DSGA 3001.009:
Data Engineering For Machine Learning

09 – Data Validation and Data Cleaning

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Center for Data Science, New York University

Course Topics

- **Introduction**
  - Intro & Real World Machine Learning Systems
  - Systems Foundations & ML Engineering
  - Case Study: A Demand Forecasting System at Amazon
  - Guest Lecture on Practical Feature Extraction
- **Systems for Machine Learning**
  - Machine Learning on Distributed Dataflow Systems
  - Distributed Machine Learning with Parameter Servers
  - Deep Learning Engines
  - Model Serving Systems
- **Data Management for Machine Learning**
  - Model Management
  - *Data Validation and Data Cleaning*
  - Fairness in Machine Assisted Decision Making
  - Research in Data Management for Machine Learning

Overview

- Announcements
- Introduction & Overview
- Exemplary Error Detection and Data Cleaning Techniques
  - Quantitative Data: Robust Univariate Outlier Detection
  - Categorical Data: String Normalization
  - Candidate Key Detection at Scale with Hyperloglog Sketches
  - Missing Value Imputation using Supervised Learning
  - Data Unit Testing with Deequ
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Solution for Assignment 3

- Forward pass in Neural Network
- Dataflow Graph Extraction

Project Topics & Teams

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- Assigned topics to **12 teams**, chose **topics from student preferences**
- One very popular topic: 4x Fair AutoML

- Will reserve **last two lectures on 12/5 and 12/12 for project presentations**
  - **10min presentation +5min questions** from me and class
  - Teams working on the same topic should present on the same day

- **Lab will become “project consulting hour”** from 11/20 on
  - Additionally office hours or appointment with me

Gong Show next week 11/14

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- **First deliverable** for each group project (worth **5 points**)
- **Single slide per team**, to be **presented by one person** from the team **in 2 minutes**
  - **Add the slide to a provided Google Doc until 11/13 at 12pm**
  - Please provide the following information on the slide

    (1) Two-sentence **summary** of the project
    (2) **Description of the data** used during your project
    (3) Description of how you will **measure the outcome** of your project
    (4) Description of the **biggest problem** you will have to solve in your project

- **Potentially answer 1 or 2 questions** about your project (2min max)

Datawig – Missing Value Imputation for Non-ML Experts

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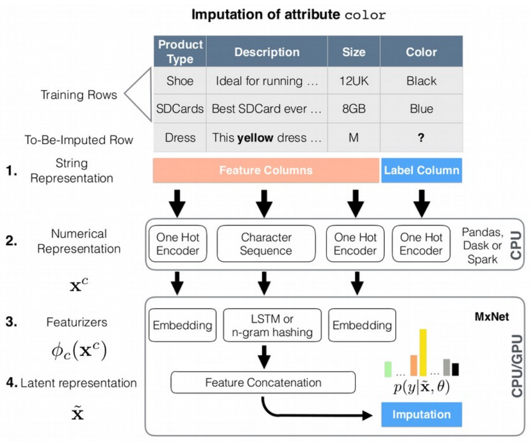
- **Project Description:**
  - **Goal:** Build an easy-to-use missing value imputation tool for categorical data
  - **Details:** Automatically train an imputation model for CSV data without requiring the user to specify an algorithm or hyperparameters

- **Data:** Amazon customer reviews dataset (reviews written on amazon.com and associated metadata from 1995 until 2015)

  https://s3.amazonaws.com/amazon-reviews-pds/readme.html

- **Evaluation:** Comparison against the `SimpleImputer` from scikit-learn, measuring the accuracy and F1-scores of the imputed values compared to the true values

- **Biggest problem:** Need to find a way to automatically compute features from heterogeneous data




```
CREATE EXTERNAL TABLE amazon_reviews_parquet(
  marketplace string,
  customer_id string,
  review_id string,
  product_id string,
  product_parent string,
  product_title string,
  star_rating int,
  helpful_votes int,
  total_votes int,
  vine string,
  verified_purchase string,
  review_headline string,
  review_body string,
  review_date bigint,
  year int)
PARTITIONED BY (product_category string)
ROW FORMAT SERDE
  'org.apache.hadoop.hive.ql.io.parquet.serde.ParquetHiveSerDe'
STORED AS INPUTFORMAT
  'org.apache.hadoop.hive.ql.io.parquet.MapredParquetInputFormat'
OUTPUTFORMAT
  'org.apache.hadoop.hive.ql.io.parquet.MapredParquetOutputFormat'
LOCATION
  's3://amazon-reviews-pds/parquet/'
```

