DATA QUALITY

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

Christian Kaestner

Required reading:

- Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L. M. (2021, May). "Everyone wants to do the model work, not the data work": Data Cascades in High-Stakes AI. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1-15).

Recommended 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)

ADMINISTRATIVA: MIDTERM

- Midterm in 1 week
- During lecture, 80 min, here
- Answer questions related to a given scenario
- All lecture content, reading, recitations in scope -- focus on topics you had opportunity to practice
- No electronics, can bring 6 pages notes on paper (handwritten or typed, both sides)
- Old midterms online, see course webpage

ADMINISTRATIVA: HOMEWORK I3

- Open ended: Try a tool and write a blog post about it
- Any tool related to building ML-enabled systems
  - Except: No pure ML frameworks
  - ML pipelines, data engineering, operations, ...
  - Open source, academic, or commercial; local or cloud
  - Also look for competitors of tools of interest
- Claim tool in Spreadsheet, first come first serve
- 1 week assignment (despite due in 3 weeks)
- Past tools: Algorithmia, Amazon Elastic MapReduce, Apache Flink, Azure ML, Dask, Databricks, DataRobot, Google Cloud AutoML, IBM Watson Studio, LaunchDarkly, Metaflow, Pycaret, Split.io, TensorBoard, Weights and Biases, Amazon Sagemaker, Apache Airflow, Apache Flume, Apache Hadoop, Apache Spark, Auto-Surprise, BentoML, CML, Cortex, DVC, Grafana, Great Expectations, Holoclean, Kedro, Kubeflow, Kubernetes, Luigi, MLflow, ModelDB, Neo4j, pydqc, Snorkel, TensorFlow Lite, TPOT
- *17-745 students: Research project instead, contact us now*

LEARNING GOALS

- Distinguish precision and accuracy; understanding the better models vs more data tradeoffs
- Use schema languages to enforce data schemas
- Design and implement automated quality assurance steps that check data schema conformance and distributions
- Devise infrastructure for detecting data drift and schema violations
- Consider data quality as part of a system; design an organization that values data quality

DATA-QUALITY CHALLENGES

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

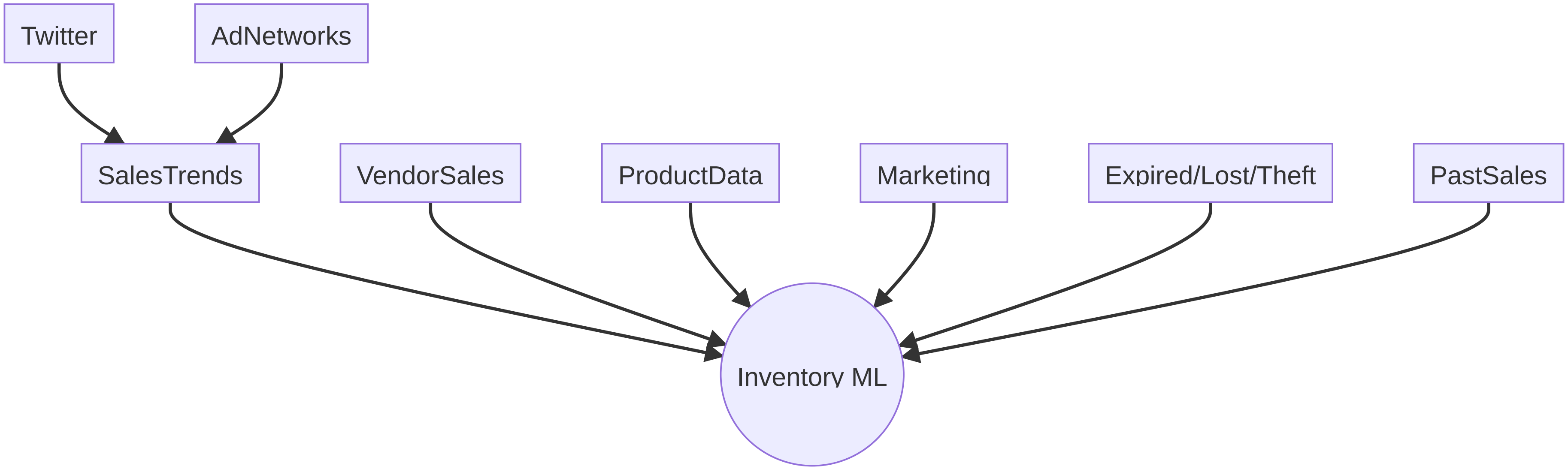
Quote: Gil Press. "Cleaning Big Data: Most Time-Consuming, Least Enjoyable Data Science Task, Survey Says." Forbes Magazine, 2016.

CASE STUDY: INVENTORY MANAGEMENT

DATA COMES FROM MANY SOURCES

- Manually entered
- Actions from IT systems
- Logging information, traces of user interactions
- Sensor data
- Crowdsourced

MANY DATA SOURCES



sources of different reliability and quality

INVENTORY DATABASE

Product Database:

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

Stock:

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

Sales history:

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

RAW DATA IS AN OXYMORON

Shipment Received Note

Goods Received Receipt

Supplier: Mr. Adam Smith			Destination: Marlon De compo			
Shipment Date	June 17, 2015		Receipt No.	09XC10	Genre: Shipment Delivery Receipt	
Order Number	67-NY25		Delivery Duration	5 days		
Goods Details	Packing Weight	Packing Size	Quantity	Delivered Quantity	Comments	

Received by: Mr. Boucle Norhad Shaker

Recommended Reading: Gitelman, Lisa, Virginia Jackson, Daniel Rosenberg, Travis D. Williams, Kevin R. Brine, Mary Poovey, Matthew Stanley et al. "Data bite man: The work of sustaining a long-term study." In "Raw Data" Is an Oxymoron, (2013), MIT Press: 147-166.

