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

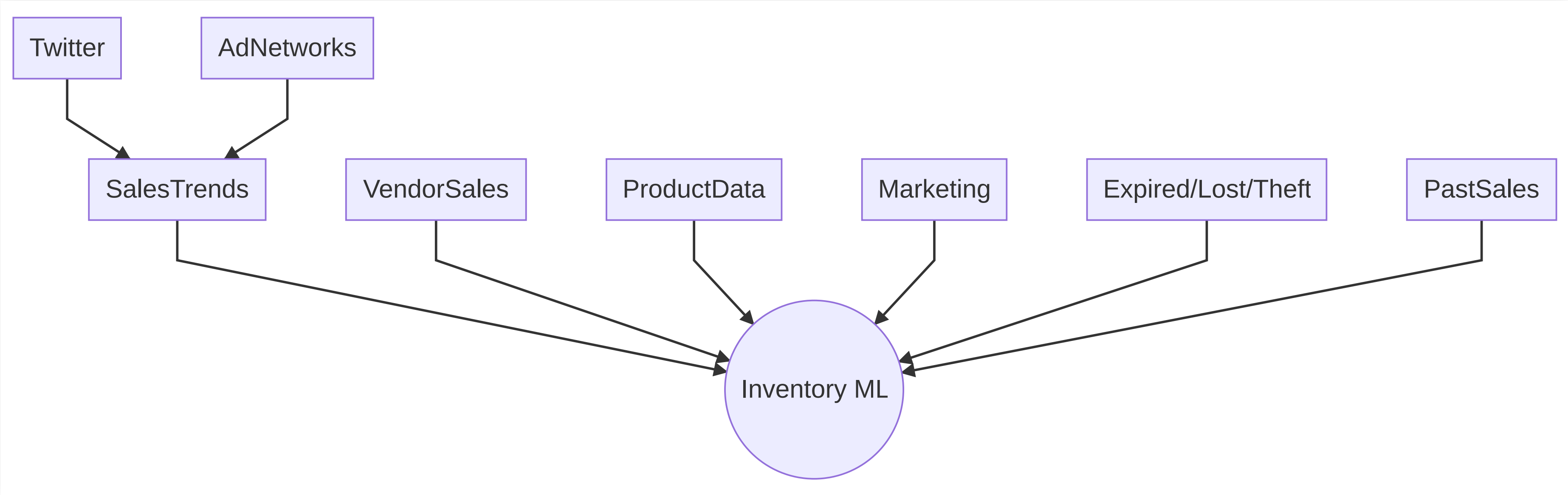
- **Examples?**

USERS MAY DELIBERATELY CHANGE DATA

- Users react to model output
- Users try to game/deceive the model

- **Examples?**

MANY DATA SOURCES

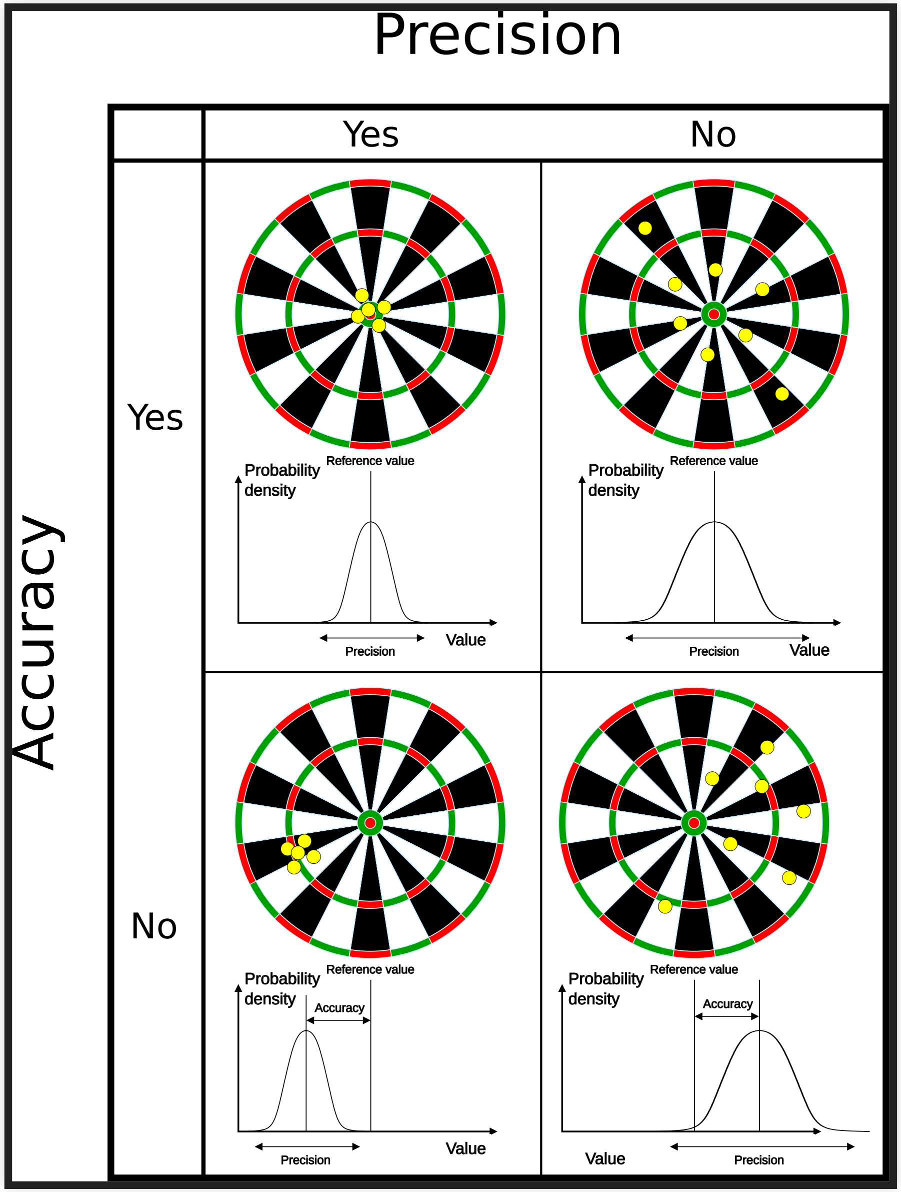


sources of different reliability and quality