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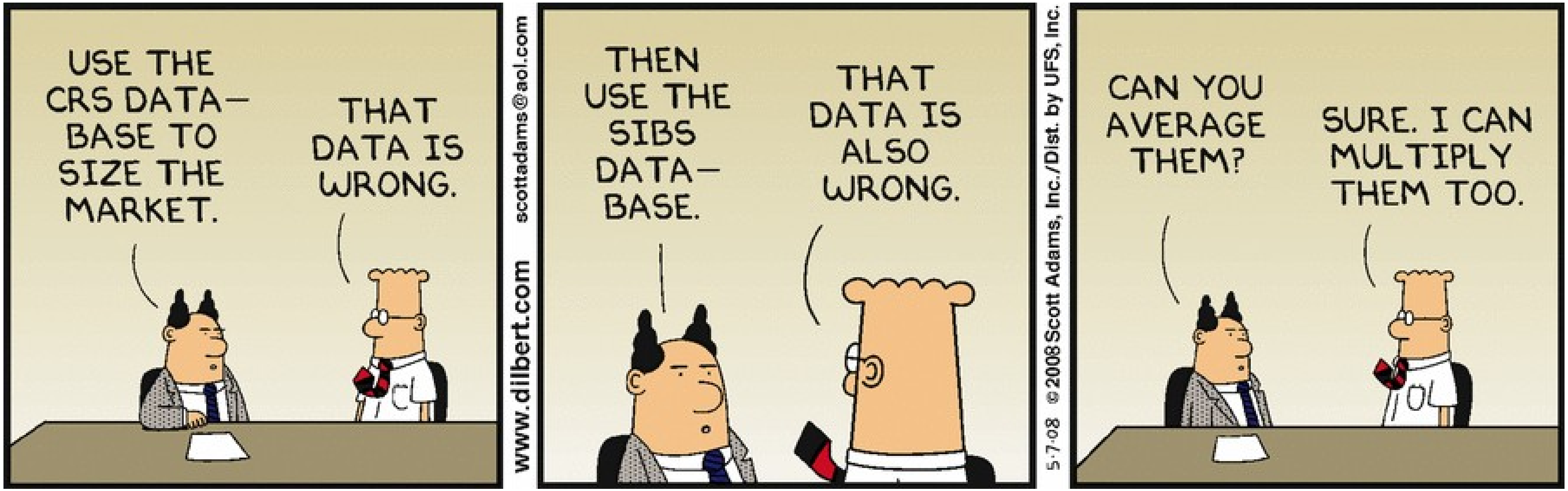

https://dilbert.com/strip/2008-05-07

Why is Data Quality Important?

- **Impact on organisational decisions**
  - Missing or incorrect data can result in wrong decision making
- **Legal obligations in certain business scenarios**
  - Plug type information required for selling electric devices in EU

- **Impact on machine learning models**
  - Cleaner data can greatly improve model performance
- **Potential for causing biased decisions in ML-based systems**
  - Not well understood, area of active research

- **Operational stability: missing and inconsistent data can cause havoc in production systems**
  - Crashes (e.g., due to “NullPointerExceptions” for missing attributes)
  - Wrong predictions (e.g., change of scale in attributes)

Data: Academia vs the Real-World

- **Academic datasets**
  - Static
  - Often down-sampled, cleaned and aggregated before publication
  - Attributes typically well understood
  - Most of time: size convenient for processing on desktop machines
  - Example: UCI ML datasets

- **Real-world data**
  - Constantly changing
  - Often hundreds of attributes
  - Data originates from multiple sources / people / teams / systems
  - Several potentially inconsistent copies
  - Often too large to conveniently handle on a desktop machine
  - Often difficult to access (e.g., data compressed and partitioned in a distributed filesystem)

Changes in Data Collection Strategies

- **Pre-Internet Era**
  - Data collected in transactional, relational databases
  - "Extract-Transform-Load" export to data warehouses for analysis (Relational databases optimized for analytical workloads)
  - Modelling of the data and its schema before collection

- **Internet Era: "Collect first, analyze later"**
  - Advent of the internet gave rise to vast amount of semi-structured data
  - New data stores established (key-value stores, document databases, data lakes)
    - Scale to very large datasets
    - Relaxed consistency (e.g. no distributed transactions)
    - Enforce fewer modelling decisions at collection time
    - "Schema-on-Read": application has to determine how to interpret data
  - Economic incentives
    - Decreasing storage costs
    - Data becomes valuable as input to ML-based applications

Sources of Error in Data

- **Data entry errors**
  - Typos in forms
  - Different spellings for the same real-world entity (e.g., addresses, names)
- **Measurement errors**
  - Outside interference in measurement process
  - Placement of sensors
- **Distillation errors**
  - Editorial bias in data summaries
  - Domain-specific statistical analyses not understood by database manager
- **Data integration errors**
  - Resolution of inconsistencies w.r.t. duplicate entries
  - Unification of units, measurement periods

Hellerstein: "Quantitative data cleaning for large databases.", 2008

Dimensions of Data Quality

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- **Completeness**
  - Degree to which data required to describe a real-world object is available
- **Consistency: Intra-relation constraints (range of admissible values)**
  - Specific data type, interval for a numerical column, set of values for a categorical column
- **Consistency: Inter-relation constraints**
  - Validity of references to other data entries (e.g., “foreign keys” in databases)
- **Syntactic and semantic accuracy**
  - Syntactic accuracy compares the representation of a value with a corresponding definition domain
    - E.g.: value *blue* for `color` attribute syntatically accurate for *red* product in online shop
  - Semantic accuracy compares a value with its real-world representation
    - E.g.: value *XL* for `color` attribute neither syntactically nor semantically accurate for this product

Batini, Carlo, et al. "Methodologies for data quality assessment and improvement."
ACM Computing Surveys 41.3 (2009): 16.