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 in inventory system?**

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 in inventory system?**

USERS MAY DELIBERATELY CHANGE DATA

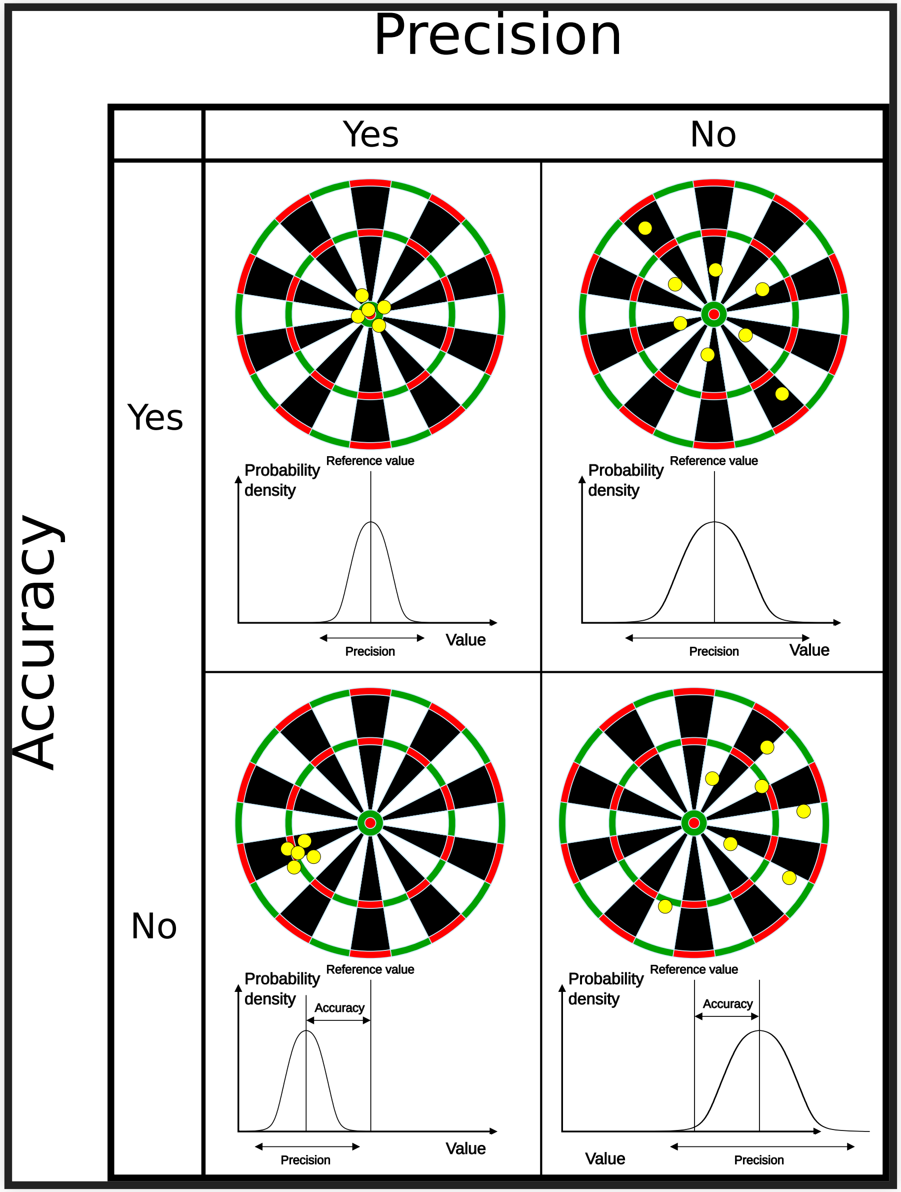
- Users react to model output
- Users try to game/deceive the model

- **Examples in inventory system?**

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

POOR DATA QUALITY HAS CONSEQUENCES

(often delayed consequences)

EXAMPLE: SYSTEMATIC BIAS IN LABELING

- Poor data quality leads to poor models
- Not detectable in offline evaluation
- Problem in production -- now difficult to correct

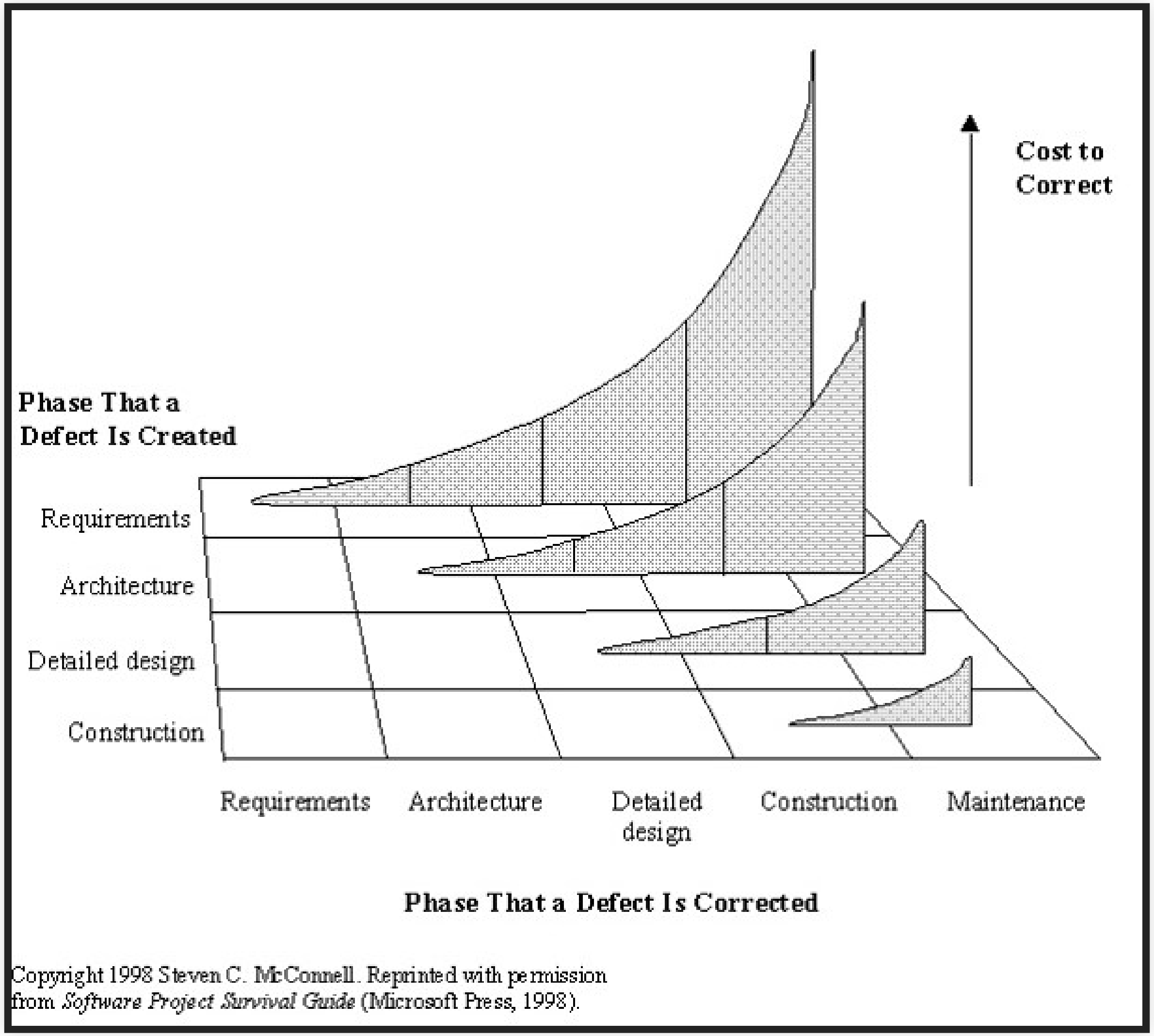
TECH AMAZON ARTIFICIAL INTELLIGENCE

Amazon reportedly scraps internal AI recruiting tool that was biased against women