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

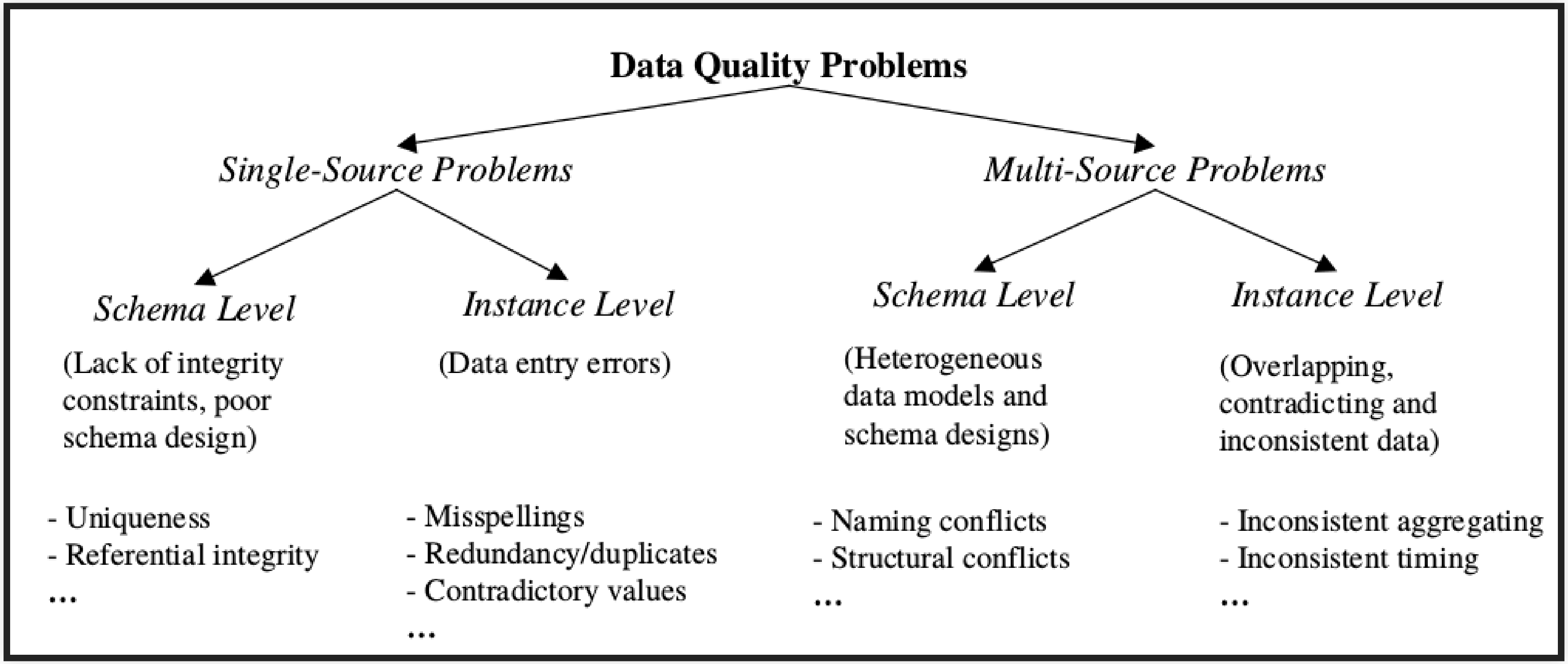
- More data -> better models (up to a point, diminishing effects)
- Noisy data (imprecise) -> less confident models, more data needed
    - some ML techniques are more or less robust to noise (more on robustness in a later lecture)
- Inaccurate data -> misleading models, biased models