Approaches to Improve Data Quality

- **Data entry interface design**
  - Enforce integrity constraints (e.g., constraints on numeric values, referential integrity)
  - Can force users to “invent” dirty data
- **Organisational management**
  - Streamlining of processes for data collection and analysis
  - Capturing of lineage and metadata
- **Automated data auditing and data cleaning**
  - Application of automated techniques to identify and rectify data errors
- **Exploratory data analysis and data cleaning**
  - Human-in-the-loop approach necessary most of the time
  - Interaction between data visualisation and data cleaning
  - Iterative process

Approaches to Improve Data Quality

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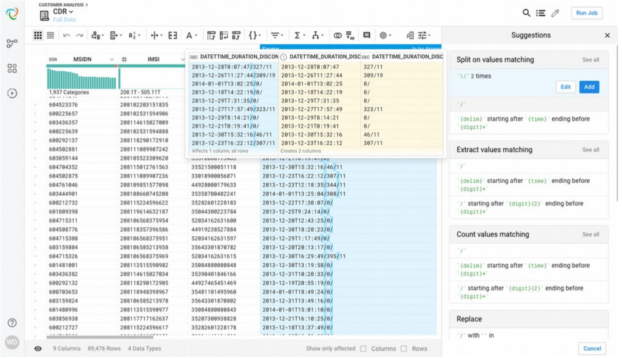
Data Cleaning: Types and Techniques

- **Quantitative data**
  - Integers or floating point numbers in different shapes (sets, tensors, time series)
  - Challenges: unit conversion (especially for volatile units like currency)
  - Foundation of cleaning techniques: **outlier detection**
- **Categorical data**
  - Names or codes to assign data into groups, no ordering or distance defined
  - Common problem: misspelling upon data entry
  - Foundation of cleaning techniques: **normalization / deduplication**
- **Postal addresses**
  - Special case of categorical data, typically entered as free text
  - Major challenge: **deduplication**
- **Identifiers / Keys**
  - Unique identifiers for data objects (e.g., product codes, phone numbers, SSNs)
  - Challenge: detect reuse of identifier across distinct objects
  - Challenge: Ensure **referential integrity**

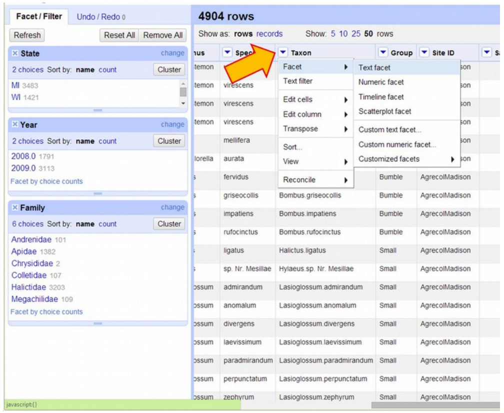
The Need for the “Human in the Loop“

- **Unrealistic assumptions about error detection in academia:**
  - Existence of error detecting rules assumed:
    Integrity Constraints, Functional Dependencies,
    Conditional Functional Dependencies, Denial Constraints
  - Often focus on most efficient and accurate way to
    apply cleaning steps according to rules

- **In practice: error detection already a very hard problem**
  - Consequence: Human-in-the-loop solutions required
  - Data exploration and visualisation crucial
  - Iterative cleaning
  - Popular implementations: Open Refine, Trifacta



https://trifacta.com



https://practicaldatamanagement.files.wordpress.com/2014/05/glbrc-bees-openrefine2.jpg

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Robust Univariate Outlier Detection

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- **Univariate analysis**
  - Simple approach: investigate the set of values of a single attribute of our dataset
  - Statistical perspective: values considered to be a sample of some data generating process
- **Center & Dispersion**
  - Set of values has a *center* that defines what is “average”
  - Set of values has a *dispersion* that defines what is “far from average”
- **Outlier detection**
  - Assumption: erroneous values “far away” from typical values in the set
  - Approach: identify outliers using statistical techniques
  - Problem: How to reliably compute them when the data is dirty / erroneous?