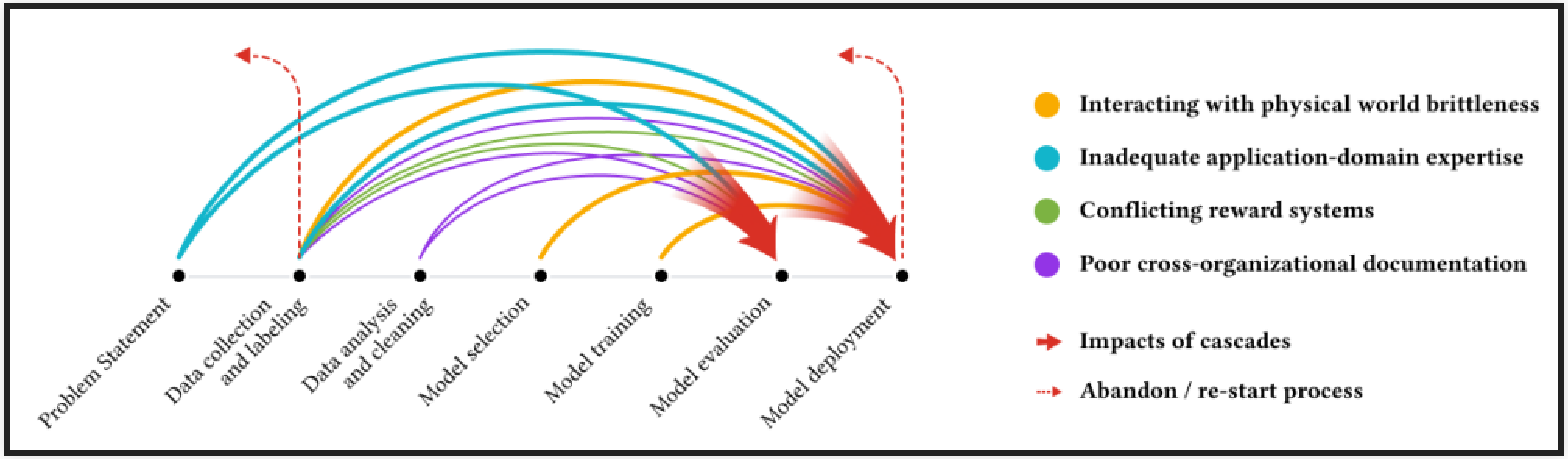
The secret program penalized applications that contained the word "women's"

By James Vincent | Oct 10, 2018, 7:09am EDT

DELAYED FIXES INCREASE REPAIR COST



DATA CASCADES



Detection almost always delayed! Expensive rework.

Difficult to detect in offline evaluation.

Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L. M. (2021, May). "Everyone wants to do the model work, not the data work": Data Cascades in High-Stakes AI. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1-15).

DATA SCHEMA

Ensuring basic consistency about shape and types

DIRTY DATA: EXAMPLE

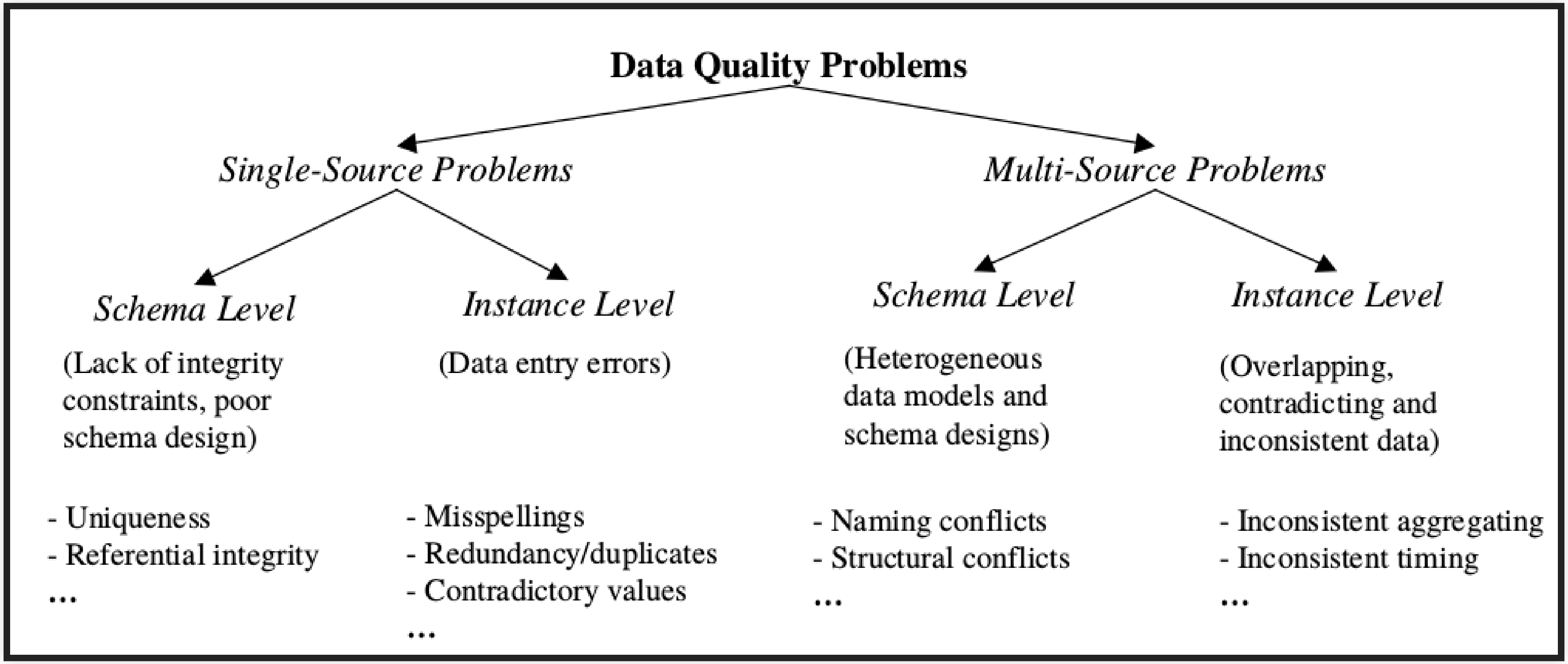
TABLE: CUSTOMER

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?



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

SCHEMA PROBLEMS

- 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

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

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));
```

WHICH PROBLEMS ARE SCHEMA PROBLEMS?

TABLE: CUSTOMER

ID	Name	Birthday	Age	Sex	Phone	ZIP
3456	Ford, Harrison	18.2.76	43	M	9999999999	15232
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TABLE: ADDRESS

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WHAT HAPPENS WHEN NEW DATA VIOLATES SCHEMA?

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
```

