!

# DIFFERENT FORMS OF DATA DRIFT

- Structural drift
  - Data schema changes, sometimes by infrastructure changes
  - e.g., 4124784115 -> 412 - 478 - 4115
- Semantic drift
  - Meaning of data changes, same schema
  - e.g., Netflix switches from 5-star to +/- rating, but still uses 1 and 5
- Distribution changes
  - e.g., credit card fraud differs to evade detection
  - e.g., marketing affects sales of certain items





# DETECTING DATA DRIFT

- Compare distributions over time (e.g., t-test)
- Detect both sudden jumps and gradual changes
- Distributions can be manually specified or learned (see invariant detection)



# DATA DISTRIBUTION ANALYSIS

- Plot distributions of features (histograms, density plots, kernel density estimation)
  - Identify which features drift
- Define distance function between inputs and identify distance to closest training data (eg., wasserstein and energy distance, see also kNN)
- Formal models for *data drift contribution* etc exist
- Anomaly detection and "out of distribution" detection
- Observe distribution of output labels

# DATA DISTRIBUTION EXAMPLE

<https://rpubs.com/ablythe/520912>

# MICROSOFT AZURE DATA DRIFT DASHBOARD



Image source and further readings: [Detect data drift \(preview\) on models deployed to Azure Kubernetes Service \(AKS\)](#)

# DISCUSSION: INVENTORY SYSTEM

*What kind of drift might be expected? What kind of detection/monitoring?*



# **QUALITY ASSURANCE FOR THE DATA PROCESSING PIPELINES**

# ERROR HANDLING AND TESTING IN PIPELINE

Avoid silent failures!

- Write testable data acquisition and feature extraction code
- Test this code (unit test, positive and negative tests)
- Test retry mechanism for acquisition + error reporting
- Test correct detection and handling of invalid input
- Catch and report errors in feature extraction
- Test correct detection of data drift
- Test correct triggering of monitoring system
- Detect stale data, stale models

*More in a later lecture.*

# SUMMARY

- Data and data quality are essential
- Data from many sources, often inaccurate, imprecise, inconsistent, incomplete, ... -- many different forms of data quality problems
- Understand the data with exploratory data analysis
- Many mechanisms for enforcing consistency and cleaning
  - Data schema ensures format consistency
  - Data quality rules ensure invariants across data points
  - Data linter detects common problems
- Concept and data drift are key challenges -- monitor
- Quality assurance for the data processing pipelines