Hellerstein: "Quantitative data cleaning for large databases", 2008

Example: Age Data

- **Set of age values of employees in a company:**

  12 13 14 21 22 26 33 35 36 37 39 42 45 47 54 57 61 68 450

Example: Age Data

- **Set of age values of employees in a company:**

12 13 14 21 22 26 33 35 36 37 39 42 45 47 54 57 61 68 450

minors

impossible age

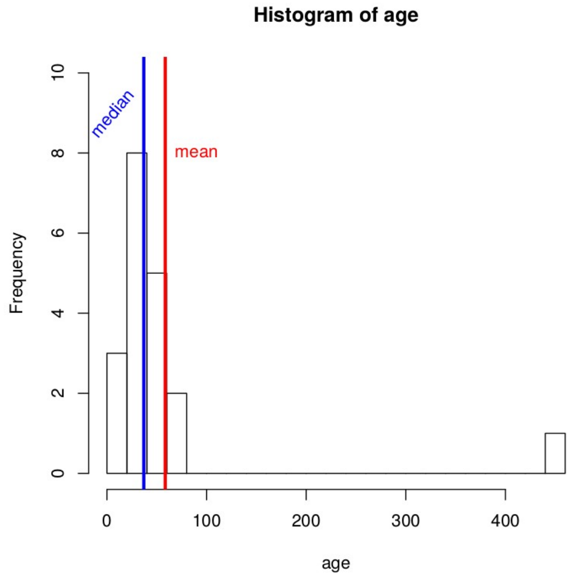
Example: Age Data

- **Set of age values of employees in a company:**

  12 13 14 21 22 26 33 35 36 37 39 42 45 47 54 57 61 68 450

- **Potential approach:**
  - Assume normal distribution of age values
  - Compute mean and standard deviation
  - Flag values more 2 standard devations away from mean
  - Interval is [96 – 2 * 59, 9 + 2 * 59] = [-22, 214]
  - Misses first three values!

- **Problem: “Masking”**
  - Magnitude of one outlier shifts center and dispersion
  - “Masks” other outliers



Robust Statistics

- **Idea: consider effect of corrupted data values on distribution**
  - Estimators should be robust to such corruptions
  - *Breakdown point*: threshold of corrupt values before estimator produces arbitrarily erroneous results

- **Robust Centers**
  - *Median*: value for which half of the dataset is smaller (affected by position not magnitude of outliers)
  - *Trimmed Mean*: remove k% of highest and lowest values, compute mean from rest

- **Robust Dispersion**
  - *Mean Absolute Deviation*: robust analogy to standard deviation
  - Measures median distance of all values from the sample median

Example: Age Data

- **Set of age values of employees in a company:**

  12 13 14 21 22 26 33 35 36 37 39 42 45 47 54 57 61 68 450

- **Cleaned set of age values:**

  21 22 22 23 24 26 33 35 36 37 39 42 45 45 47 54 57 61 68

- **Robust centers in example closer to center on clean data:**
  - Median 37 (dirty) 39 (clean)
  - Mean ~96 (dirty) ~40 (clean)
  - 10%-Trimmed mean ~39 (dirty)
- **Robust dispersion provides better interval on dirty data:**
  - 1 standard deviation [37, 155] (includes six non-outliers)
  - 1.48 MAD [16, 61] (includes one non-outlier)

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Normalization of String Data

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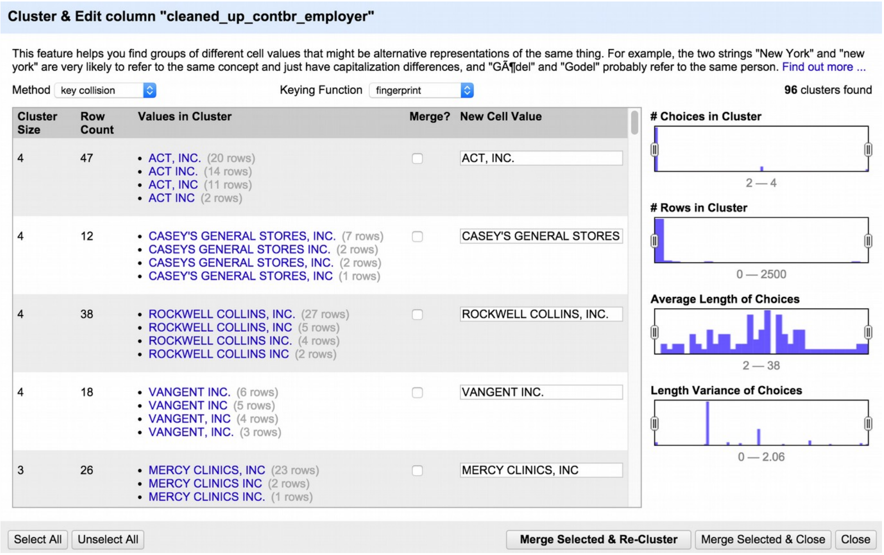
- **Free-text entry of categorical attributes very error-prone:**
  - Different spellings (Jérôme vs Jerome)
  - Different punctuation (ACME Inc. vs ACME, Inc)
  - Typos (Alice → Ailce)
  - Misunderstandings (Rupert → Robert)

