Data Curation for ML: Toward a Principled Approach

Laure Berti-Equille

laure.berti@ird.fr

Espace-Dev, IRD, Univ Montpellier, Univ Guyane, Univ La Réunion, Univ Antilles,
Univ Nouvelle Calédonie, Montpellier France

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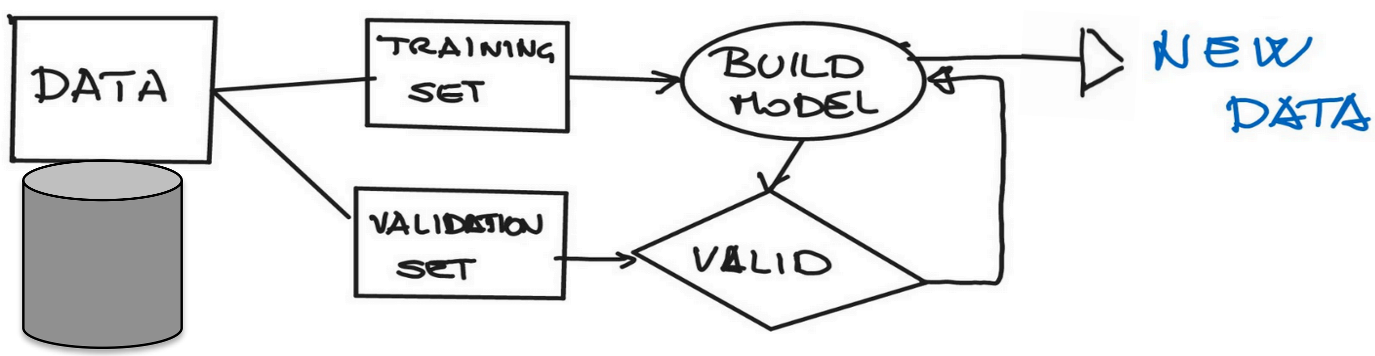
May 15, 2024

Learning from dirty data is risky



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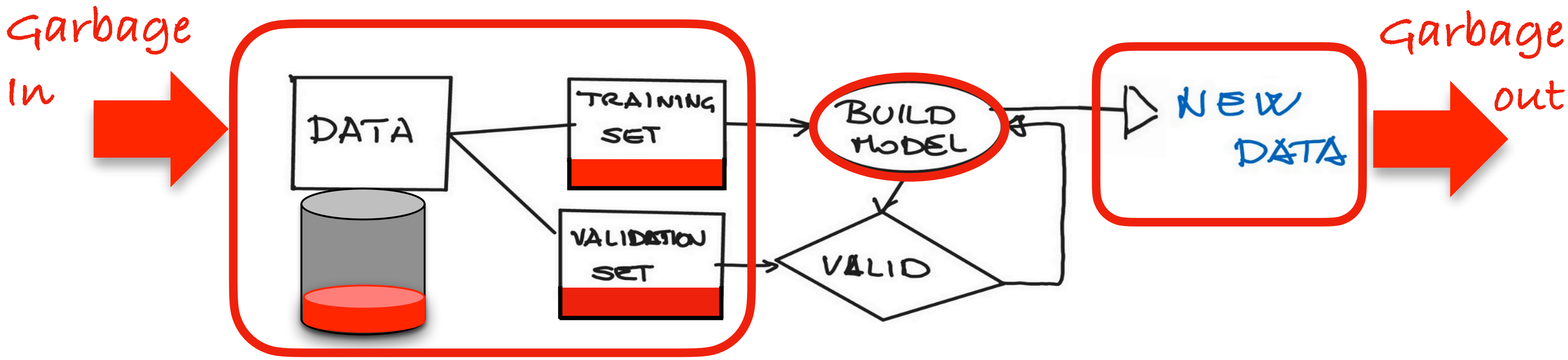
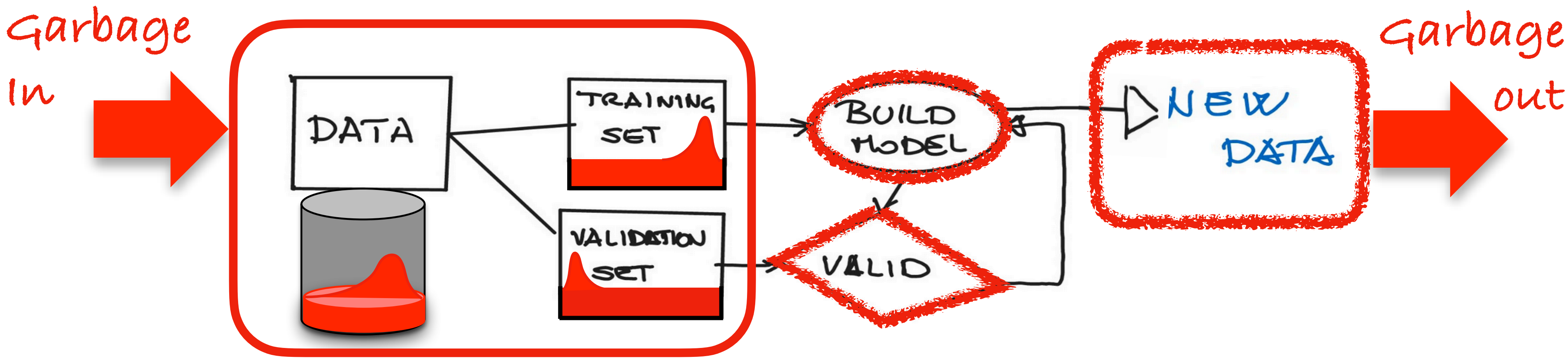


Learning from dirty data is risky



Glitch types and distributions can be very different in the datasets used for training, testing, and validation and they affect accuracy of ML models in different ways.

Two complementary approaches

INTERVENE

How to efficiently fix the data:

- ✦ Detect the anomalies
- ✦ Correct them with minimal cost (domain expert intervention, time, external master data, etc.)
- ✦ Select the repair/preparation strategies that will maximize the ML result quality

MITIGATE

How to reduce the impact of dirty data:

- ✦ Robustify the ML algorithms and apply ML ensembling strategies
- ✦ Use AutoML to find optimal parameter setting
- ✦ Select portions of the data and/or augment the data

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Outline

1. **Detection of data quality problems**
   Profiling data quality

2. **Data cleaning**
   Leveraging the patterns of glitches

3. **Data preparation strategies for ML**
   Learning to clean and prepare the data

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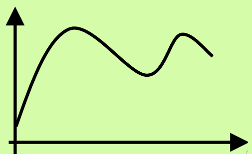
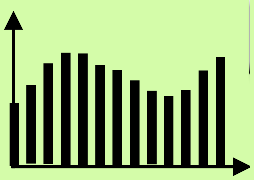
Data Quality Problems

DATA TYPES



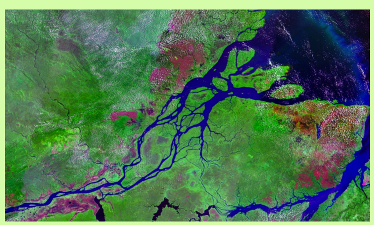


The New York Times

Obama Unveils Afghan Plan to Add Troops and Set Goals

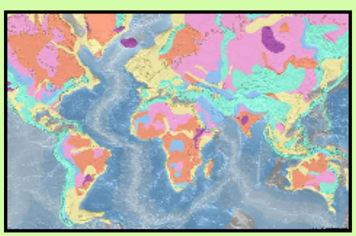
Suicide Bomber Kills 48 in Pakistan

0101010101



ACACGTGT

John Doe



High
Medium
Low

RELATIONSHIPS

- Structural (record)
- Sequential
- Graph-based
- Temporal
- Spatial
- Spatio-Temporal

DATA QUALITY PROBLEMS

TYPE

- Missing Data
- Anomalous Data
- Duplicate Data
- Inconsistent Data
- Obsolete Data
- Incorrect data

CARDINALITY

- Single-Point
- Collection

DETECTION MODE

- Model-based
- Data distribution-based
- Constraint-based
- Pattern-based

Data Quality Problems: Example 1

Relational data quality problems

Nobel Laureates in Chemistry

Misfielded Value

Representation

Name	Institution	Institution_City	DoB
Skłodowska-Curie Marie	Institut Pasteur	Varsovie	07-11-1867
M. Curie	Pasteur Institute	Paris	1867-11-07
Melvin Calvin	UC Berkeley	Berkeley	1911-04-08
Marie Curien	Paris	Pasteur Institute	2007-11-07
Avram Hershko	NULL	Haifa	NULL
Ronald Hoffman		US	00000000

Duplicates

Typos

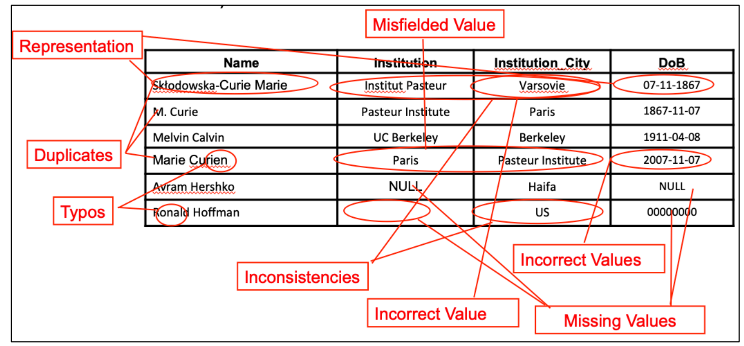
Incorrect Values

Inconsistencies

Incorrect Value

Missing Values

Data Quality Problems: Example 2



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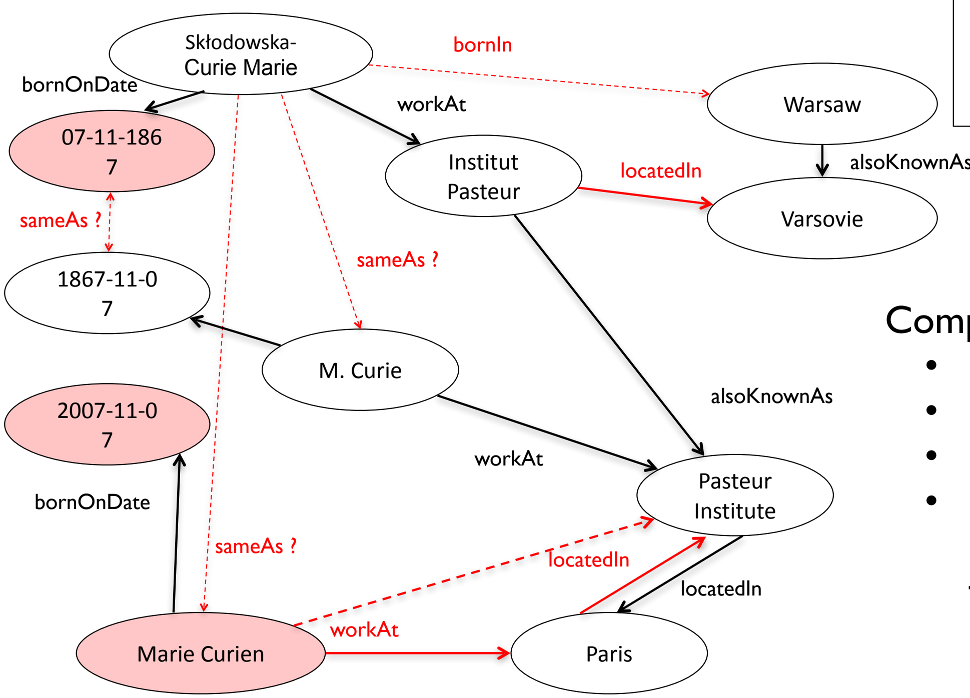
Knowledge Graph data problems

Nobel Laureates in Chemistry: Excerpt

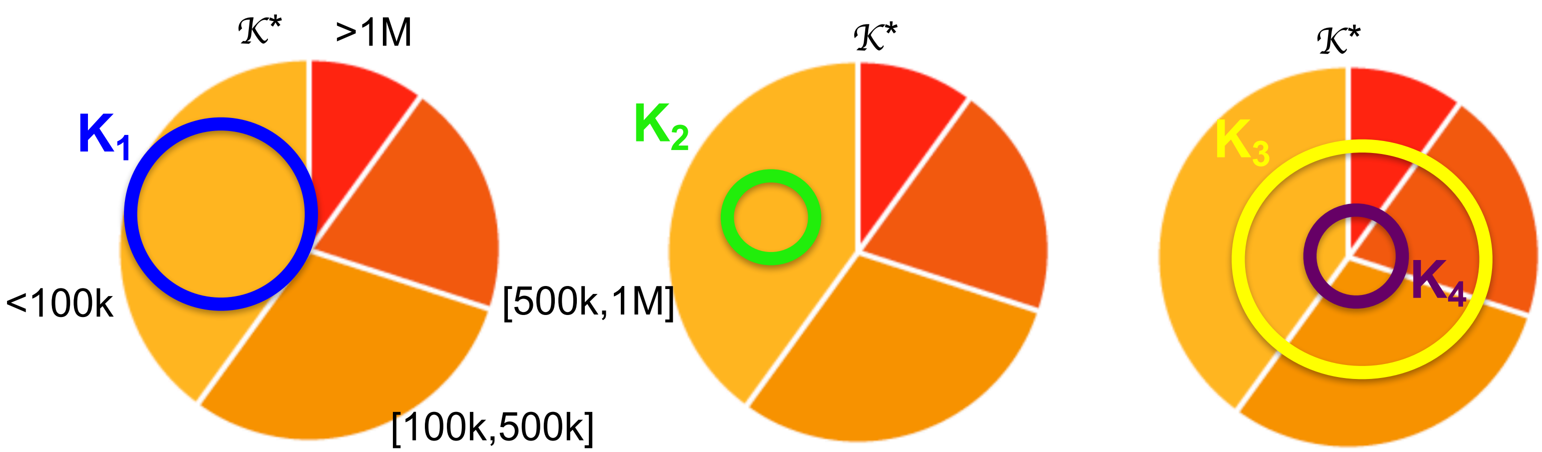


Complex combination of:

- Missing links and entities
- Spurious links : existence, type, direction
- Erroneous entity name
- Errors in literal values with various degrees of severity: formatting, up-to-dateness, veracity issues

Data Quality Problems: Example 3
Completeness

Suppose you have the accurate and complete knowledge of the world-wide populations per city grouped into 4 categories: e.g. (<100k, [100k,500k], [500k,1M], >1M) and 4 KBs.