SCHEMA LIBRARY: 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"
        }
    ]
}
```

SCHEMA LIBRARY: 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 LIBRARIES/FORMATS

Examples

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

DISCUSSION: DATA SCHEMA CONSTRAINTS FOR INVENTORY SYSTEM?

Product Database:

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

Stock:

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

Sales history:

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

SUMMARY: SCHEMA

- Basic structure and type definition of data
- Well supported in databases and many tools
- Very low bar

INSTANCE-LEVEL PROBLEMS

Inconsistencies, wrong values

DIRTY DATA: EXAMPLE

TABLE: CUSTOMER

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TABLE: ADDRESS

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Problems with the data beyond schema problems?

INSTANCE-LEVEL PROBLEMS

- 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

Can we detect these?

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

DISCUSSION: INSTANCE-LEVEL PROBLEMS IN SCENARIO?

DATA CLEANING OVERVIEW

- Data analysis / Error detection
    - Usually focused on specific kind of problems, e.g., duplication, typos, missing values, distribution shift
    - 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 EXAMPLES

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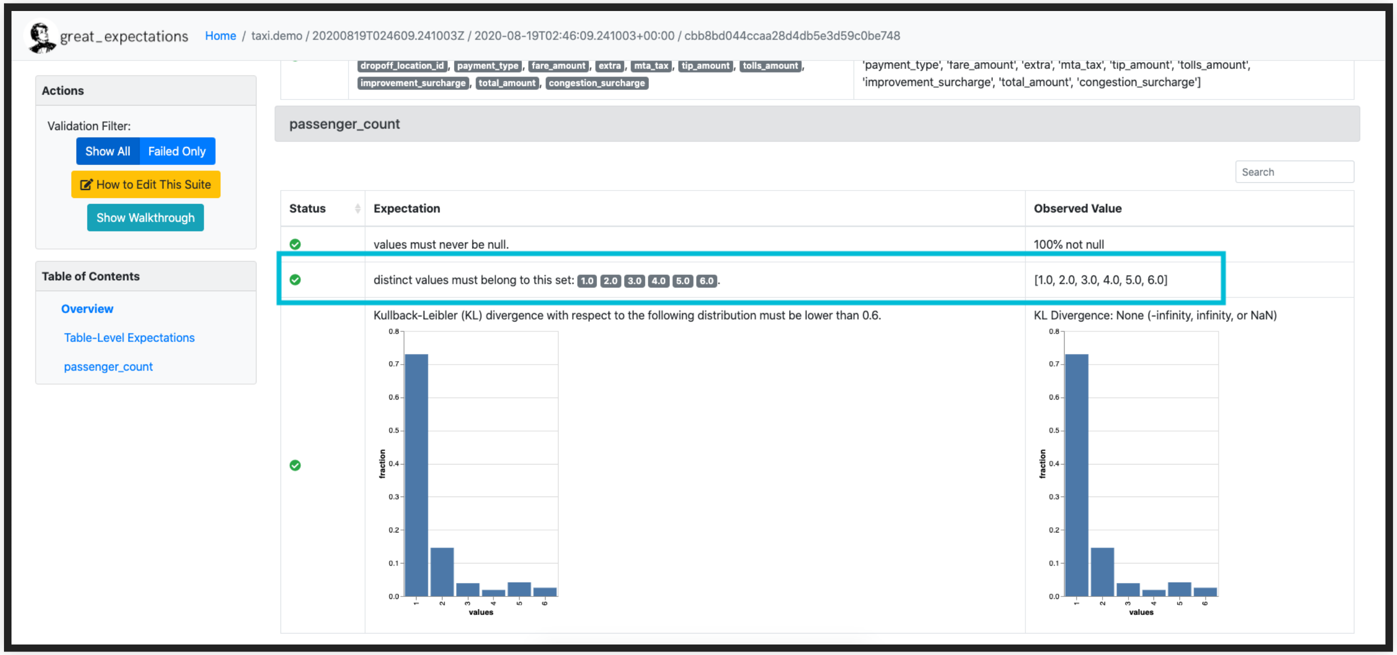
Q. Can we (automatically) detect errors? Which errors are problem-dependent?

EXAMPLE TOOL: GREAT EXPECTATIONS