- 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

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

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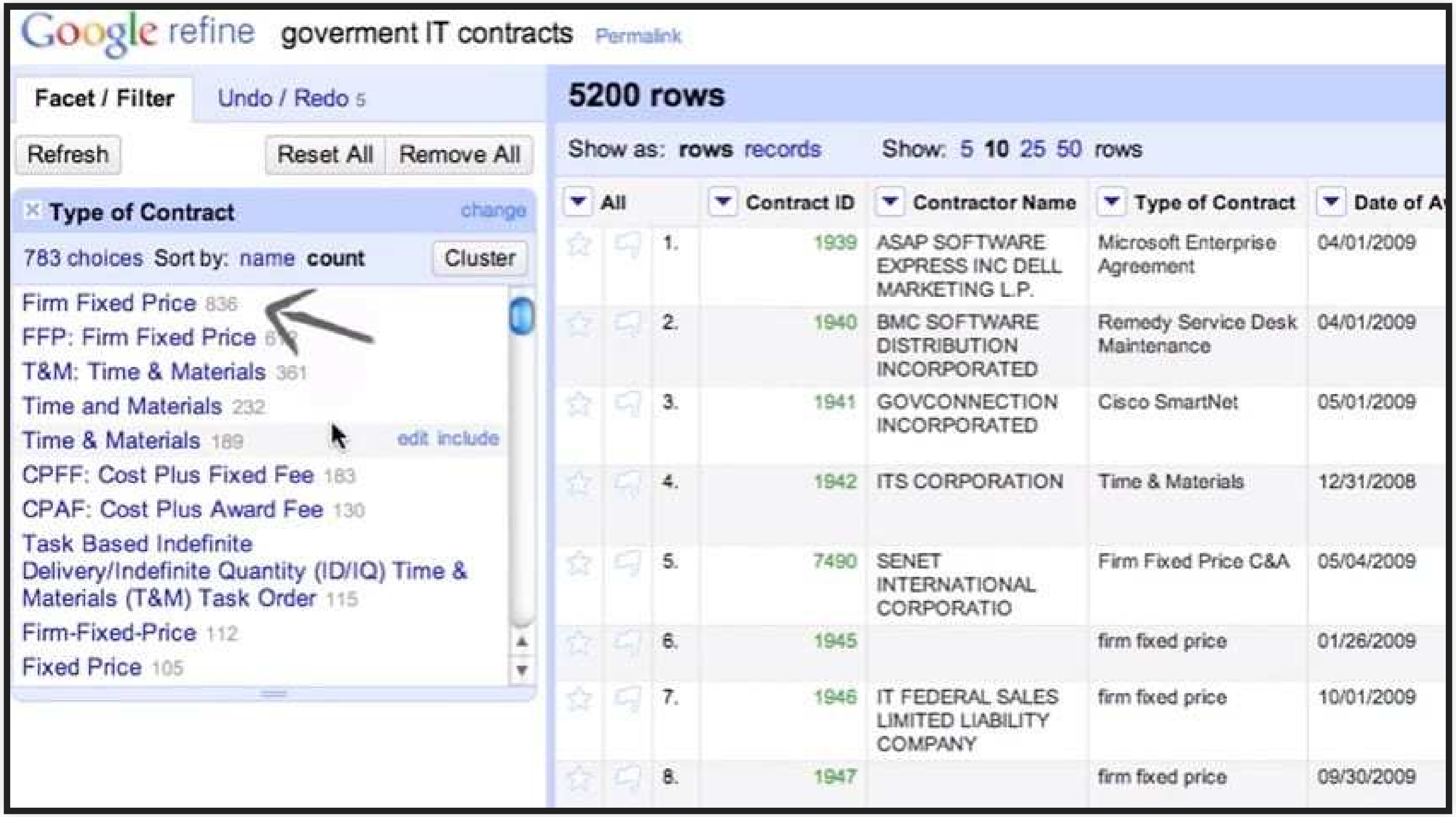
Q. Can we (automatically) detect errors? Which errors are problem-dependent?