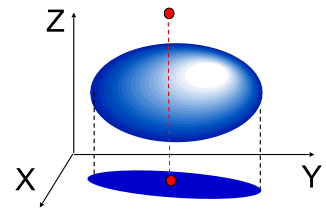


K_1 is more complete than K_2 but both are somehow biased toward one category

K_1 and K_2 are not as representative as K_3 or K_4

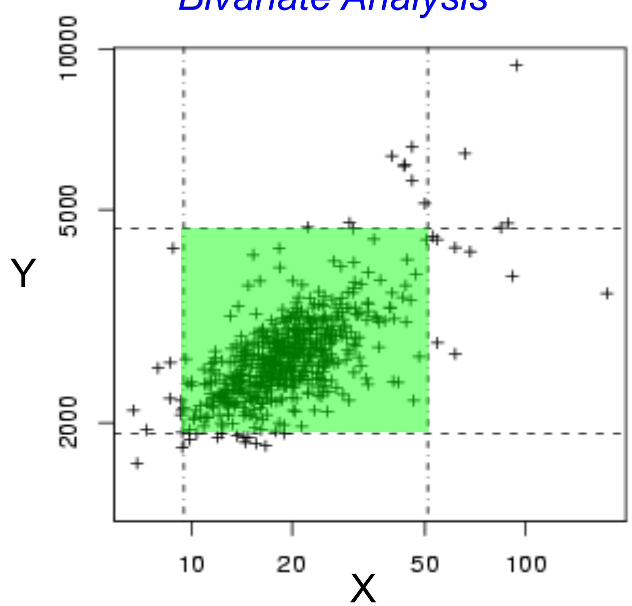
- *Soulet, Giacometti, Markhoff, Suchanek: Representativeness of Knowledge Bases with the Generalized Benford's Law. International Semantic Web Conference (1) 2018: 374-390*
- *Wagner, Garcia, Jadidi, Strohmaier: It's a man's Wikipedia? Assessing gender inequality in an online encyclopedia. ICWSM. pp. 454–463 (2015)*
- *Callahan, Herring: Cultural bias in Wikipedia content on famous persons. J. of the Association for Information Science and Technology, 62(10), 1899–1915 (2011)*
- *Pitoura, Tsaparas, Flouris, Fundulaki, Papadakos, Abiteboul, Weikum. On Measuring Bias in Online Information. SIGMOD Record, Vol.46 No.4, December 2017*

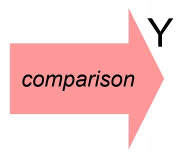
Example 4. Numerical Outliers



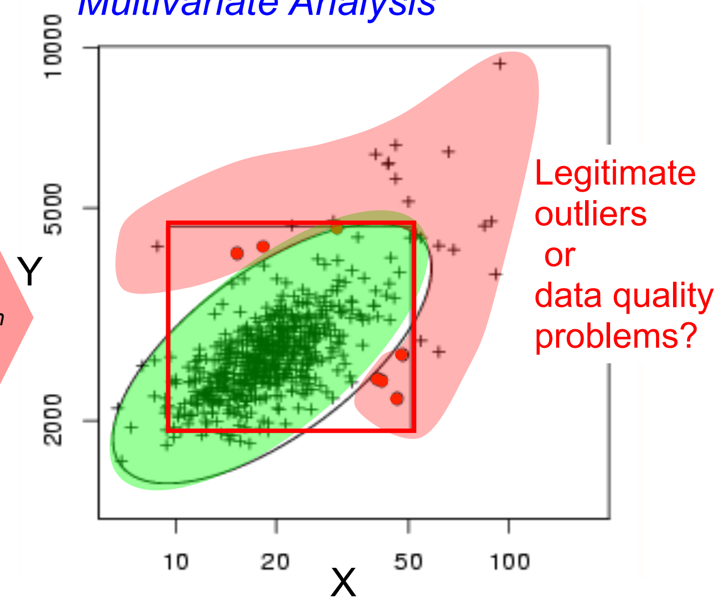
(Classical Setting)

Bivariate Analysis





Multivariate Analysis



Rejection area: Data space excluding the area defined between 2% and 98% quantiles for X and Y

Rejection area based on:
Mahalanobis_dist(cov(X,Y)) > $\chi^2(.98,2)$

Example 5: Up-to-dateness
Asynchronous Real World and KG evolution

https://www.dbpedia.org/resources/ontology/

Table 1. DBpedia - Classes and Properties

Version	OWL Class				RDF Property				Object Prop.			Datatype Prop.		
	#	Δ	(-)	(+)	#	Δ	(-)	(+)	#	(-)	(+)	#	(-)	(+)
3.2/3	**174**				**720**				**384**			**336**		
3.4	**204**	**30**	**-2**	**32**	**2168**	**1448**	**-271**	**1719**	**1144**	**-139**	**899**	**1024**	**-132**	**820**
3.5	**255**	**51**	**-6**	**57**	**1274**	**-894**	**-1198**	**304**	**601**	**-673**	**130**	**673**	**-525**	**174**
3.6	**272**	**17**	**0**	**17**	**1335**	**61**	**-37**	**98**	**629**	**-26**	**54**	**706**	**-11**	**44**
3.7	**319**	**47**	**-1**	**48**	**1643**	**308**	**-17**	**325**	**750**	**-6**	**127**	**893**	**-11**	**198**
3.8	**359**	**40**	**-1**	**41**	**1775**	**132**	**-3**	**135**	**800**	**-1**	**51**	**975**	**-2**	**84**
3.9	**529**	**170**	**-1**	**171**	**2333**	**558**	**-8**	**566**	**927**	**-6**	**133**	**1406**	**-2**	**433**
2014	**683**	**154**	**-5**	**159**	**2795**	**462**	**-46**	**508**	**1079**	**-9**	**161**	**1716**	**-37**	**347**
2015-04	**735**	**52**	**-5**	**57**	**2819**	**24**	**-103**	**127**	**1098**	**-23**	**42**	**1721**	**-80**	**85**
2015-10	**739**	**4**	**-5**	**9**	**2833**	**14**	**-9**	**23**	**1099**	**-3**	**4**	**1734**	**-6**	**19**
2016-04	**754**	**15**	**0**	**15**	**2849**	**16**	**-2**	**18**	**1103**	**-1**	**5**	**1746**	**-1**	**13**

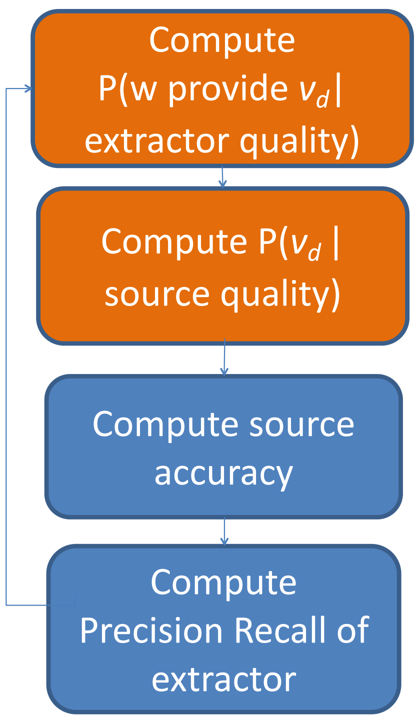
Today's DBpedia Ontology: 768 classes described by 3000 properties 4,233,000 instances.

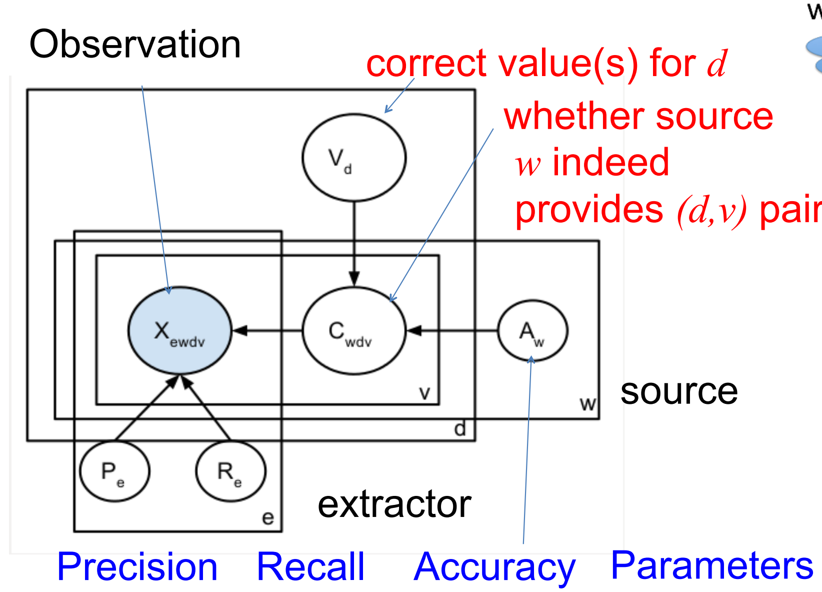
Mihindukulasooriya, Poveda-Villalon, Garcia-Castro, Gomez-Perez. Collaborative Ontology Evolution and Data Quality -An Empirical Analysis, in OWL: Experiences and Directions – Reasoner Evaluation, Springer International Publishing, Cham, 2017, pp. 95–114. https://www.w3.org/community/owled/files/2016/11/OWLED-ORE-2016_paper_9.pdf

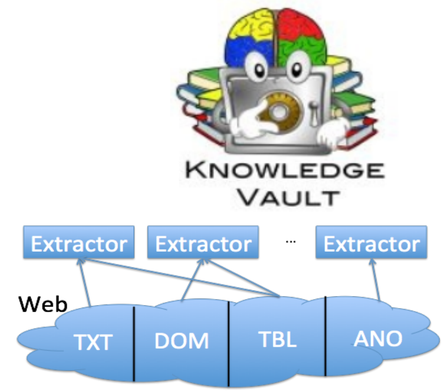
Example 6. Veracity and Trustworthiness

ML-based approach for knowledge-based trust:

- Multi-Layer Model based on EM and Bayesian inference
- Distinguish extractor errors from source errors

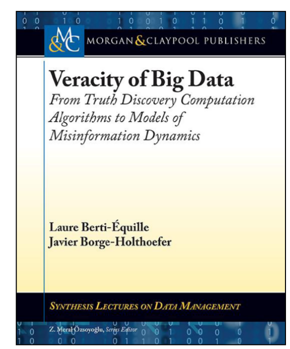






#Triples	3.0B (0.3B w. pr>=0.7)
#URLs	2.5B (28M Websites)
#Extractors	16

As of 2014



X. L. Dong, K. Murphy, E. Gabrilovich, G. Heitz, W. Horn, N. Lao, W. Zhang. Knowledge Vault: A Web-scale approach to probabilistic knowledge fusion. VLDB 2015