```
expect_column_values_to_be_between(
    column="passenger_count",
    min_value=1,
    max_value=6
)
```



https://greatexpectations.io/

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

MACHINE LEARNING FOR 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

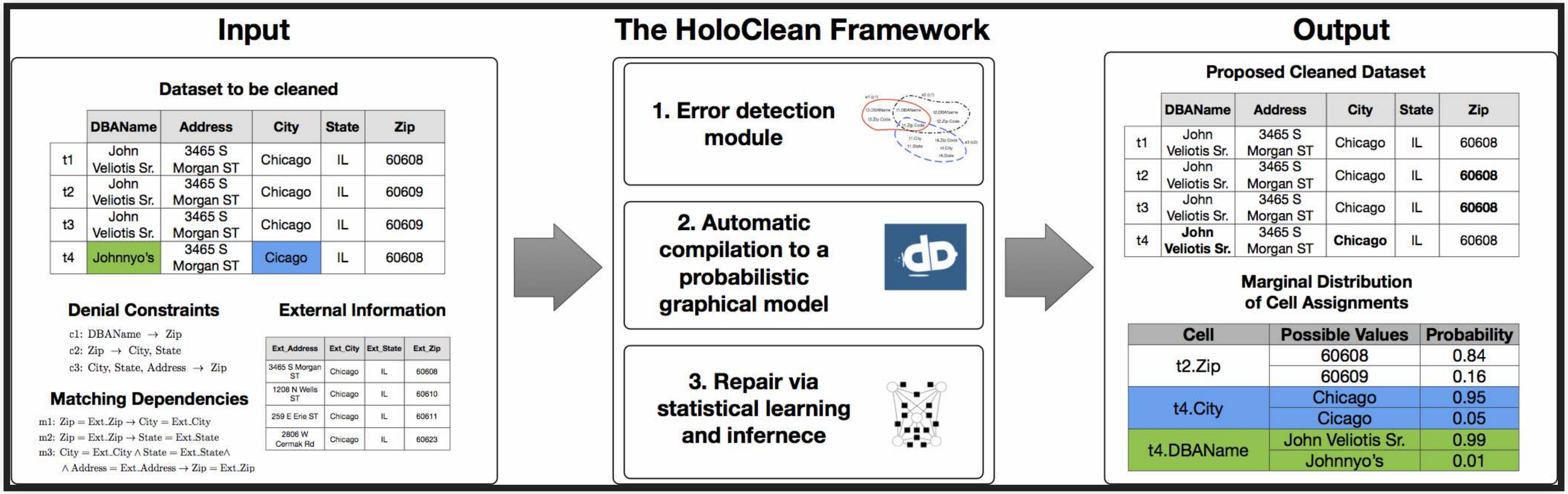
Conflicts

Does not obey data distribution

Conflict

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

EXAMPLE: 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)

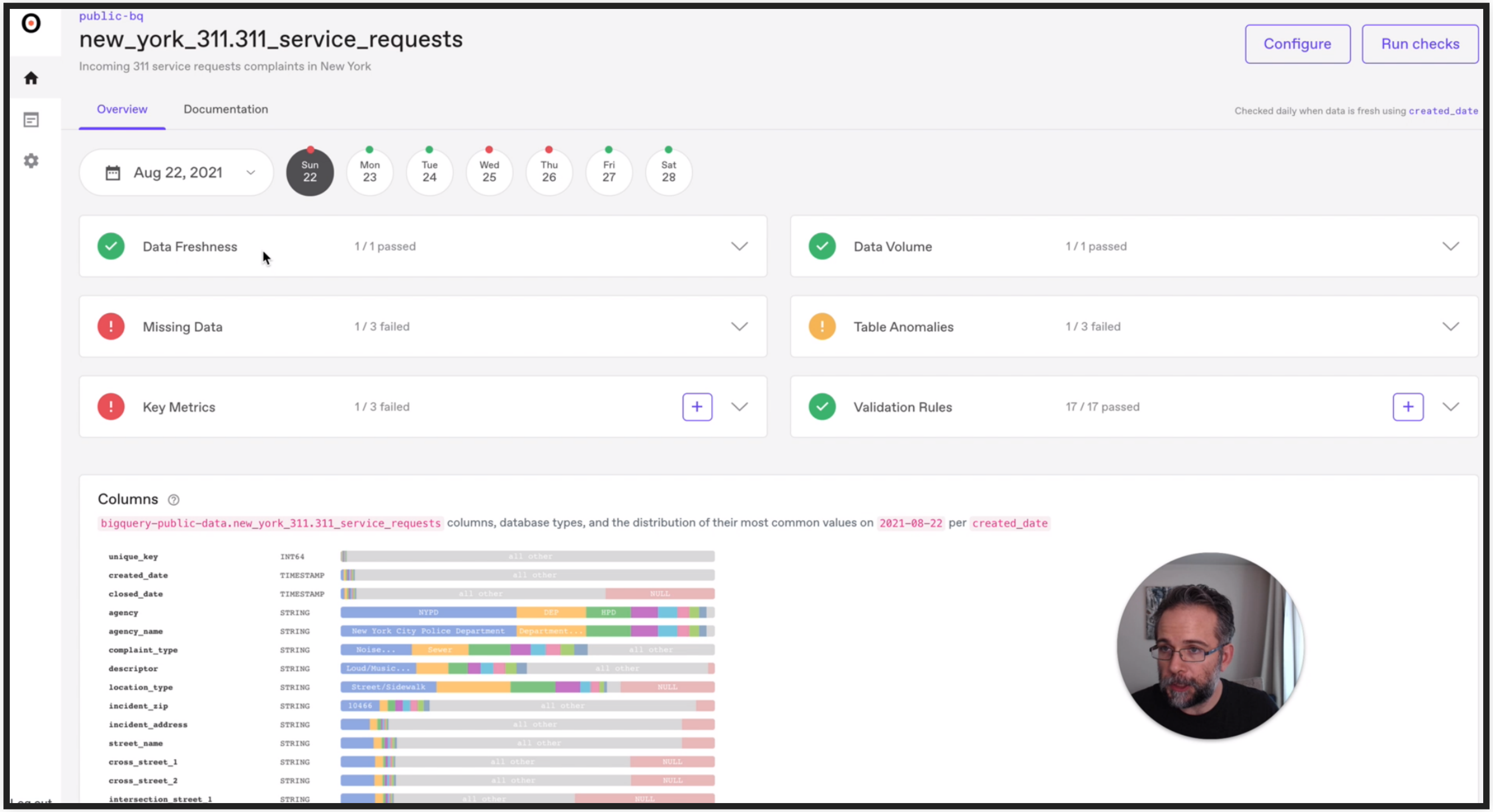
(also useful tool for exploratory data analysis)

Further readings: Standard algorithms and many variations, see Wikipedia

DISCUSSION: DATA QUALITY RULES IN INVENTORY SYSTEM

DETECTING DRIFT

MONITORING FOR CHANGES



https://www.anomalo.com/

DRIFT & MODEL DECAY

- **Concept drift** (or concept shift)
  - 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
- **Data drift** (or covariate shift or population drift)
  - characteristics of input data changes (e.g., customers with face masks)
  - input data differs from training data
  - over time: predictions less confident, further from training data
- **Upstream data changes**
  - external changes in data pipeline (e.g., format changes in weather service, new worker performing manual entry)
  - model interprets input data incorrectly
  - over time: abrupt changes due to faulty inputs

How do we fix these drifts?

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

BREAKOUT: DRIFT IN THE INVENTORY SYSTEM

What kind of drift might be expected?

As a group, in slack `#lecture` write plausible example of:

- Concept Drift:
- Data Drift:
- Upstream data changes:

WATCH FOR DEGRADATION IN PREDICTION ACCURACY