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 > 2σ
- Normalization
    - e.g., range [0, 1], power transform
- Fill in missing values

DATA CLEANING TOOLS



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
...	...	...	...	...	...

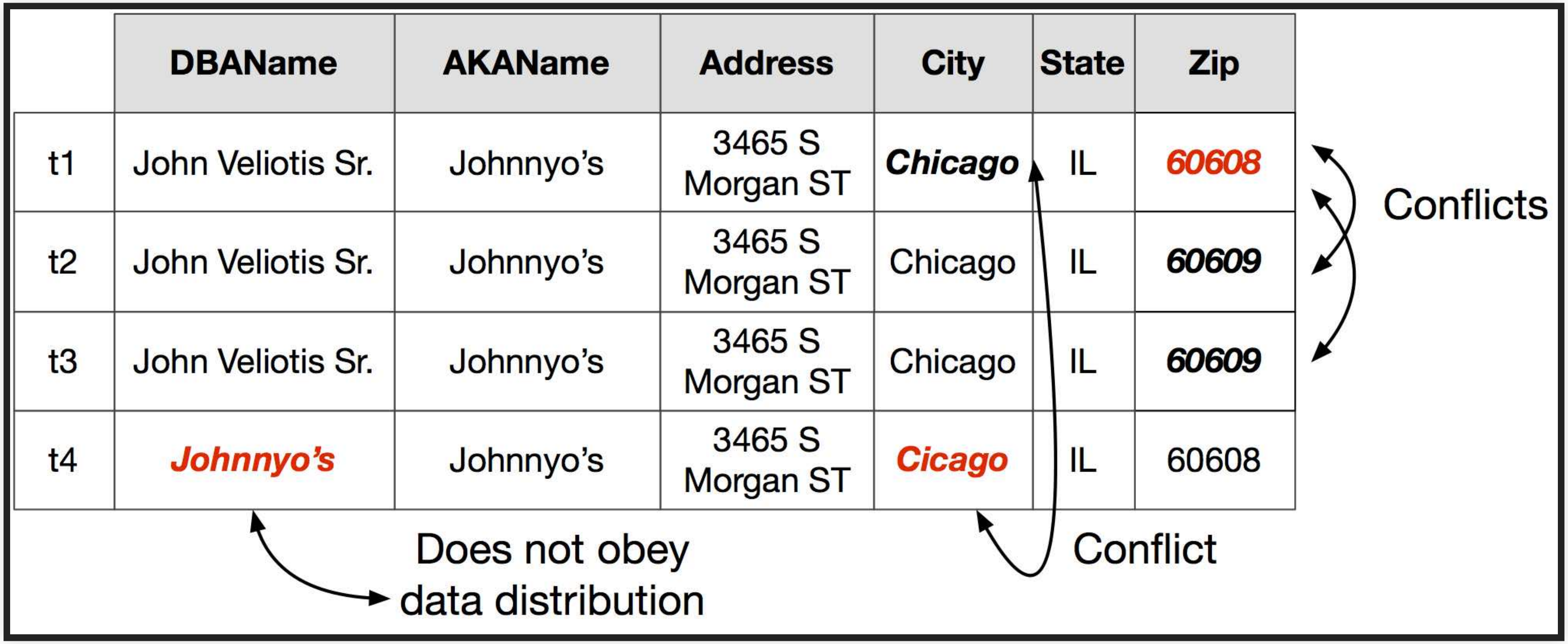
Stock:

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

Sales history:

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

DETECTING INCONSISTENCIES



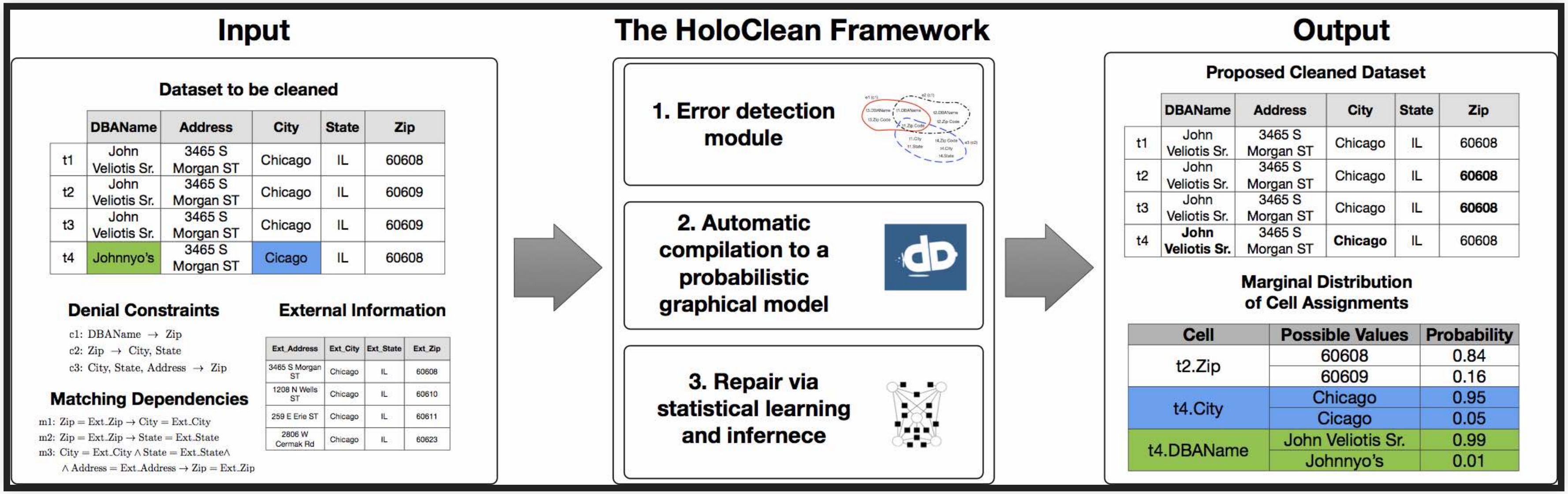
	DBAName	AKAName	Address	City	State	Zip
t1	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	***Chicago***	IL	***60608***
t2	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	***60609***
t3	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	***60609***
t4	***Johnnyo's***	Johnnyo's	3465 S Morgan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

Image source: Theo Rekatsinas, Ihab Ilyas, and Chris Ré, "HoloClean - Weakly Supervised Data Repairing." Blog, 2017.