Existing approaches for detecting/fixing DQ problems

Declarative

- Data debugging
- Checking data assertions
- Transform

ML-based

Learn from clean data and replace

Declarative Approaches

Checking data assertions and transform

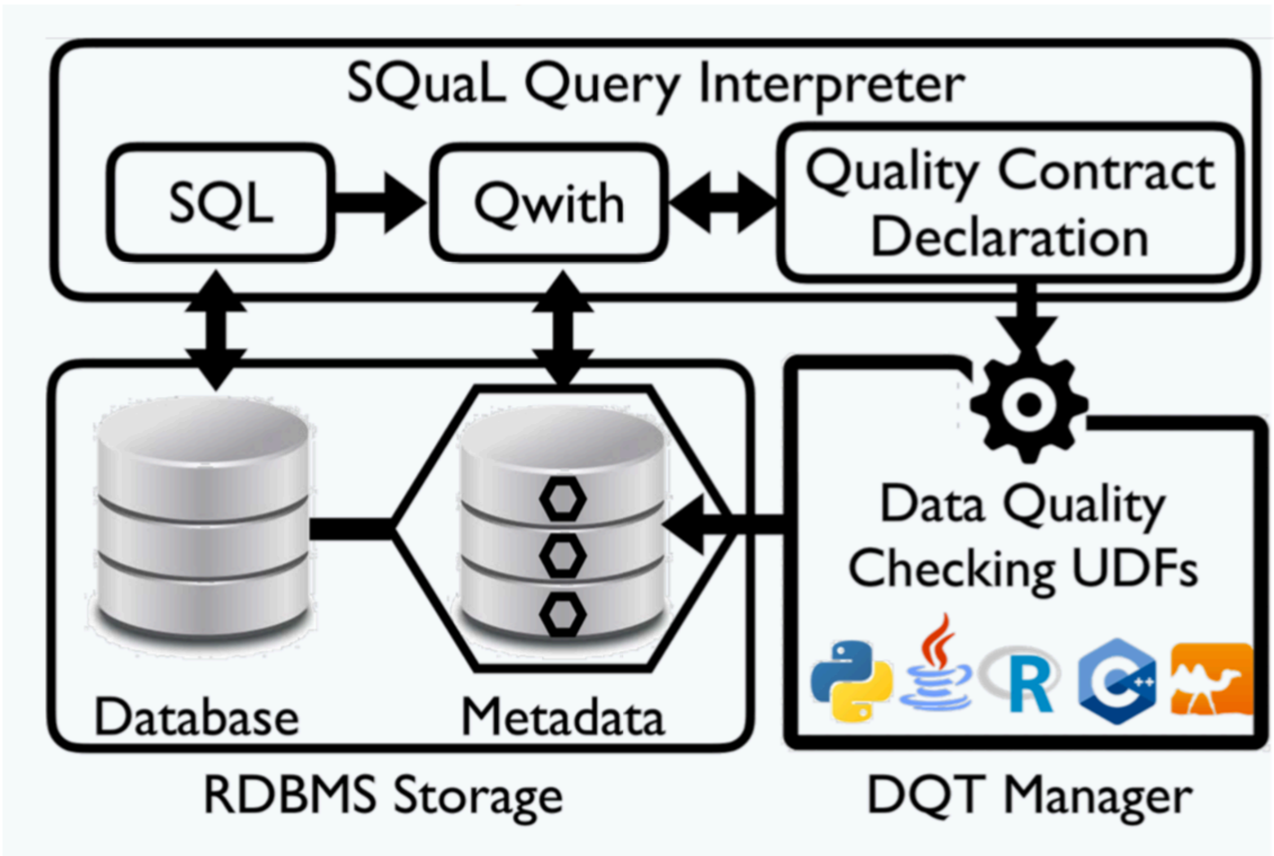
✦ ***Deequ*** [Schelter et al. ,VLDB 2018] requires cloud infrastructure and manual integration into training and serving systems; dependent on Apache Spark

✦ ***TensorFlow Data Validation*** (TFDV) [Caveness et al., SIGMOD 2020] integrated with Google TFX difficult to use outside of these platforms

✦ Lightweight Python-based approaches like ***great_expectations*** (https://greatexpectations.io) or ***hooqu*** (https://github.com/mfcabrera/hooqu) not integrated with the ML development process

Joint work with Ugo Comignani and Noel Novelli (AMU)
[EDBT 2020]

Declarative data profiling with MeSQuaL

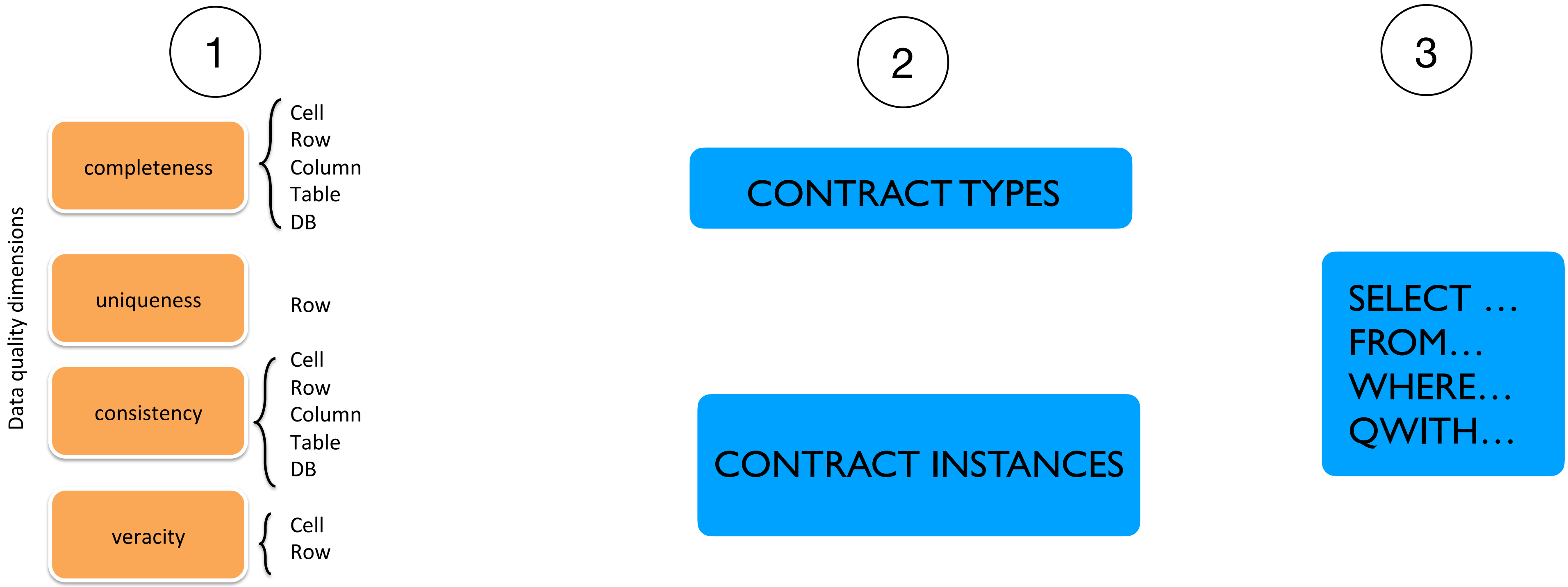


https://github.com/ucomignani/MeSQuaL

Joint work with Ugo Comignani and Noel Novelli (AMU)
[EDBT 2020]

MeSQuaL Key Concepts

Flexible declarative data quality profiling with UDFs



Procedural approach with UDFs **Declarative approach** **Extended query**

Joint work with Ugo Comignani and Noel Novelli (AMU)

[EDBT 2020]

MeSQuaL Examples

DECLARATION

```
CREATE CONTRACTTYPE StatTests (
  autocorrelation BY FUNCTION 'durbinWatsonTest.py' LANGUAGE PYTHON,
  multicollinearity BY FUNCTION 'varInflationFactor.py' LANGUAGE PYTHON,
  heteroscedasticity BY FUNCTION 'BreuschPaganTest.py' LANGUAGE PYTHON,
  KMerrorNormality BY FUNCTION 'KolmogorovSmirnov.py' LANGUAGE PYTHON,
  SWerrorNormality BY FUNCTION 'ShapiroWilkTest.py' LANGUAGE PYTHON);
```

```
CREATE CONTRACT RegressionAssumptions (
  StatTests.autocorrelation > 0
  AND StatTests.autocorrelation < 4
  AND StatTests.multicollinearity <= 4
  AND StatTests.heteroscedasticity < 0.05
  AND StatTests.SWerrorNormality < 0.05);
```

```
CREATE CONTRACTTYPE CheckQDB (
  completeness BY FUNCTION 'completeness.py' LANGUAGE PYTHON,
  uniqueness BY FUNCTION 'uniqueness.py' LANGUAGE PYTHON,
  consistency BY FUNCTION 'consistency.py' LANGUAGE PYTHON,
  outlyingness BY FUNCTION 'outlyingness.py' LANGUAGE PYTHON);
```

```
CREATE CONTRACT CheckBeforeAnalysis (
  RegressionAssumptions
  AND CheckQDB.consistency > 0.9
  AND CheckQDB.outlyingness < 0.2);
```

MANIPULATION

AoT	{ SELECT * FROM ChicagoDataset } QWITH CheckQDB.completeness> 0.95;
	{ SELECT * FROM ChicagoDataset } QWITH CheckBeforeAnalysis AND RegressionAssumptions;
	{ SELECT timestamp, node_id,value_raw,valuehrf FROM ChicagoDataset WHERE ChicagoDataset.sensor = 'o3' } QWITH CheckBeforeAnalysis AND CheckQDB.completeness> 0.95;
MIMIC-III	{ SELECT * FROM Admissions } QWITH CheckQDB.completeness> 0.95;
	{ SELECT * FROM Admissions WHERE Admissions.insurance = 'Private' } QWITH CheckBeforeAnalysis AND CheckQDB.completeness> 0.95;
	{ SELECT gender, dob, admittime FROM Admissions INNER JOIN (SELECT * FROM Patients WHERE dob < '2090-12-12 00:00:00' QWITH CheckQDB.completeness> 0.95) as Pat ON Admissions.subject_id=Pat.subject_id; } QWITH CheckQDB.completeness> 0.95;

Joint work with Ugo Comignani and Noel Novelli (AMU)

[EDBT 2020]

MeSQuaL GUI

https://github.com/ucomignani/MeSQuaL

ML-based Approaches

Learn from clean data and replace/repair

- Pattern enforcement
  - Syntactic patterns (date formatting)
  - Semantic patterns (name/address)
- Value update to satisfy a set of rules, constraints, FDs, CFDs, Denial Constraints (DCs), Matching Dependencies (MDs) with minimal number of changes.
- Value replacement
- Entity resolution

EXAMPLES

✦ SCARE: Scalable Automatic Repair

✦ On-demand ETL [Yang et al., VLDB'15]

✦ ActiveClean [Krishnan et al., VLDB'16]

✦ HoloClean [Rekatsinas et al., VLDB 2017]

✦ Deep learning for Entity Resolution

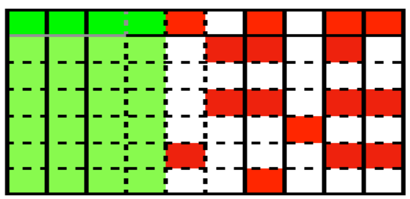
✦ Transformers for data prep

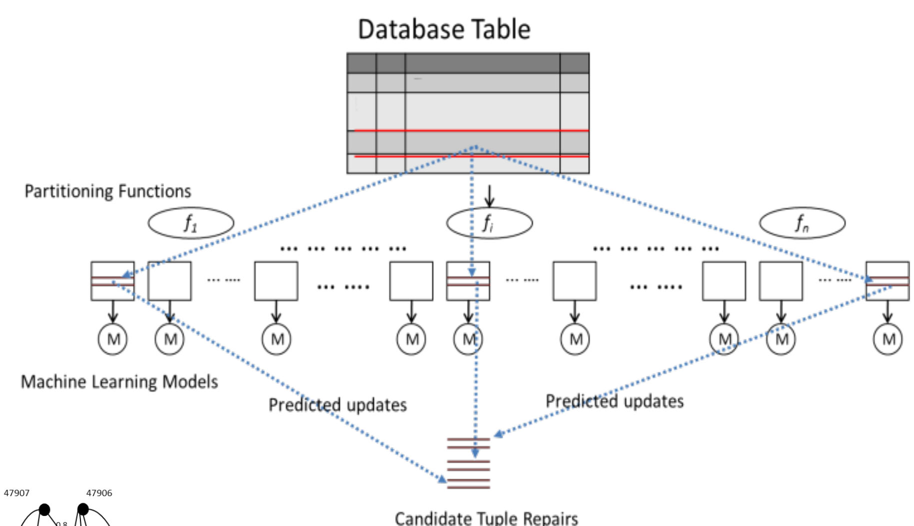
SCARE: SCalable Automatic Repair

[Yakout, Berti-Equille, Elmagarmid, SIGMOD 2013]

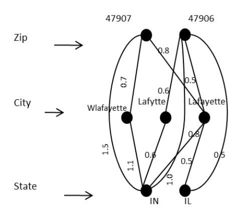
Goal: Find the repair that would maximize the sum of the probabilities of the values co-occurrence (i.e., association strength between predicted and reliable values) under a certain update cost budget.