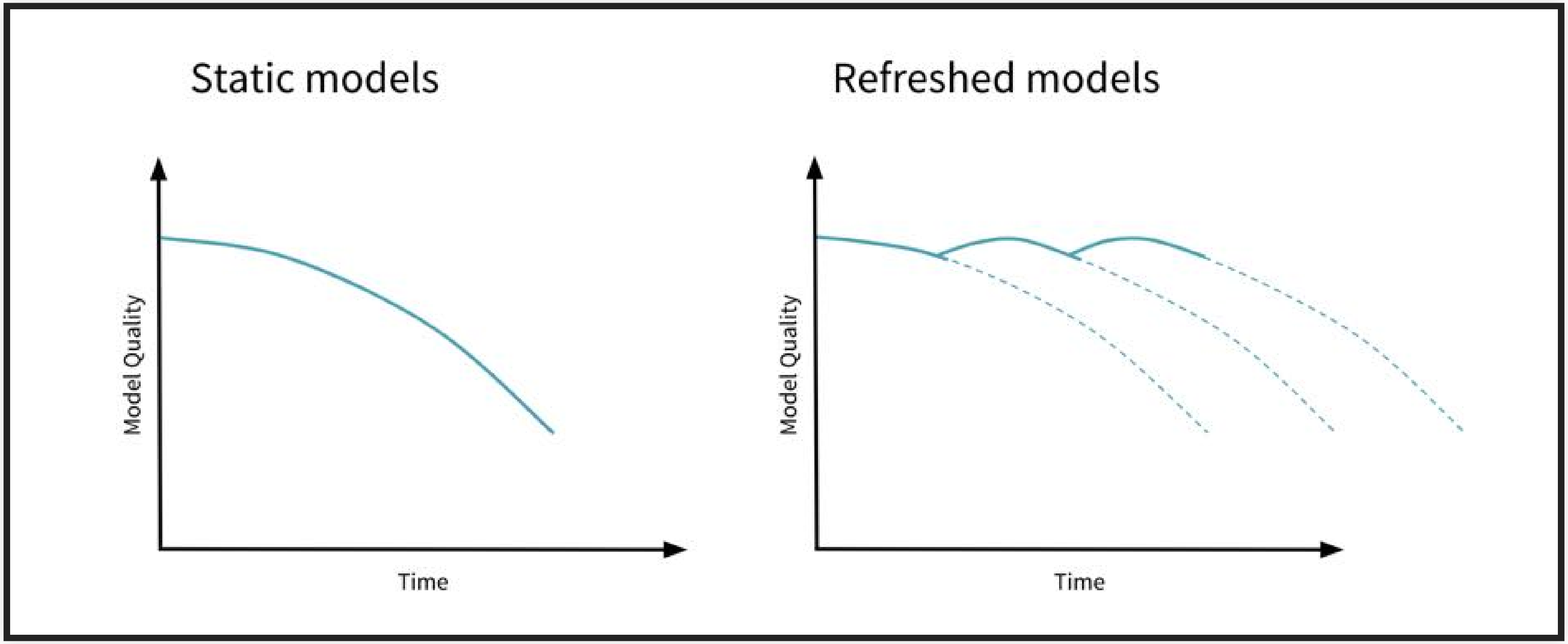


Image source: Joel Thomas and Clemens Mewald. Productionizing Machine Learning: From Deployment to Drift Detection. Databricks Blog, 2019

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

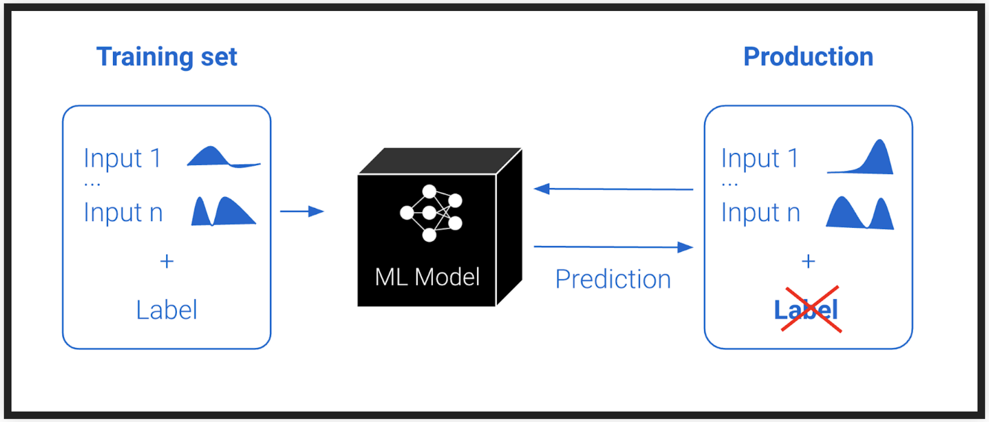
(many papers on this topic, typically on statistical detection)

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!

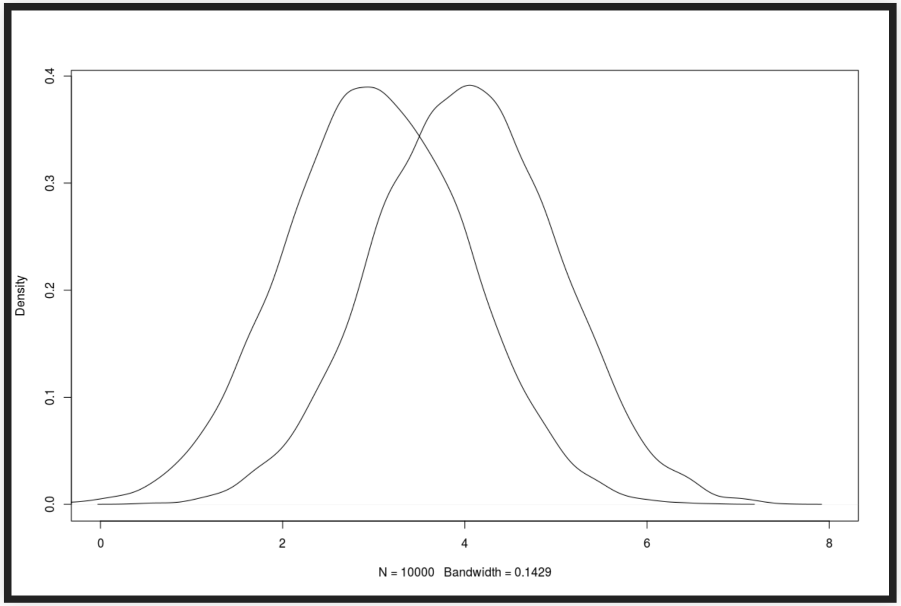
DIFFERENT FORMS OF DATA DRIFT

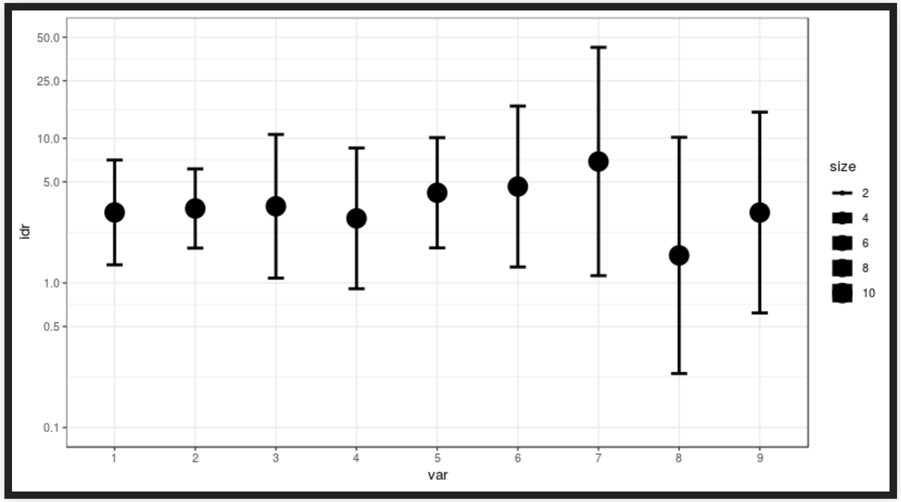
- Structural drift
  - Data schema changes, sometimes by infrastructure changes
  - e.g., `4124784115` -> `412-478-4115`
- Semantic drift
  - Meaning of data changes, same schema
  - e.g., Netflix switches from 5-star to +/- rating, but still uses 1 and 5
- Distribution changes
  - e.g., credit card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

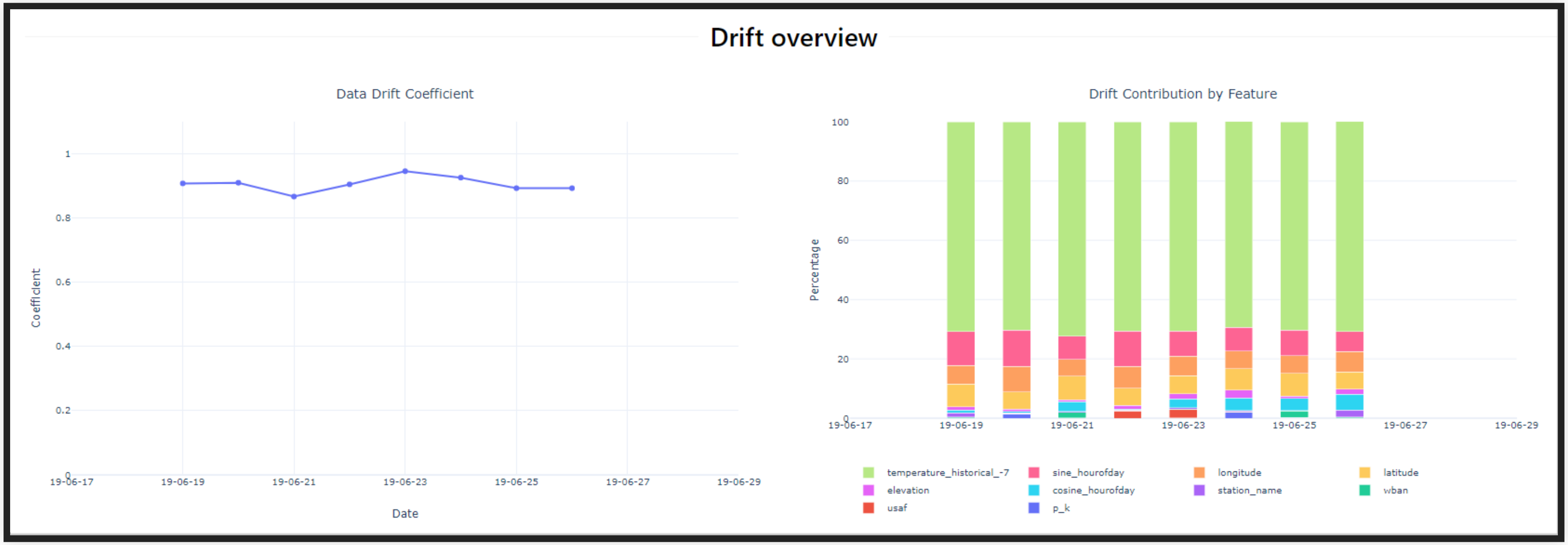
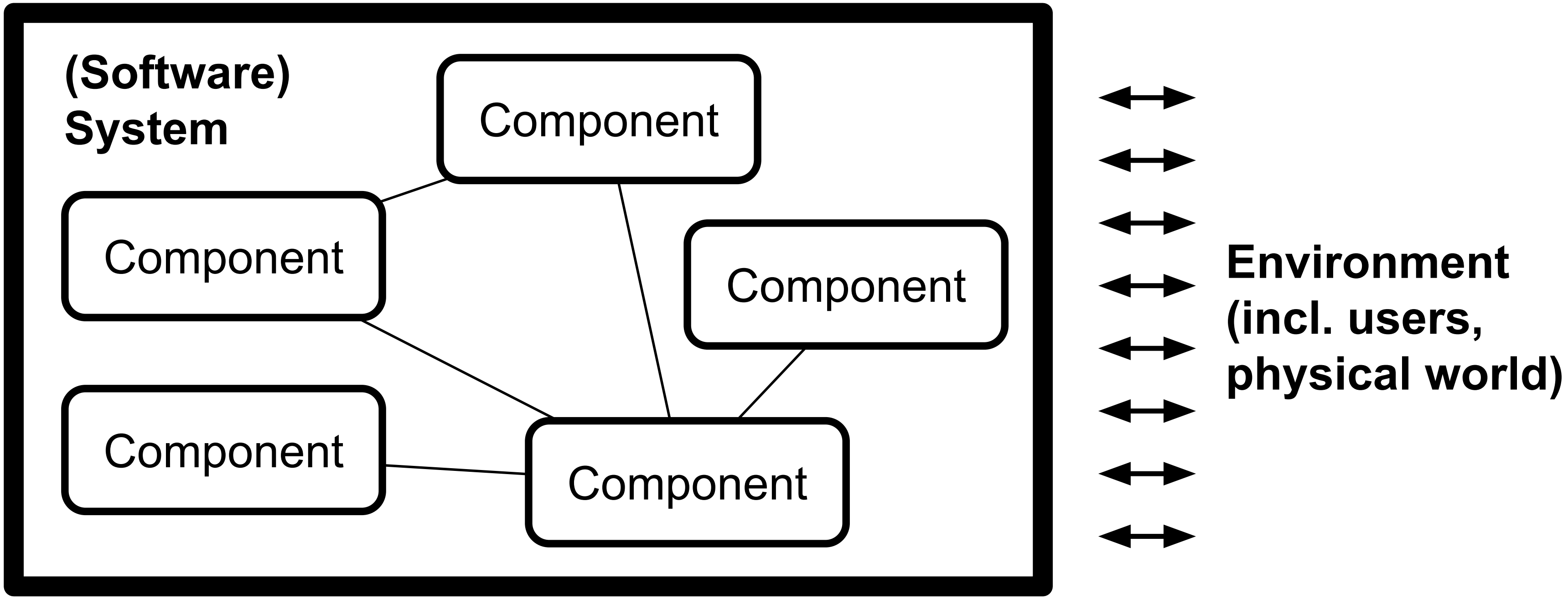


Image source and further readings: Detect data drift (preview) on models deployed to Azure Kubernetes Service (AKS)

BREAKOUT: DRIFT IN THE INVENTORY SYSTEM

What kind of monitoring for drift in Inventory scenario?

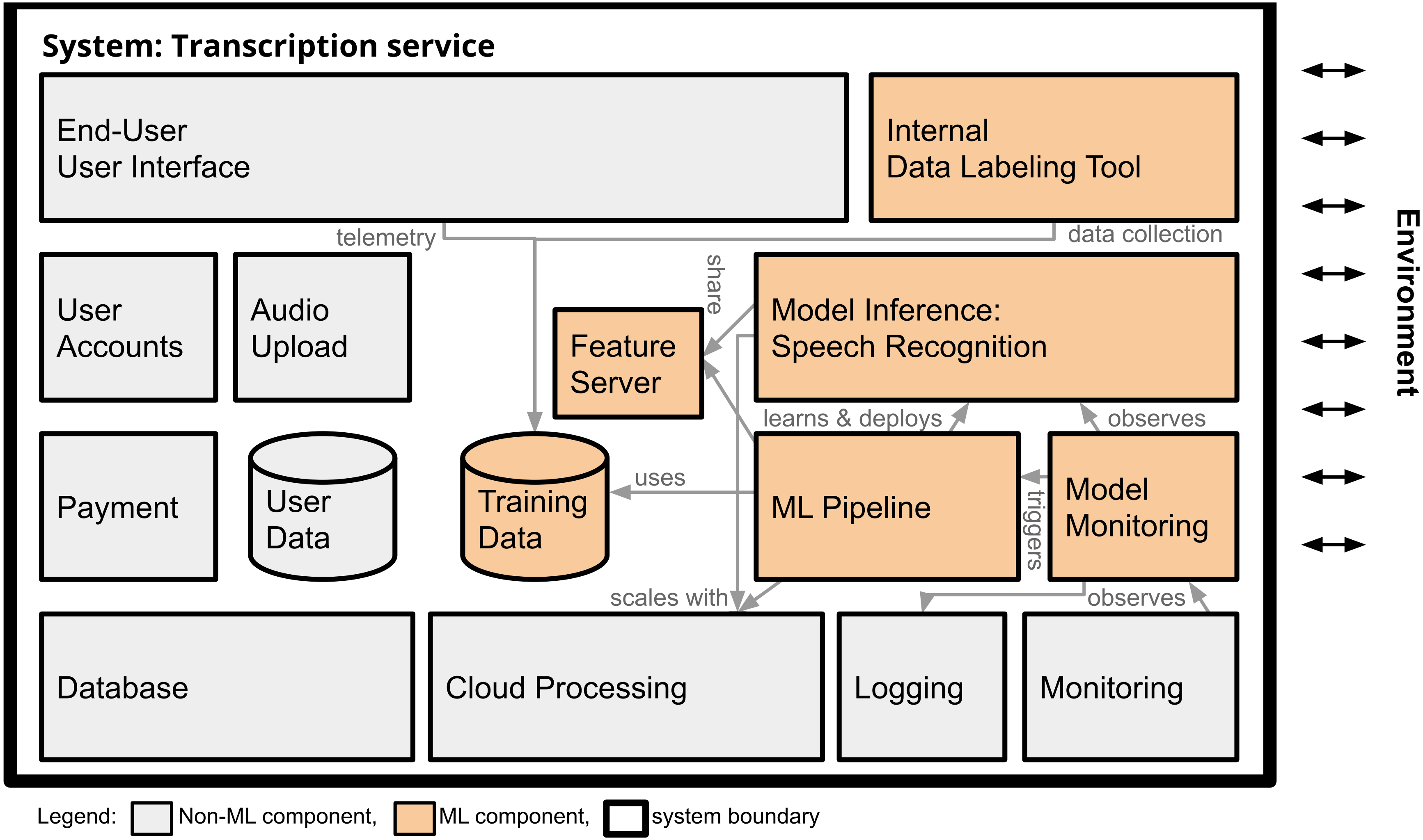
DATA QUALITY IS A SYSTEM-WIDE CONCERN



Everyone wants to do the model work, not the data work

Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L. M. (2021, May). “Everyone wants to do the model work, not the data work”: Data Cascades in High-Stakes AI. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1-15).

DATA FLOWS ACROSS COMPONENTS



DATA QUALITY IS A SYSTEM-WIDE CONCERN

- Data flows across components
    - e.g., from user interface into database to crowd-sourced labeling team into ML pipeline