- **Normalization with simple heuristic clustering algorithm:**
  - Keying function *k*
  - Compute key *k(s)* per string *s*
  - group pairs *(s, k(s))* by *k(s)* and count pairs
  - Automatic: Replace all strings in a group with string with highest cardinality
  - Human-in-the-Loop: shows groups and statistics to user

- Extensively used in OpenRefine



http://www.padjo.org/files/tutorials/open-refine/fingerprint-cluster-popup.png

String Normalization

- **“Fingerprint keying”:** remove punctuation and case sensitivity
  - remove whitespace around the string
  - lowercase the string
  - remove all punctuation and control characters
  - find ASCII equivalents of characters
  - tokenize (split by whitespace)
  - order fragments and deduplicate them

```
ACT,INC. → act inc
ACT INC  → act inc
ACT,Inc  → act inc
Act Inc  → act inc
```

String Normalization

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- **“SOUNDEX”:** Algorithm for **phonetic indexing of English strings**

  - Save the first letter.
  - Remove all occurrences of a, e, i, o, u, y, h, w
  - Replace all consonants (include the first letter) with digits as follows:
    b, f, p, v → 1 ; c, g, j, k, q, s, x, z → 2 ; d, t → 3, l → 4 ; m, n → 5 ; r → 6
  - Replace all adjacent same digits with one digit.
  - If the saved letter's digit is the same as the resulting first digit, remove the digit (keep the letter).
  - Append 3 zeros if result contains less than 3 digits. Remove all except first letter and 3 digits after it

```
Robert → R163
Rupert → R163
```

Knuth: “The art of computer programming: sorting and searching”, Vol. 3., 1997

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Frequency Statistics of Categorical Data

- **In some cases: frequency of values more important than actual values**
  - Especially for categorical data attributes (where values have no ordering and no distance)
  - E.g. “species code” in a dataset of animal sightings

- **Application: Discovery of “Candidate Keys”**
  - Key: attribute or combination of attributes that uniquely identifies a tuple in a relation
  - In clean data:
    - Frequency of every value of the candidate key attribute should be 1
    - Number of distinct values equals number of tuples
  - Both conditions can be violated in case of dirty data

Heuristics for Discovering "Dirty Keys"

- **Idea:** discover attributes intended to be used as keys in dirty data

- **"Unique Row Ratio"**
  - Ratio of distinct values of an attribute to the number of tuples
  - Attribute is potential key if heuristic close to 1.0
  - Problem: "frequency outliers": small number of values with very high frequency often caused by UIs forcing users to "invent" common "dummy values" like 00000 or 12345

- **"Unique Value Ratio"**
  - Ratio of unique values to number of distinct values
  - Attribute is potential key if heuristic close to 1.0
  - More robust against frequency outliers

- **Problem of both approaches**: high memory requirements during computation

item_id
1
3
000
4
5
6
8
10
000
000

Cardinality Estimation with HLL Sketches

- **Problem: exact counting requires memory linear in the number of distinct elements**
  - E.g., to maintain a hashtable with values and counts
  - Does not scale to large or unbounded datasets

- HyperLogLog (HLL) Sketch
  - **“Sketch” data structure:** approximate counting with drastically less memory
  - Uses **randomization to approximate the cardinality of a multiset**

Flajolet "Hyperloglog: the analysis of a near-optimal cardinality estimation algorithm.", Discrete Mathematics and Theoretical Computer Science, (2007).
Heule: "HyperLogLog in practice: algorithmic engineering of a state of the art cardinality estimation algorithm.", EDBT, (2013).

HyperLogLog: Idea

- Apply **hash function *h*** to every element to be counted (*h* must produce uniformely distributed outputs)
- Keep track of the **maximum number of leading zeros** of the bit representations of all observed hash values
- Intuitively: **hash values with more leading zeros are less likely and indicate a larger cardinality**
- If bit pattern $0^{q-1}1$ is observed at the beginning of a hash value, estimate size of multiset as 2^q

```
h(“hello”) → 10011
h(“world”) → 11011
h(“hello”) → 10011
h(“alice”) → 00101
h(“world”) → 11011
```

HyperLogLog: Details

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- Algorithm applies several **techniques to reduce variability of these measurements**
  - Input stream divided into m substreams S_i with $m = 2^p$
  - p number of bits of hash values to store
  - array of registers M, $M[i]$ stores max number of leading zeros + 1 from stream S_i
  - Final estimate uses bias-corrected harmonic mean of the estimations on the substreams

$$\alpha_m m^2 \sum_{i=1}^{m} 2^{-M[i]}$$

- Extremely **powerful in practice**
  - **Low memory requirements**: e.g., SparkSQL implementation uses less than 3.5 KB for the registers, works on billions of elements
  - **Easy to parallelize** as registers can be cheaply merged via max function
  - Allows to run **cardinality estimation** on multiple columns of huge tables **with a single scan**