Reliable *Flexible*





1. Modeling Dependency and Predicting Updates
2. Data Partitioning
3. Tuple Repair Selection



Value predictions for Flexible Attributes E1, E2, E3

HoloClean

[Rekatsinas et al., VLDB 2017]
https://github.com/HoloClean/HoloClean

HoloClean generates a factor graph capturing co-occurrences, correlations based on a set of constraints and external evidences. It uses SGD to learn parameters and infer the marginal distribution of unknown variables with Gibbs sampling.

	Address	City	State	Zip
t1	3465 S Morgan ST	Chicago	IL	60608
t2	3465 S Morgan ST	Chicago	IL	60609
t3	3465 S Morgan ST	Chicago	IL	60609
t4	3465 S Morgan ST	Cicago	IL	60608

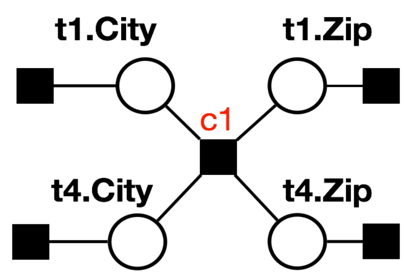
Each cell is a random variable

Value co-occurrences capture data statistics

Constraints introduce correlations

c1: Zip $\rightarrow$ City

"Address= 3465 S Morgan St"



○ : Unknown (to be inferred) RV

■ : Factor (encodes correlations)

Denial constraints:

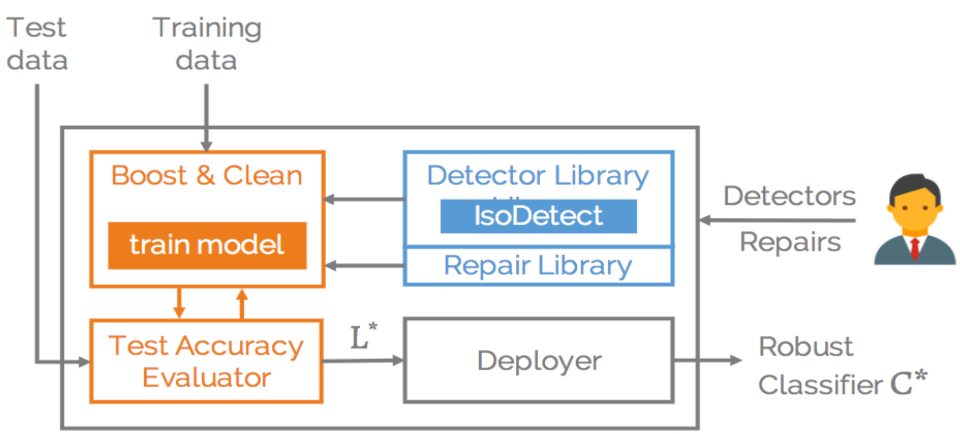
$\forall t_1, t_2 \in D : \neg(t1[Zip] = t2[Zip] \wedge t1[City] \neq t2[City])$

$\forall t_1, t_2 \in D : \neg(t1[Zip] = t2[Zip] \wedge t1[State] \neq t2[State])$

BoostClean

[Krishnan et al., 2017]

BoostClean selects an ensemble of methods (statistical and logic rules) for error detection and for repair combinations using statistical boosting.



Algorithm : Boost-and-Clean Algorithm

Data: (X, Y)

Initialize $W_i^{(1)} = \frac{1}{N}$

$\mathcal{L}$ generates a set of classifiers $\mathcal{C}\{C^{(0)}, C^{(1)}, ..., C^{(k)}\}$ where $C^{(0)}$ is the base classifier and $C^{(1)}, ..., C^{(k)}$ are derived from the cleaning operations.

for $t \in [1, T]$ **do**

  C_t = Find $C_t \in \mathcal{C}$ that maximizes the weighted accuracy on the test set. ϵ_t = Calculate weighted classification error on the test set $\alpha_t = \ln(\frac{1-\epsilon_t}{\epsilon_t})$

  $W_i^{(t+1)} \propto W_i^{(t)} e^{-\alpha_t y_i C_t(x_i)}$: down-weight correct predictions, up-weight incorrectly predictions.

return $C(x) = \text{sign}(\sum_t^T \alpha_t C_t(x))$

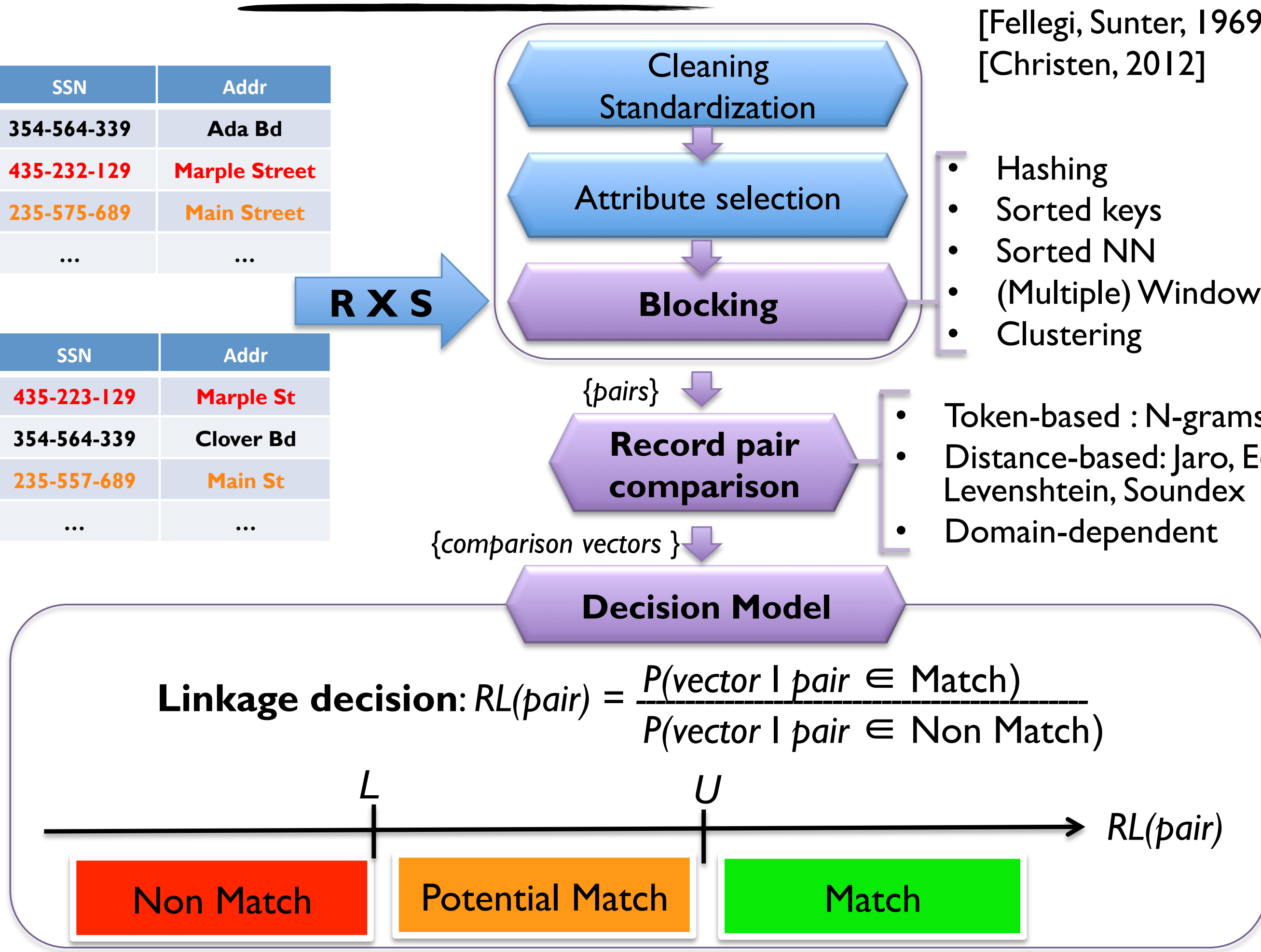
Record Linkage (RL): Generic Workflow

Database R

Name	SSN	Addr
Will Forth	354-564-339	Ada Bd
Jacky Khan	435-232-129	Marple Street
Dom Hack	235-575-689	Main Street
…	…	…

Database S

Name	SSN	Addr
Jack Khan	435-223-129	Marple St
Hans Ford	354-564-339	Clover Bd
Tom Hack	235-557-689	Main St
…	…	…

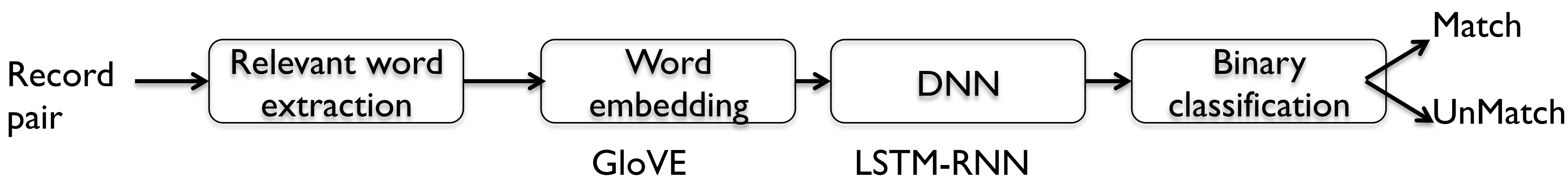


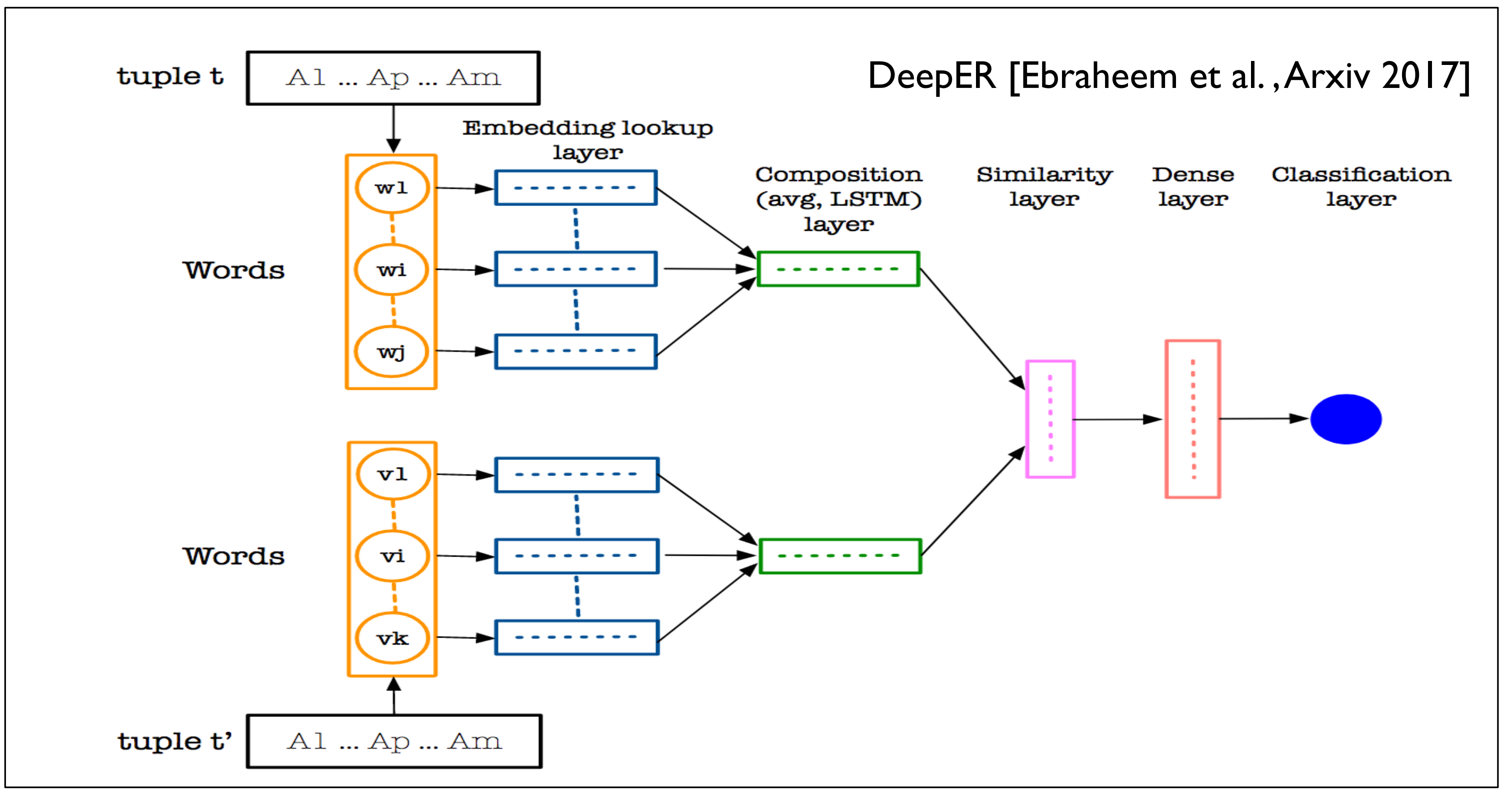
[Fellegi, Sunter, 1969]
[Christen, 2012]