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

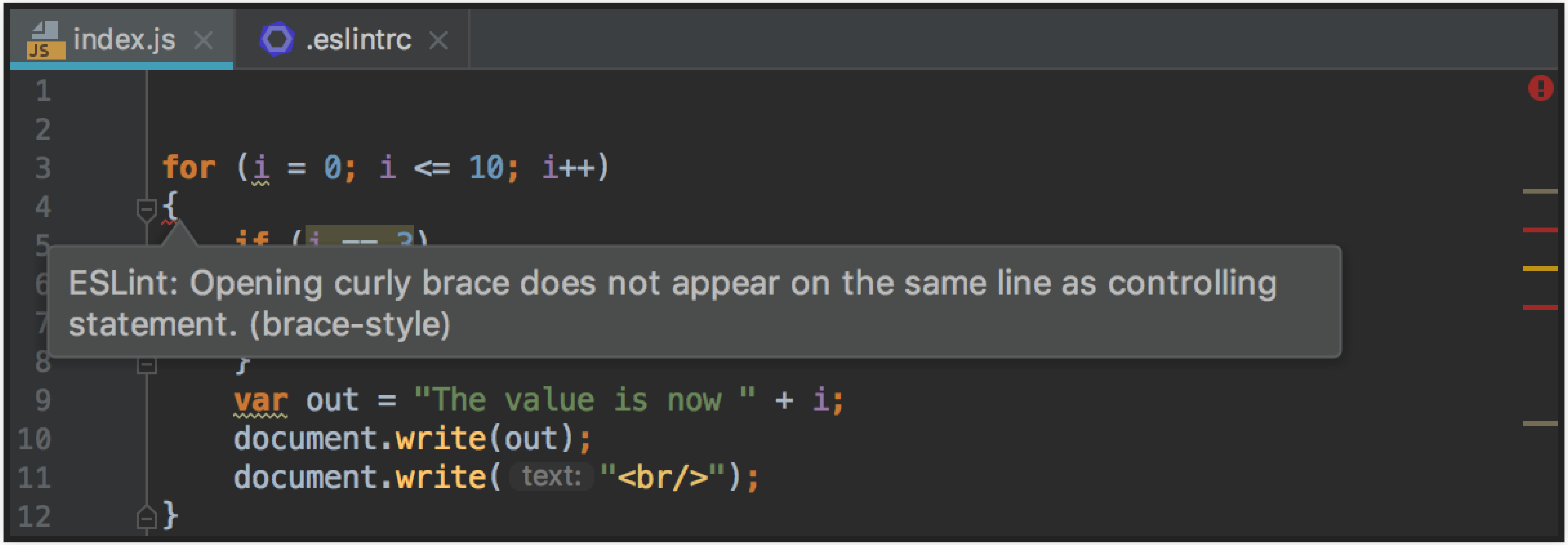
```
if (user.jobTitle = "manager") {
   ...
}
```

```
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



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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  - characteristics of input data changes (e.g., customers with face masks)
  - 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

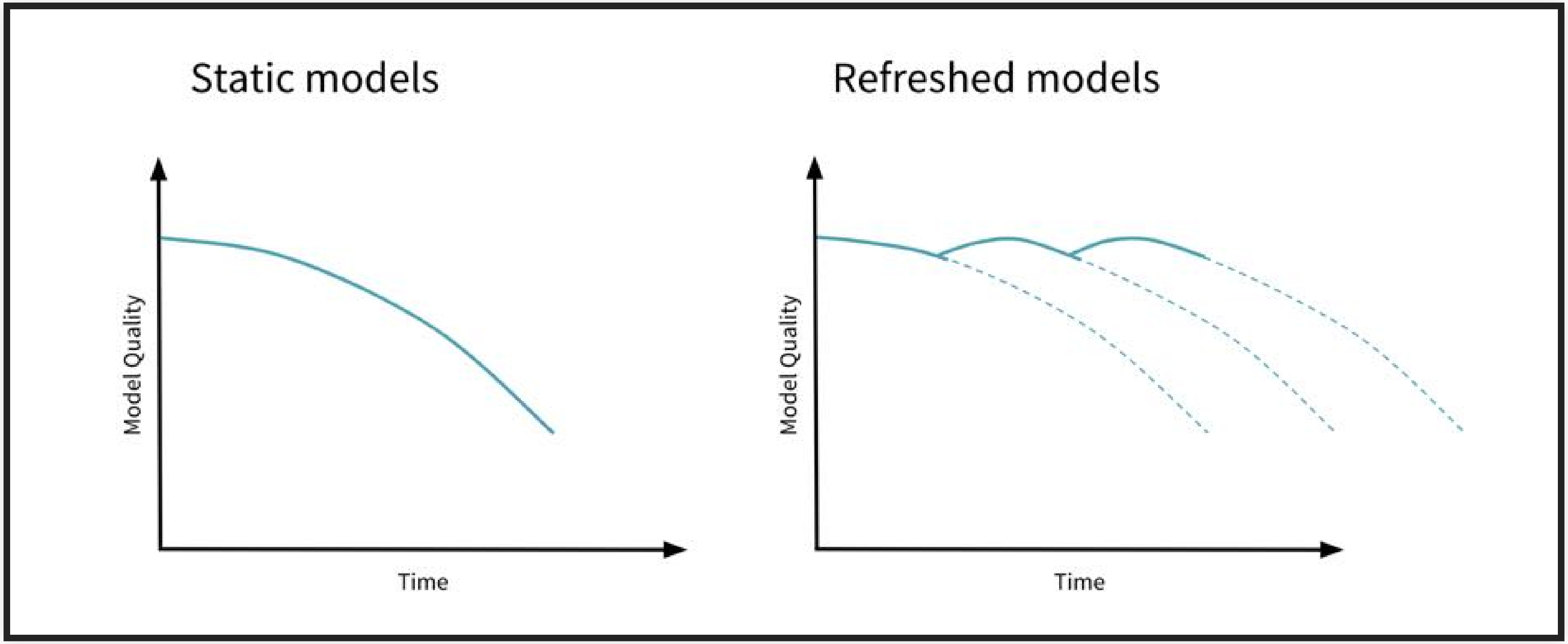