- Basis of key detection in data validation library “deequ”

  https://github.com/awslabs/deequ

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Missing Value Imputation

- Missing data is a central data quality problem
- Missing for various reasons: **Missing Completely at Random** (MCAR), **Missing at Random** (MAR), **Not Missing at Random** (NMAR)
- **Example: Questionaire about income**
  - **MCAR: missingness completely random** (as if we lost some questionaires by chance)
  - **MAR: Missingness random within certain subgroups**
    (manager more likely to not share income then engineers)
  - **MNAR: Reason for missing data depends on missing data itself**
    (e.g., people with less than $1000 do not want to share their income)

- Various ways to handle missing data for ML applications
  - **Complete-case analysis** (remove examples with missing attributes)
  - Add **placeholder symbol** for missing values
  - **Impute missing values**
    - Often implemented with techniques from popular ML libraries, like mean and mode imputation
    - ML: supervised learning for missing value imputation

Imputation of Categorical Data (1)

- Assume tabular data
- Want to impute missing values in a column with categorical data

- Idea: apply techniques from supervised learning

- Example: product catalog, colors missing
  p(color=yellow | other columns, imputation model)

- Treat imputation problem as multi-class classification problem

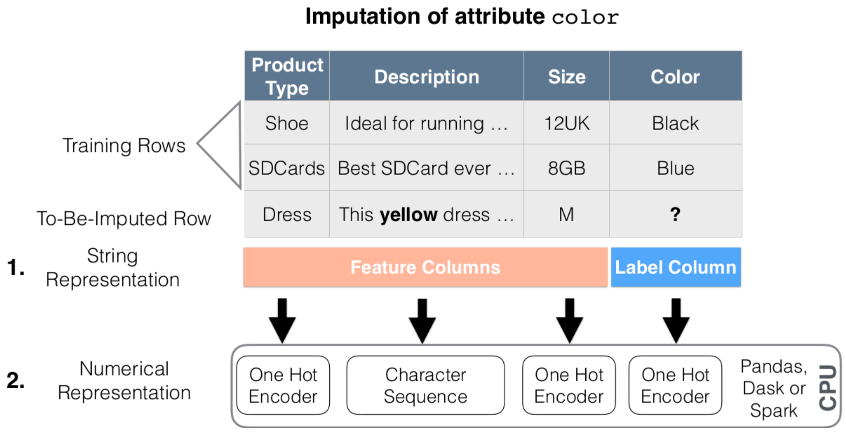
Product Type	Description	Size	Color
Shoe	Ideal for running …	12UK	Black
SDCards	Best SDCard ever …	8GB	Blue
Dress	This **yellow** dress …	M	**?**

Biessmann, et al. "Deep Learning for Missing Value Imputation in Tables with Non-Numerical Data." ACM CIKM (2018).

Imputation of Categorical Data (2)

- Must encode table data from feature columns to a numerical representation

- Standard encoding techniques
  - **“One-hot” encoding of categorical columns** (zero vector with as many dimensions as distinct values, 1 in corresponding dimensions)
  - **Standardisation of numerical columns** (substract mean, divide by standard deviation)
  - **Character sequences for textual columns**



Imputation of Categorical Data (3)

- **Train neural network to predict likelihood of values to impute**

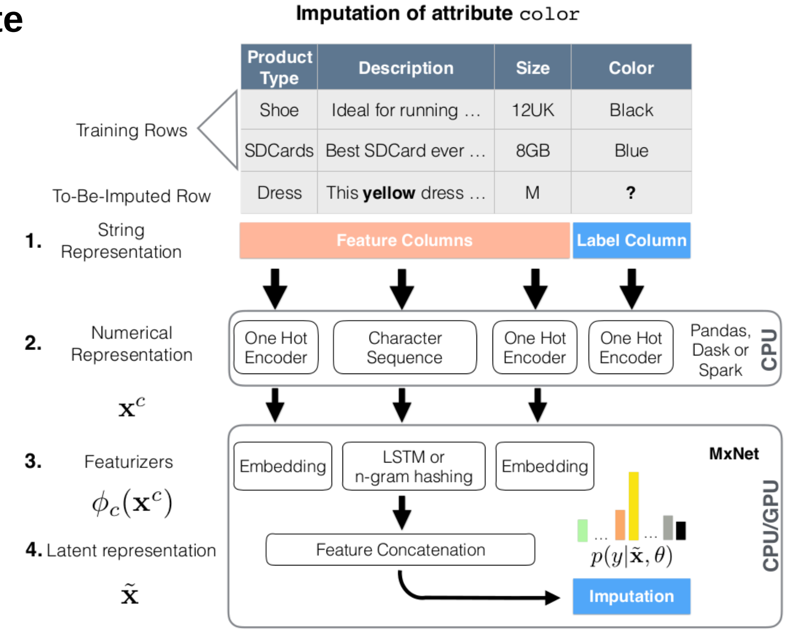
$$p(y|\tilde{\mathbf{x}}, \boldsymbol{\theta}) = \mathtt{softmax}\left[\mathbf{W}\tilde{\mathbf{x}} + \mathbf{b}\right]$$