- Hashing
- Sorted keys
- Sorted NN
- (Multiple) Windowing
- Clustering

- Token-based : N-grams…
- Distance-based: Jaro, Edit, Levenshtein, Soundex
- Domain-dependent

Deep learning for Entity Resolution





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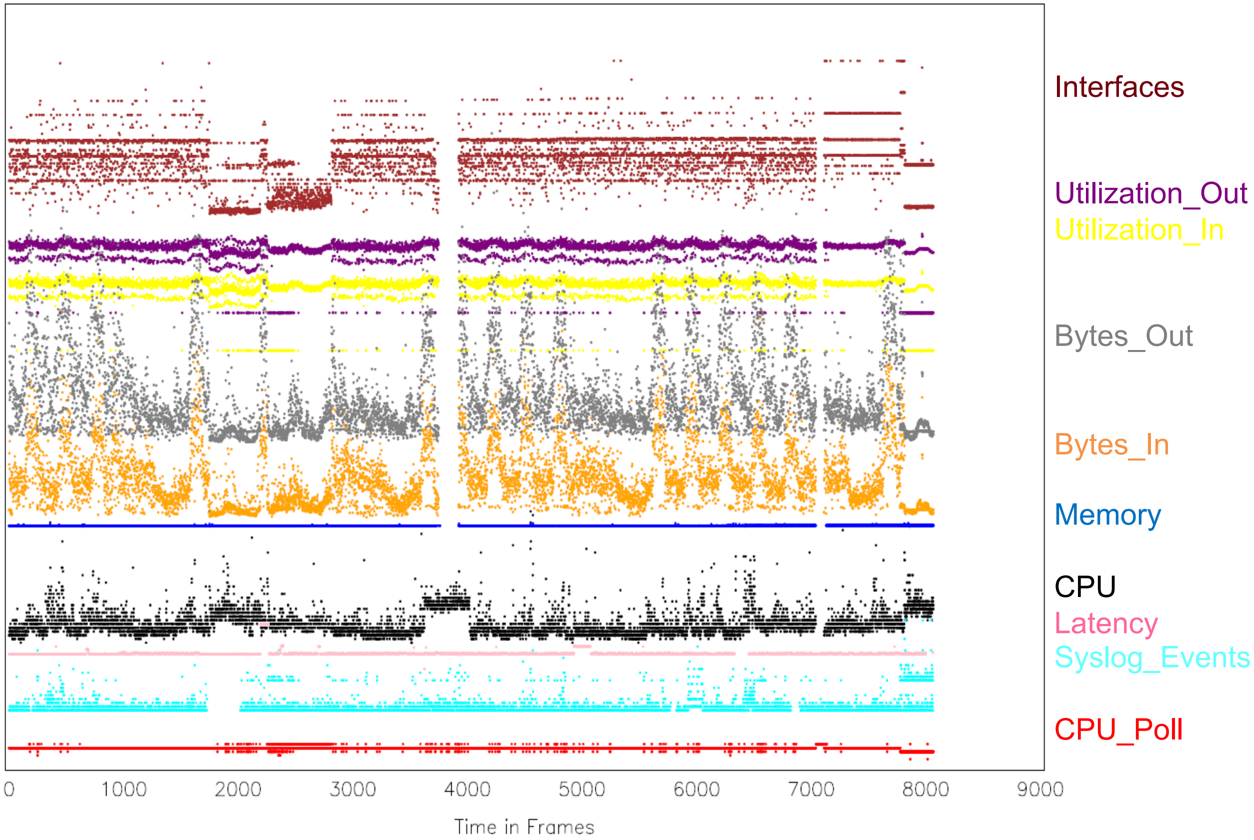
SNMP Data Analysis

- Periodic inbound and outbound traffic measurements from interfaces of network devices
- 10 attributes, every 5 minutes, over 4 weeks
- Axes transformed for plotting



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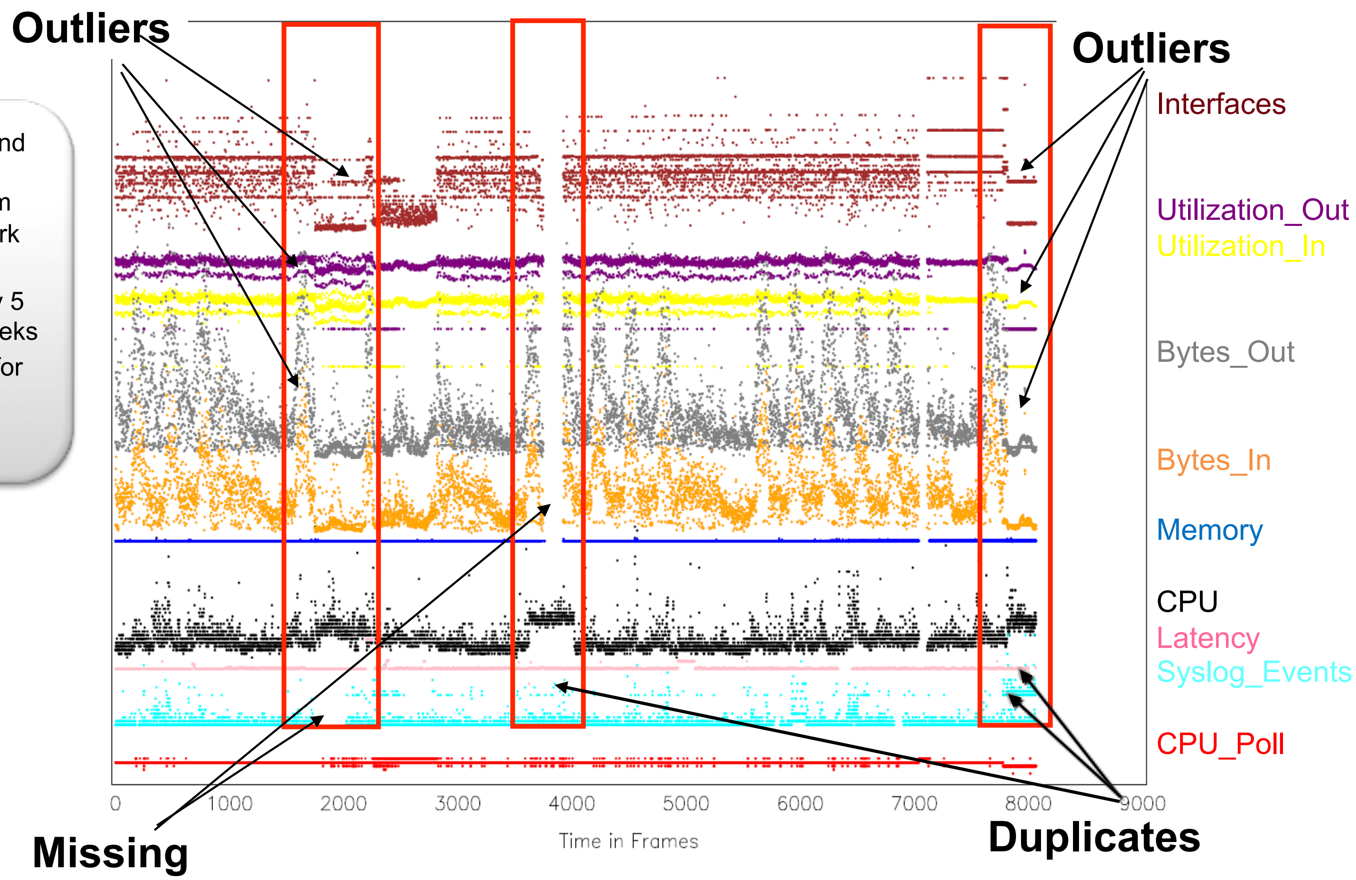
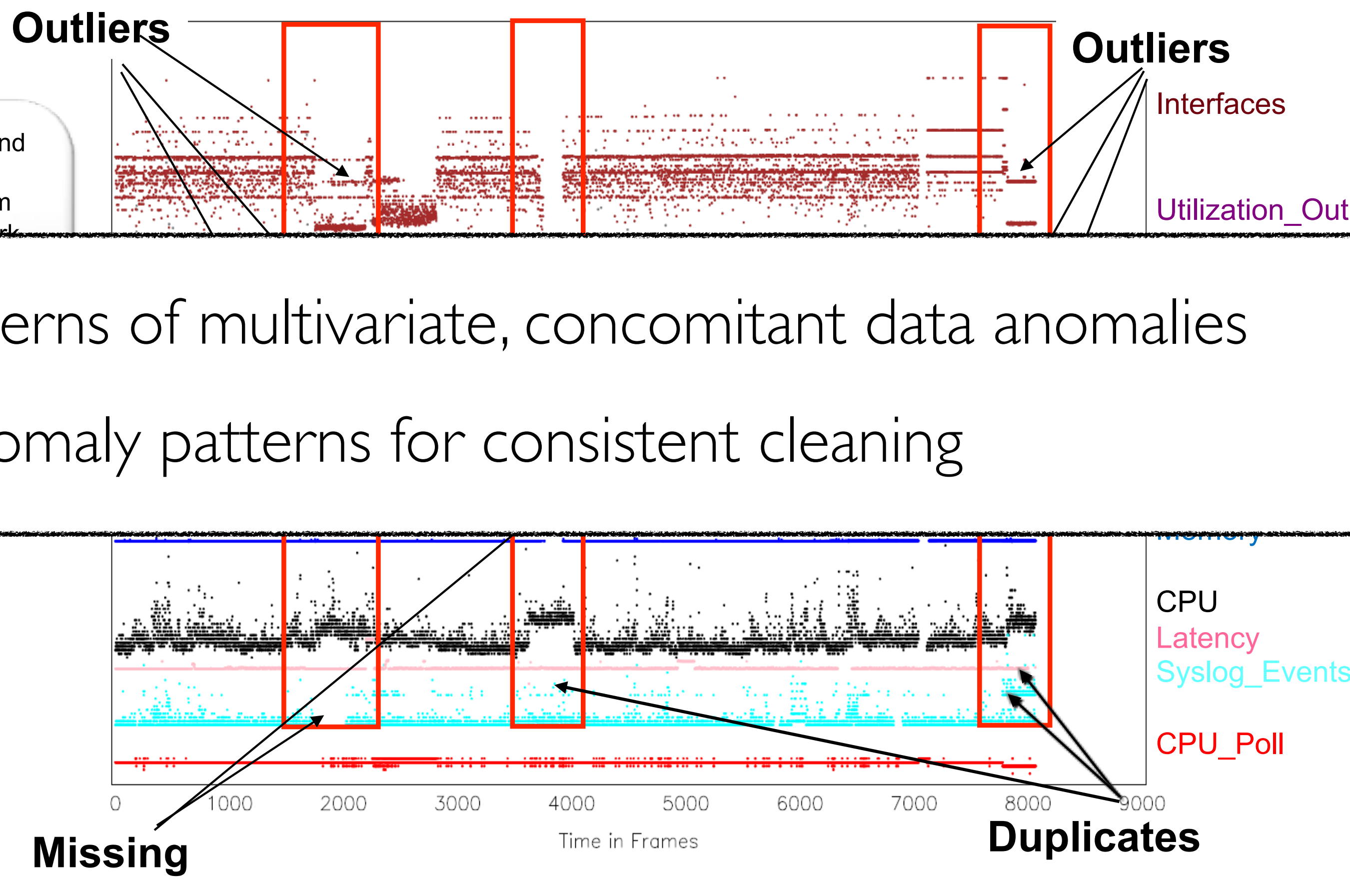