Image source: Joel Thomas and Clemens Mewald. Productionizing Machine Learning: From Deployment to Drift Detection. Databricks Blog, 2019

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

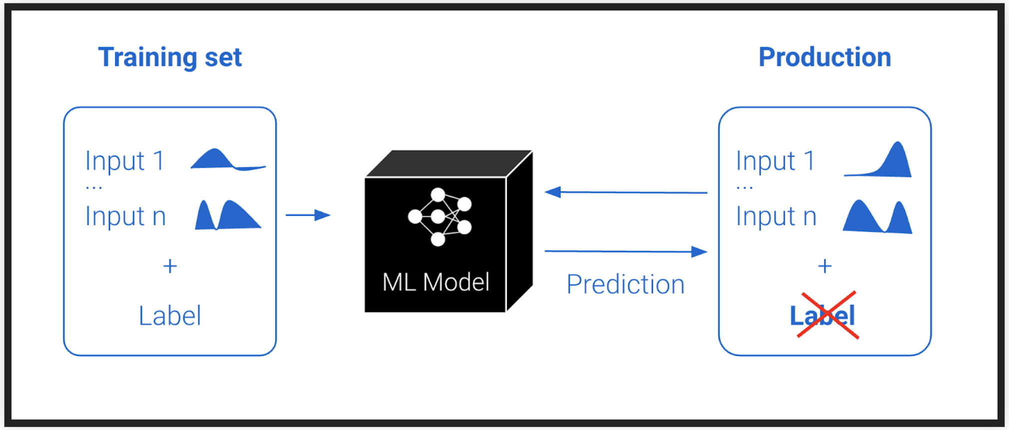
(many papers on this topic, typically on statistical detection)

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!

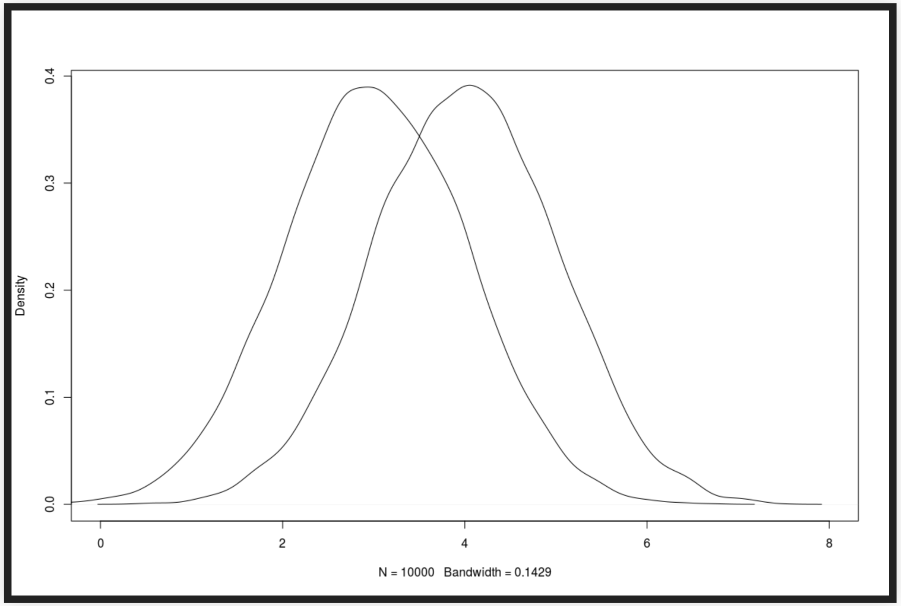
DIFFERENT FORMS OF DATA DRIFT

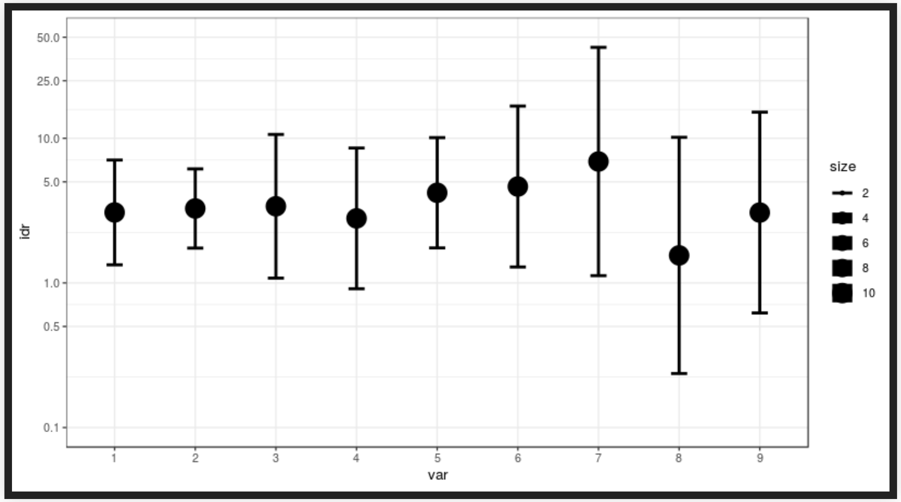
- Structural drift
  - Data schema changes, sometimes by infrastructure changes