- **Concatenation of featurizers into single feature vector**

$$\tilde{\mathbf{x}} = [\phi_1(\mathbf{x}^1), \phi_2(\mathbf{x}^2), \ldots, \phi_C(\mathbf{x}^C)] \in \mathbb{R}^D$$

- Standard featurization techniques
  - Embeddings for one-hot encoded categories
  - Hashed n-grams or LSTMs for character sequences

- Open source implementation “datawig” available at https://github.com/awslabs/datawig



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Unit Tests for Data

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- **Inspiration from software engineering:**
  - Unit tests, integration tests, deployment pipelines
- **‘Unit Tests for Data’**
  - Assume **structured data** (database table, CSV file, flattened json file, ...)
  - Users should be able to easily define ‘unit tests’ for data in a **declarative** manner
  - ‘Unit-Tests’ consist of **constraints on statistics of the data combined with user-defined validation code**
  - Data pipelines can **‘quarantine’ data** in case of failing validations

Example: a Unit Test for the Quality of Video Logs

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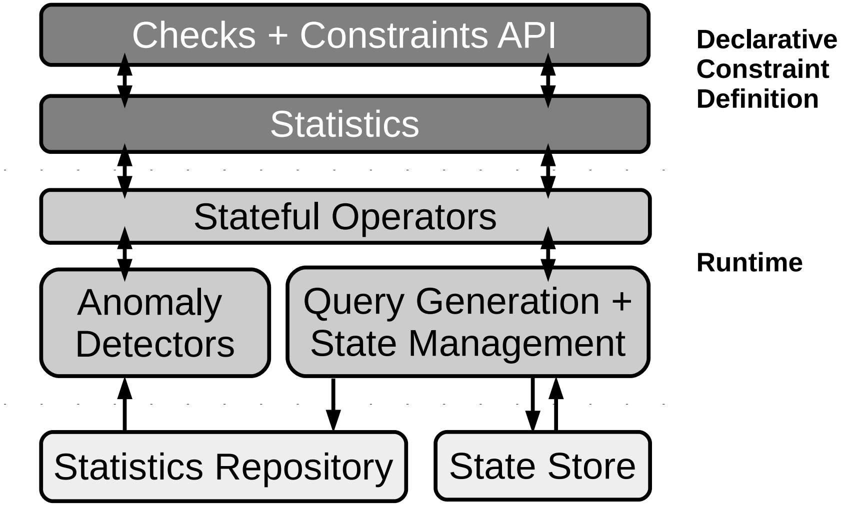
```
val check = Check()
  // Data integrity
  .isComplete("customerId", "title", "impressionStart", "impressionEnd", "deviceType", "priority")
  .isUnique("customerId", "countryResidence", "deviceType", "title")
  .hasApproxCountDistinct("title", _ <= callRestService(...))
  .isNonNegative("count")
  .isInValidRange("priority", ("hi", "lo"))
  // No anomalies over time
  .hasNoAnomalies(OnlineNormal(stdDevs=3), Size)
  // Relaxed functional dependencies
  .isPredictableFrom("countryResidence", ("zipCode", "cityResidence"), precision=0.98)

Verification.run(check, data)
```

Execution using Aggregation Queries

(1) Identification of required data quality statistics

(2) **Translation of statistics computations to aggregation queries** in SQL (optimized for scan-sharing)

(3) Invocation of **user-defined validation code** to query results to evaluate constraints



- Implementation internally supports huge variety of quality statistics on which constraints can be defined, e.g., *Completeness, ApproxCountDistinct, UniqueValueRatio, RegexCompliance, Minimum, Maximum, Mean, StandardDeviation, Entropy, Correlation, ApproxQuantiles, TypeCompliance, Predictability, ValueRangeCompliance*

Stateful Computation of Data Quality Statistics

- **Data is seldomly static**, many systems continuously produce data
- Support scenarios with regular ingestion/update of new data partitions

- Goal: update data quality statistics without requiring access to previously processed data
  - Allows to **scale computations with the size of delta**

- **Approach**:
  - (1) Compute „**mergeable states**“ on data partitions
  - (2) Compute statistics from merged states
  - (3) In light of changes, only re-compute states for changed partitions