SNMP Data Analysis

- Periodic inbound and outbound traffic measurements from



1. Detect patterns of multivariate, concomitant data anomalies

2. Use the anomaly patterns for consistent cleaning

Understanding Complex Glitch Patterns

Benefits

- A common root cause can generate correlated data errors
- In-depth anomaly analysis could help for:
  - Characterizing anomaly sources, processes, and propagation mechanisms
  - Systematizing data cleaning

Current methods

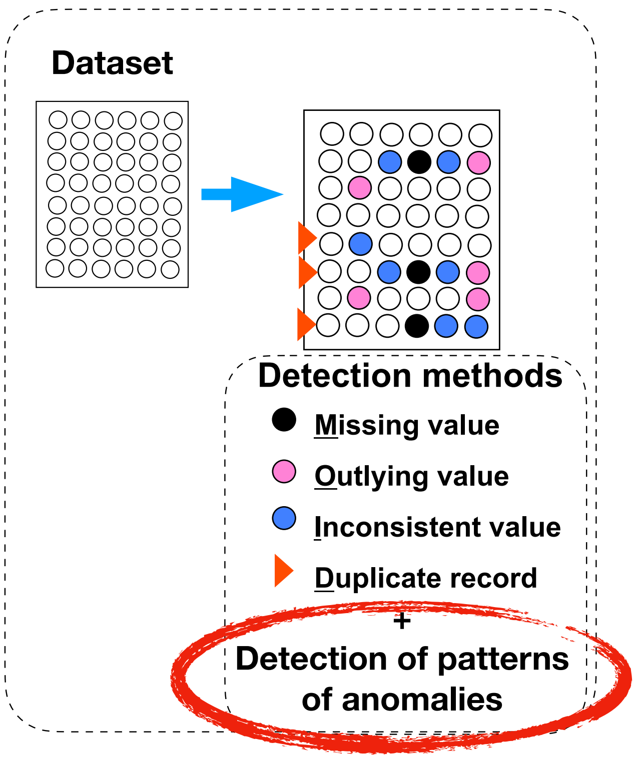
- Make unrealistic assumptions (e.g., MAR)
- Treat glitches in isolation
- Are one-shot approaches (no reiteration between detection and cleaning)

Data cleaning and preprocessing may introduce new errors and distortions.

Joint work with Parni Dasu and Divesh Srivastava (AT&T Lab Research)
[ICDE 2011]

Detection-Exploration-Cleaning Framework

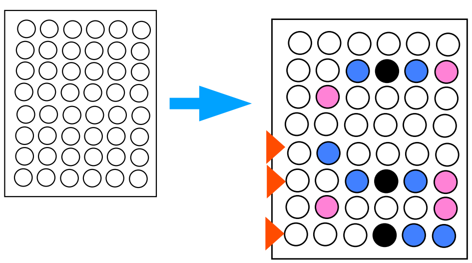
Input:



Detection-Exploration-Cleaning Framework

Input:

Dataset



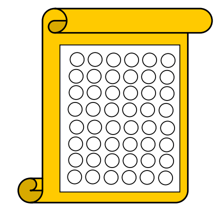
Detection methods

- **Missing value**
- **Outlying value**
- **Inconsistent value**
- **Duplicate record**

+

Detection of patterns of anomalies

Specifications of the ideally preprocessed dataset

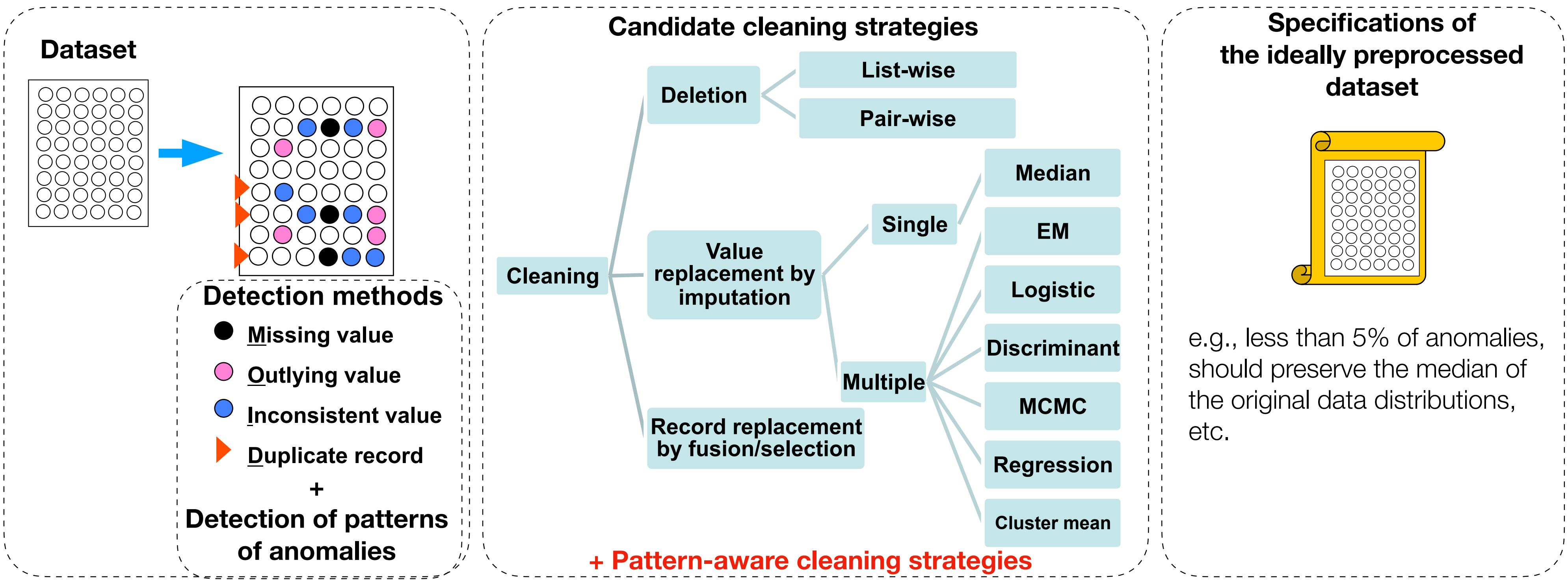


e.g., less than 5% of anomalies, should preserve the median of the original data distributions, etc.

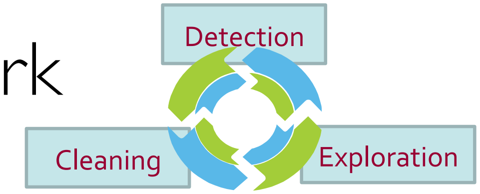
[ICDE 2011]

Detection-Exploration-Cleaning Framework

Input:



Detection-Exploration-Cleaning Framework



[Berti-Equille, Dasu,Srivastava, ICDE 2011]

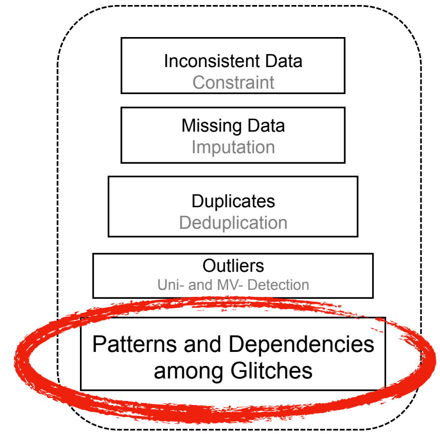
<u>*Problem Statement:*</u>

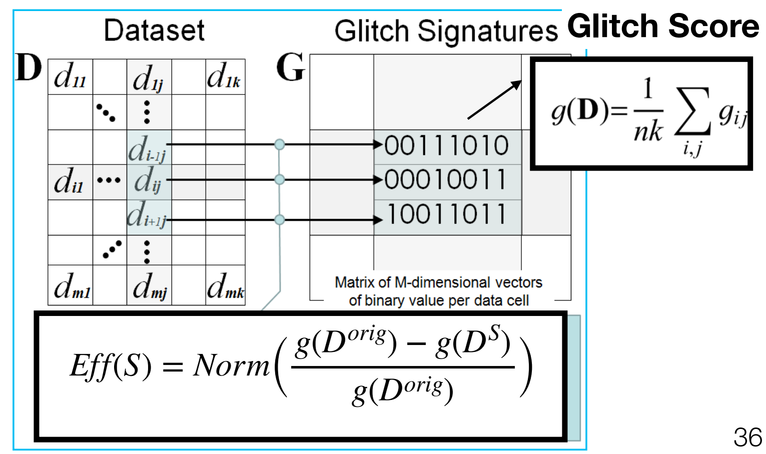
Find the quantitative cleaning strategy B composed of M methods among the candidate strategies $\boldsymbol{S}$ such that its resulting dataset D^B is the closest to an ideal dataset D^* specified from D as

$$D^B = \underset{\{s \in S\}}{\arg\min}\left(\mathrm{dist}(D^s, \mathrm{D}^*)\right)$$

$$\text{subject to } \ Cost(s) \leq \mathrm{U} \text{ and } Eff(s) \geq \Gamma > 0$$

- **dist** is the Kullback-Leibler distance between two data distributions
- **U** is a pre-defined upper bound for the cost of strategy s
- **Γ** is the lower bound of $Eff(s)$, the effectiveness of strategy s





Experiments

Real-world and semi-synthetic data

- **EPO Dataset:** 754,075 records, 4 non-key attributes (string, categorical and numerical data)
- **Intel Berkeley Research lab Dataset:** 2,313,682 million readings, 8 attributes (timestamp, sensorID, temperature, light, voltage) collected every 31 seconds from 54 sensors deployed in the between February 28th and April 5th, 2
- **SNMP Dataset:** (8,632 tuples, 11 variables) collected every 5 minutes during one month (timestamps, categorical and numerical values)

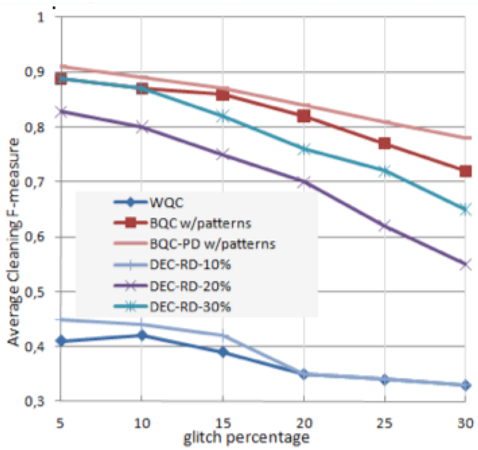
Comparison of various cleaning strategies

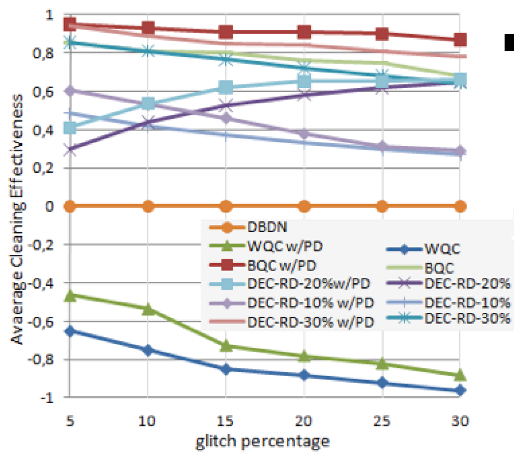
- Cost-based
- Effectiveness-based
- Resource-driven to treat just p% of glitches (DEC-RD)
- Specification-driven to treat a particular glitch type (DEC-SD)
- Pattern-based (DEC-PD)

[ICDE 2011]

Experimental results

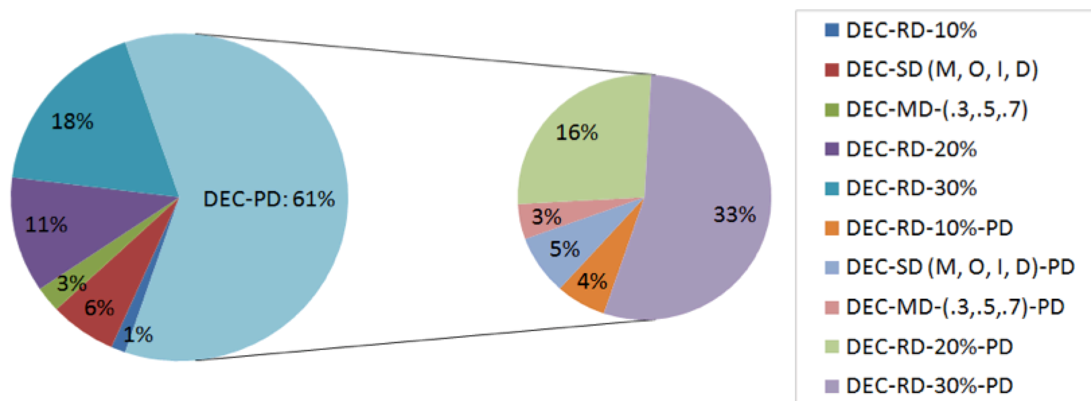
SNMP





- **Pattern discovery always improves the accuracy when glitch percentage increases.**
- **Effectiveness is improved by + 8% in average.**