- Documentation at the interfaces is important
- Humans interacting with the system
    - Entering data
    - Labeling data
    - Observed with sensors/telemetry
    - Incentives, power structures, recognition
- Organizational practices
    - Value, attention, and resources given to data quality

DATA QUALITY DOCUMENTATION

- Teams rarely document expectations of data quantity or quality
- Data quality tests are rare, but some teams adopt defensive monitoring
    - Local tests about assumed structure and distribution of data
    - Identify drift early and reach out to producing teams
- Several ideas for documenting distributions, including Datasheets and Dataset Nutrition Label
    - Mostly focused on static datasets, describing origin, consideration, labeling procedure, and distributions
    - Example

- Nahar, Nadia, Shurui Zhou, Grace Lewis, and Christian Kästner. "Collaboration Challenges in Building ML-Enabled Systems: Communication, Documentation, Engineering, and Process." In Proceedings of the 44th International Conference on Software Engineering (ICSE), May 2022.
- Gebru, Timnit, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé Iii, and Kate Crawford. "Datasheets for datasets." Communications of the ACM 64, no. 12 (2021): 86-92.

COMMON DATA CASCADES

- Interacting with physical world brittleness
  - Idealized data, ignoring realities and change of real-world data
  - Static data, one time learning mindset, no planning for evolution
- Inadequate domain expertise
  - Not understanding the data and its context
  - Involving experts only late for trouble shooting
- Conflicting reward systems
  - Missing incentives for data quality