Toy Example

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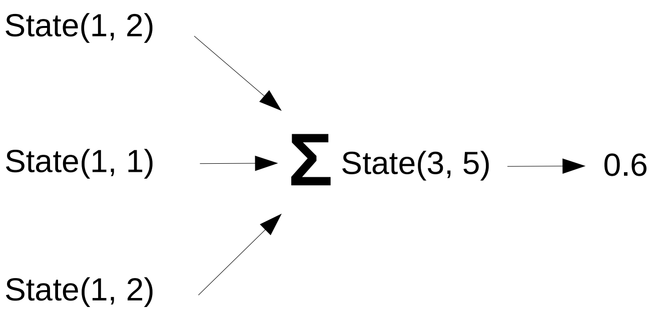
```scala
val check = Check()
  .hasCompleteness("origin", _ > 0.7)

Verification
  .runOnPartitionedData(check, Map(
    "US" -> dataUS,
    "IN" -> dataIN,
    "EU" -> dataEU))
  .saveStatesTo("s3://...")
```

item	origin	market
item1	US	US
item3	NULL	US

item	origin	market
item4	US	IN

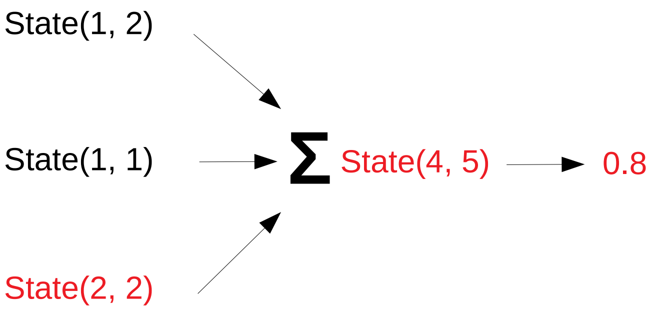
item	origin	market
item5	NULL	EU
item6	DE	EU



Toy Example


```
val check = Check()
  .hasCompleteness("origin", _ > 0.7)

Verification
  .runOnPartitionedData(check, Map("EU" -> newDataEU))
  .loadStatesFrom("s3://...")
```



Implementation via adjusted catalyst-based aggregation functions in Spark

item	origin	market
item5	IT	EU
item6	DE	EU

Algebraic Foundations

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- Define states and merge functions for data statistics using **commutative monoids** as algebraic basis

Monoid $(\mathcal{S}, \oplus, \mathbb{0})$ *Merge function for states* $\oplus \;:\; \mathcal{S} \times \mathcal{S} \;\rightarrow\; \mathcal{S}$

Incremental statistics computation $m(s(d_1 \cup d_2)) = m(s(d_1) \oplus s(d_2))$

- **Applicable to a wide variety of statistics**, e.g.:
  - Completeness: ratio of non-null values in a column, corresponding monoid is (N^2, +, [0, 0])
  - Maximum value in a column, corresponding monoid is (R, max, -∞)
  - Approximate cardinality of a column, (computed with hyperloglog sketches), corresponding monoid is ($\{0,1\}^d$, v, [0,…,0])

Overview

- Introduction & Overview
- Exemplary Error Detection and Data Cleaning Techniques
  - Quantitative Data: Robust Univariate Outlier Detection
  - Categorical Data: String Normalization
  - Candidate Key Detection at Scale with Hyperloglog Sketches
  - Missing Value Imputation
  - Data Unit Testing with Deequ
- **Summary & References**

Summary

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- Data quality important for: decision making, conforming to legal obligations, improving the performance of ML models, operation of data processing systems
- Real-world data is always messy and difficult to handle

- Dimensions of data quality: completeness, consistency, syntactic & semantic accuracy

- Data cleaning techniques
  - Quantitative data: outlier detection
  - Categorical data: normalisation / deduplication
  - Postal addresses: deduplication
  - Identifiers / keys: ensuring referential integrity

- Error detection is already a very hard problem: typically requires iterative cleaning, visualisation and a human-in-the-loop

References

- Hellerstein, Joseph M. "Quantitative data cleaning for large databases." United Nations Economic Commission for Europe (UNECE) (2008).
- Batini, Carlo, et al. "Methodologies for data quality assessment and improvement." ACM Computing Surveys 41.3 (2009): 16.
- Geerts, Floris, et al. "The LLUNATIC data-cleaning framework." PLVDB 6.9 (2013): 625-636.
- Chu, Xu, et al. "Discovering denial constraints." PVLDB 6.13 (2013): 1498-1509.
- Flajolet, Philippe, et al. "Hyperloglog: the analysis of a near-optimal cardinality estimation algorithm.", Discrete Mathematics and Theoretical Computer Science, (2007).
- Heule, Stefan et al. "HyperLogLog in practice: algorithmic engineering of a state of the art cardinality estimation algorithm.", EDBT, (2013).
- Schelter, Sebastian, et al. "Automating large-scale data quality verification." PVLDB 11.12 (2018): 1781-1794.
- Biessmann, Felix, et al. "Deep Learning for Missing Value Imputation in Tables with Non-Numerical Data." ACM CIKM (2018).