- ***61% of the best strategies are pattern-based.***



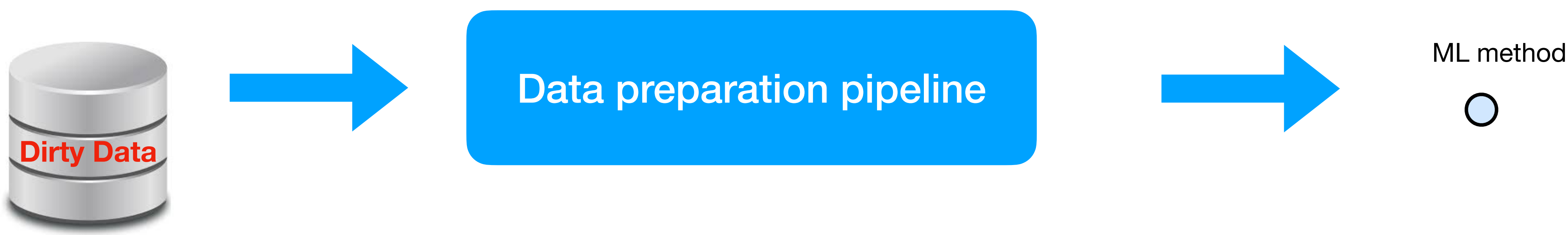
Outline

1. **Detection of data quality problems:**
   Profiling data quality with MeSQuaL

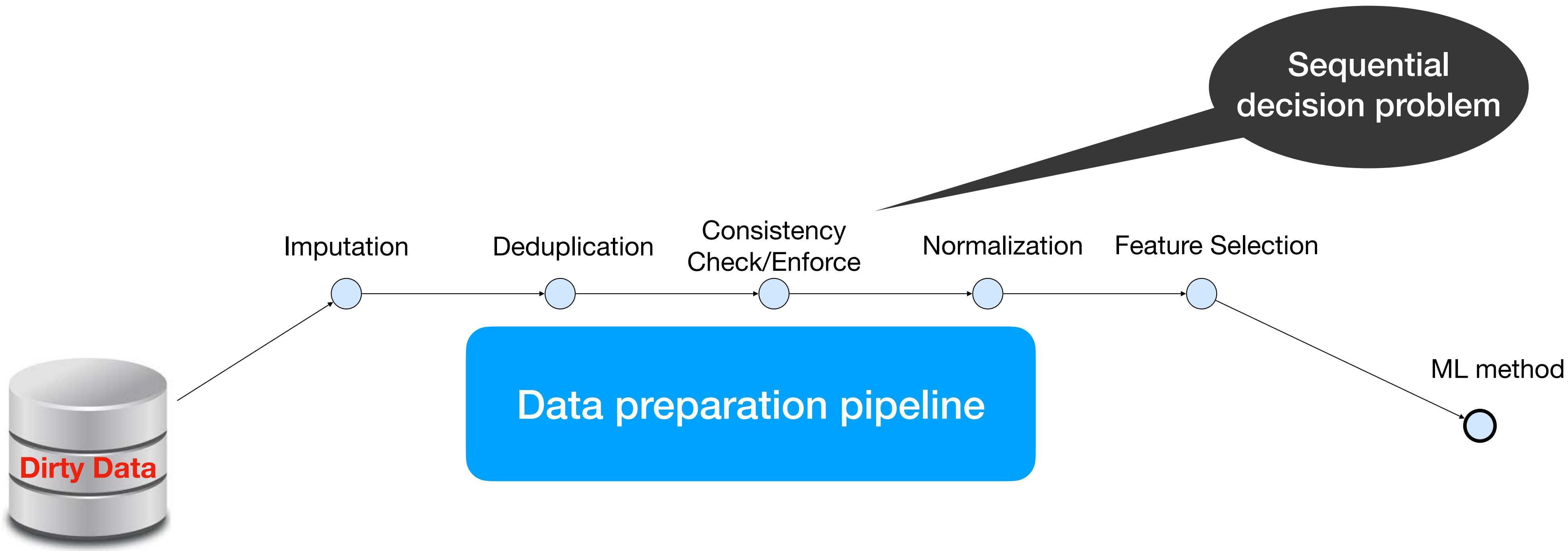
2. **Data cleaning**
   Leveraging the patterns of glitches

3. **Data preparation strategies**
   Learning to clean and prepare the data

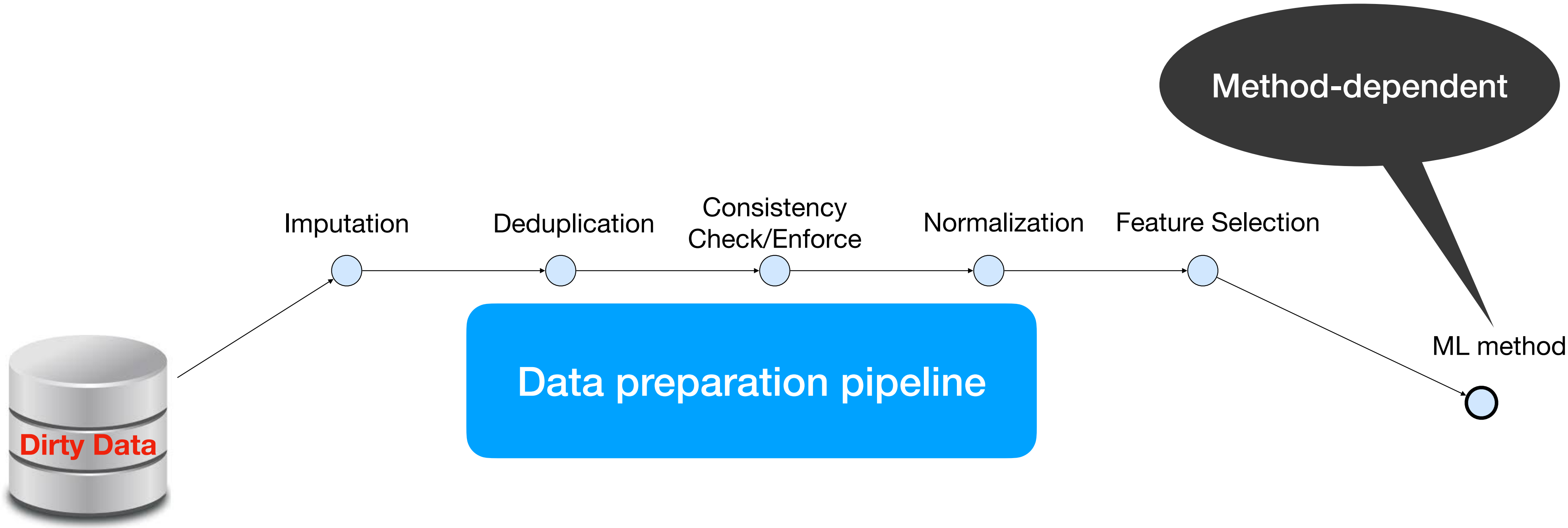
Data preprocessing is challenging



Data preprocessing is challenging



Data preprocessing is challenging



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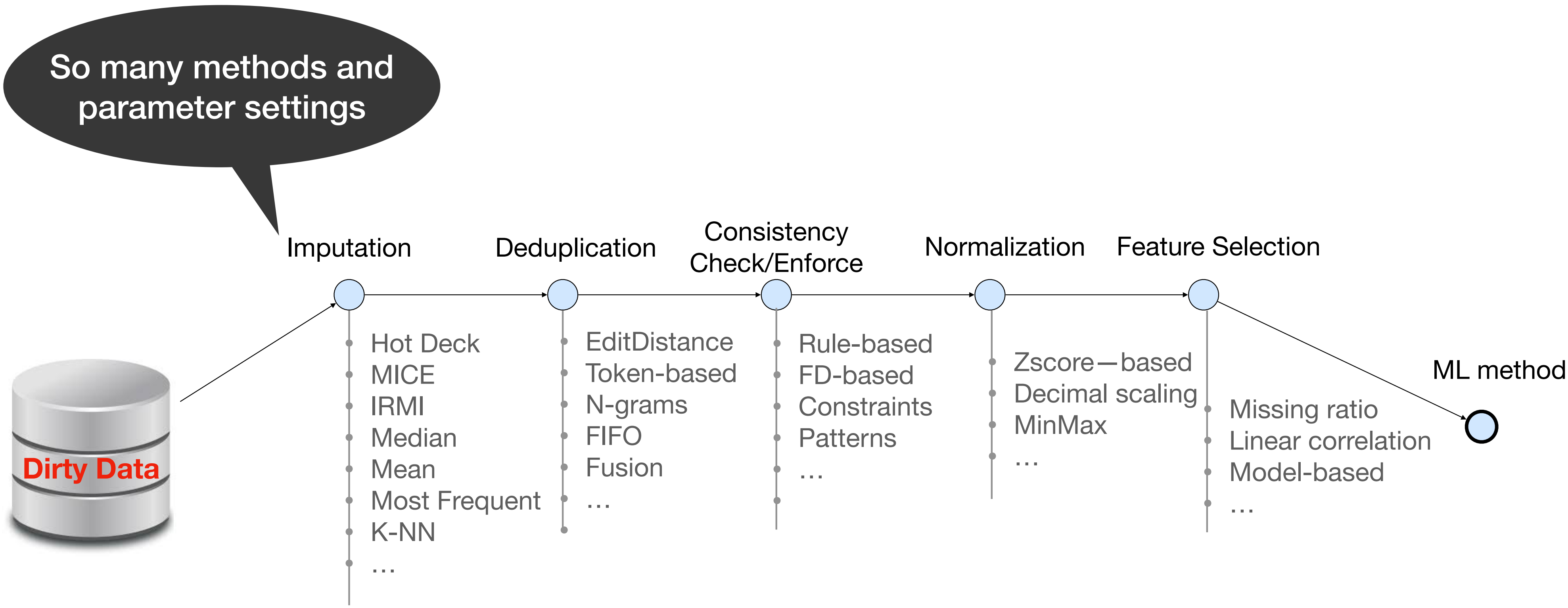
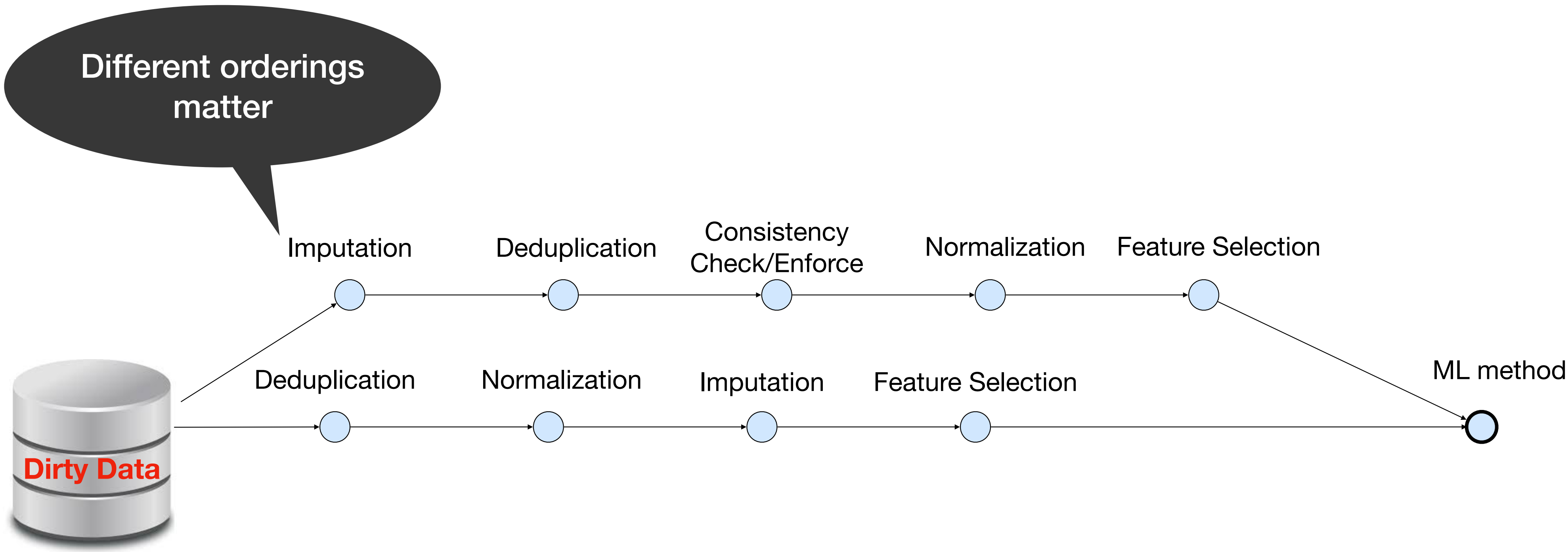