  - e.g., `4124784115` -> `412-478-4115`
- Semantic drift
  - Meaning of data changes, same schema
  - e.g., Netflix switches from 5-star to +/- rating, but still uses 1 and 5
- Distribution changes
  - e.g., credit card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

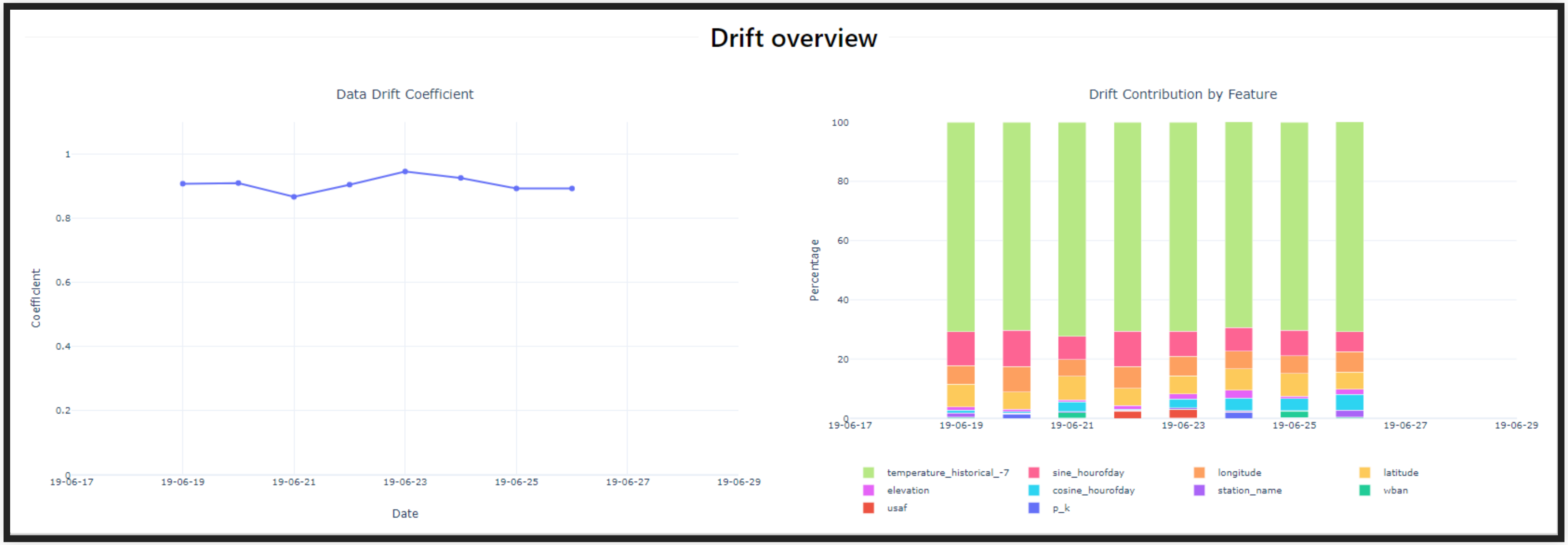


Image source and further readings: Detect data drift (preview) on models deployed to Azure Kubernetes Service (AKS)

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