  - Not recognizing data quality importance, discard as technicality
  - Missing data literacy with partners
- Poor (cross-organizational) documentation
  - Conflicts at team/organization boundary
  - Undetected drift

Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L. M. (2021, May). "Everyone wants to do the model work, not the data work": Data Cascades in High-Stakes AI. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1-15).

DISCUSSION: POSSIBLE DATA CASCADES IN INVENTORY SCENARIO?

- Interacting with physical world brittleness
- Inadequate domain expertise
- Conflicting reward systems
- Poor (cross-organizational) documentation

ETHICS AND POLITICS OF DATA

Raw data is an oxymoron

INCENTIVES FOR DATA QUALITY? VALUING DATA WORK?

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.

BONUS: 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

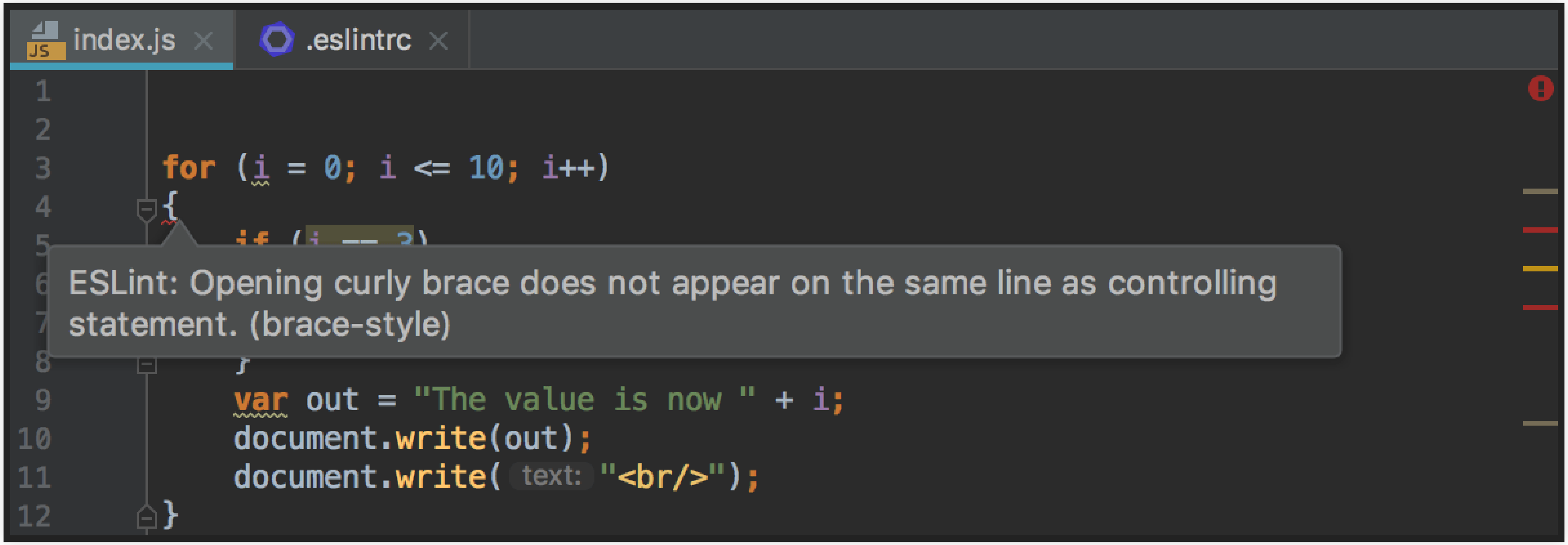
```
if (user.jobTitle = "manager") {
   ...
}
```

```
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.

SUMMARY

- Data and data quality are essential
- Data from many sources, often inaccurate, imprecise, inconsistent, incomplete, ... -- many different forms of data quality problems
- Many mechanisms for enforcing consistency and cleaning
    - Data schema ensures format consistency
    - Data quality rules ensure invariants across data points
- Concept and data drift are key challenges -- monitor
- Data quality is a system-level concern
    - Data quality at the interface between components
    - Documentation and monitoring often poor
    - Involves organizational structures, incentives, ethics, ...
- Quality assurance for the data processing pipelines