Data preprocessing is challenging



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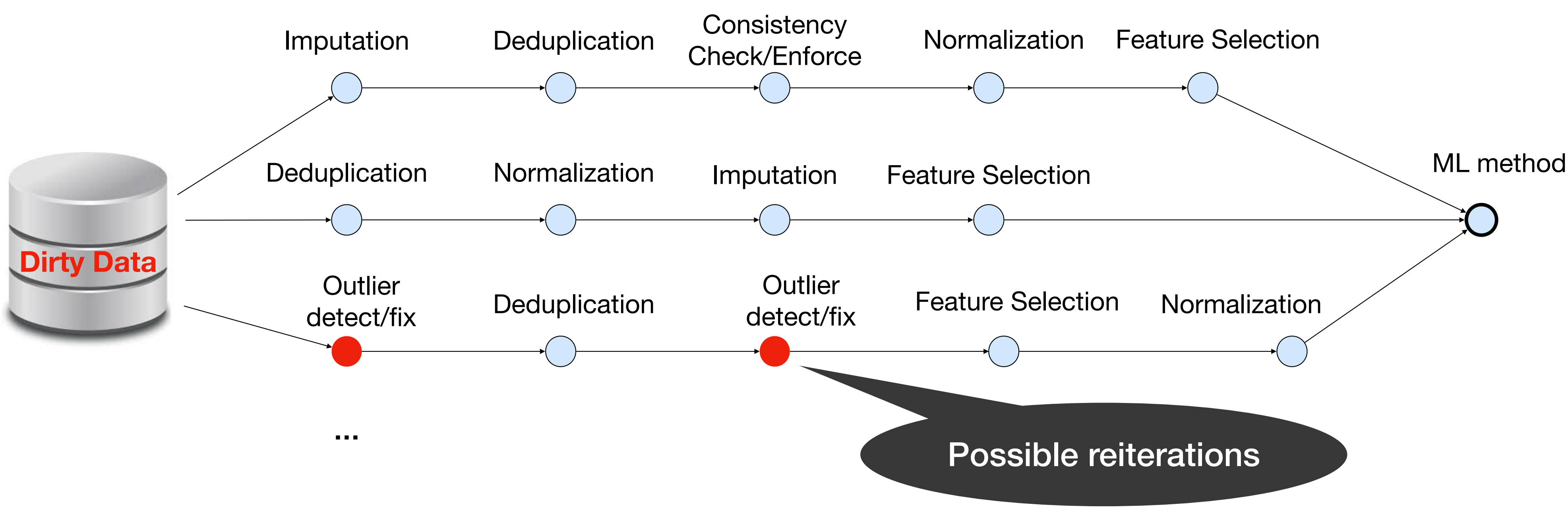
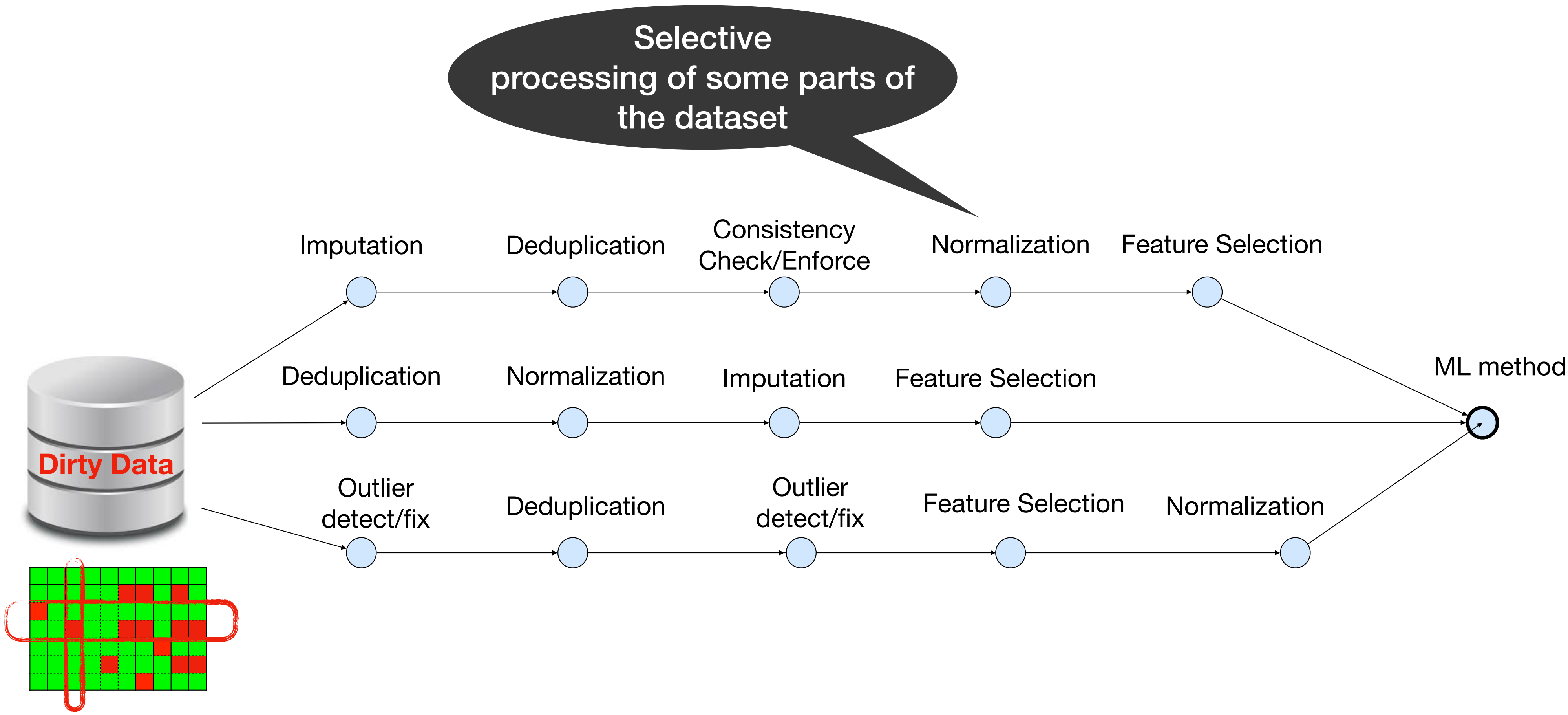
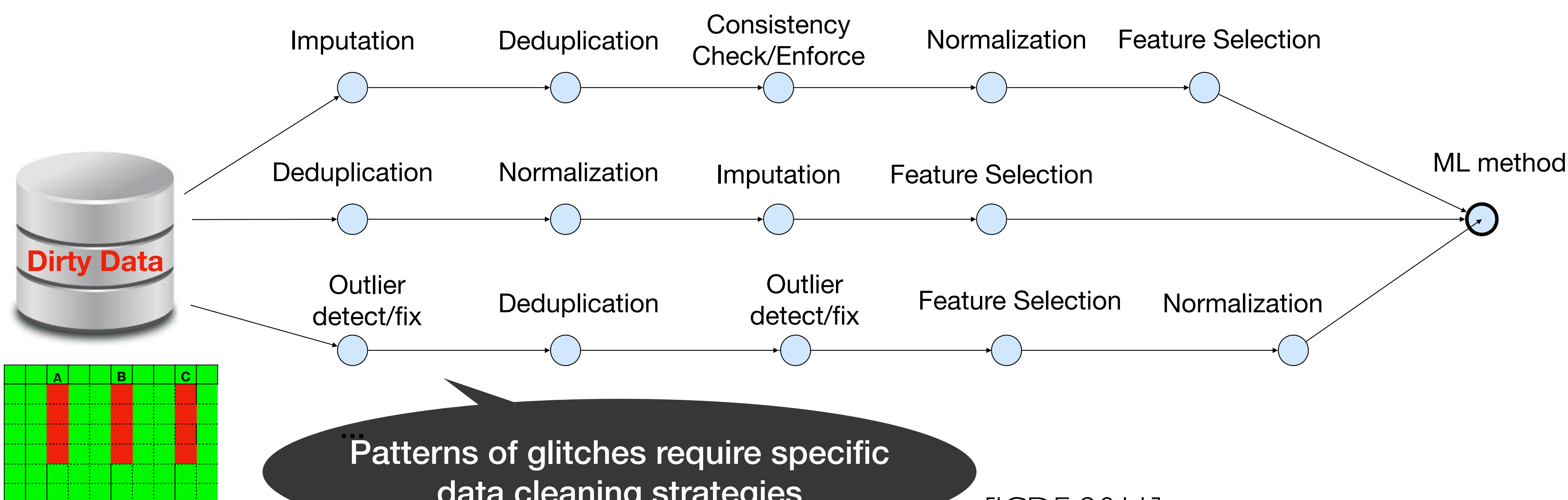


Data preprocessing is challenging



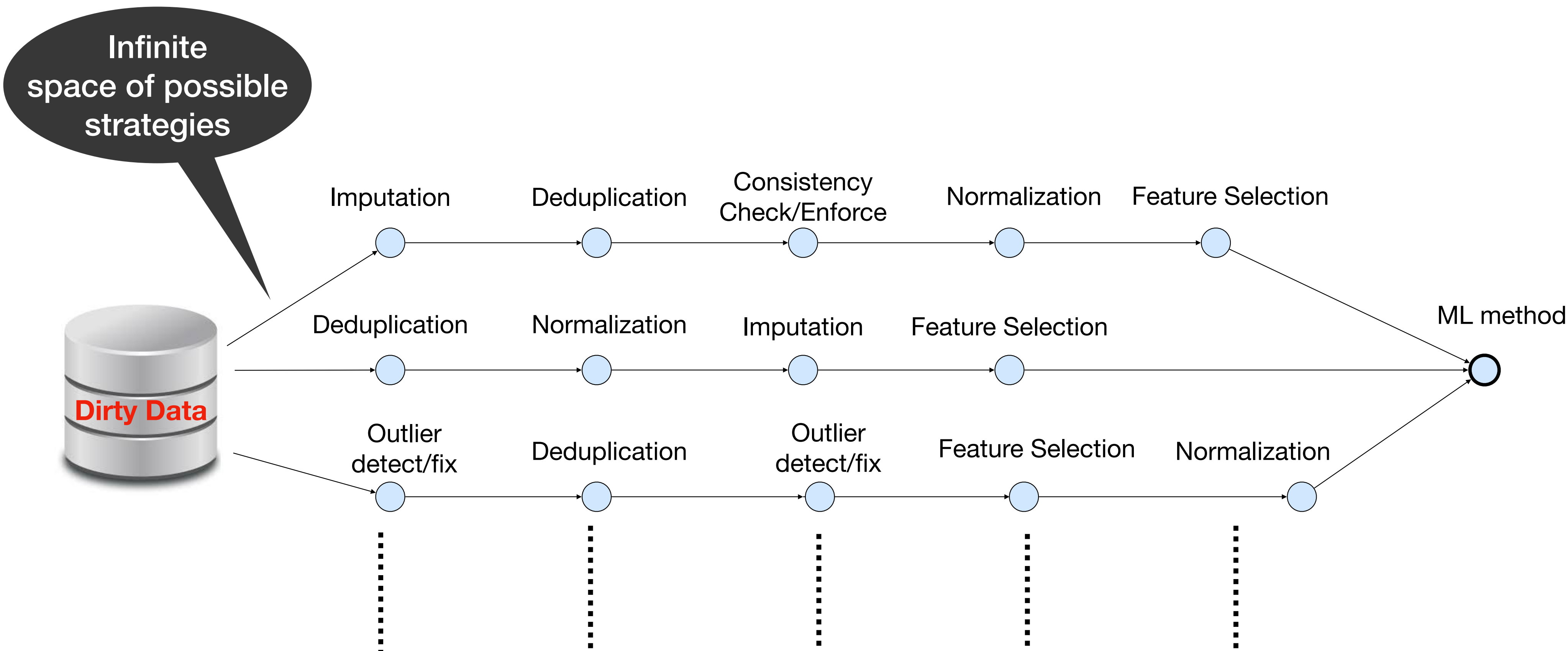
Data preprocessing is challenging



Patterns of glitches require specific data cleaning strategies

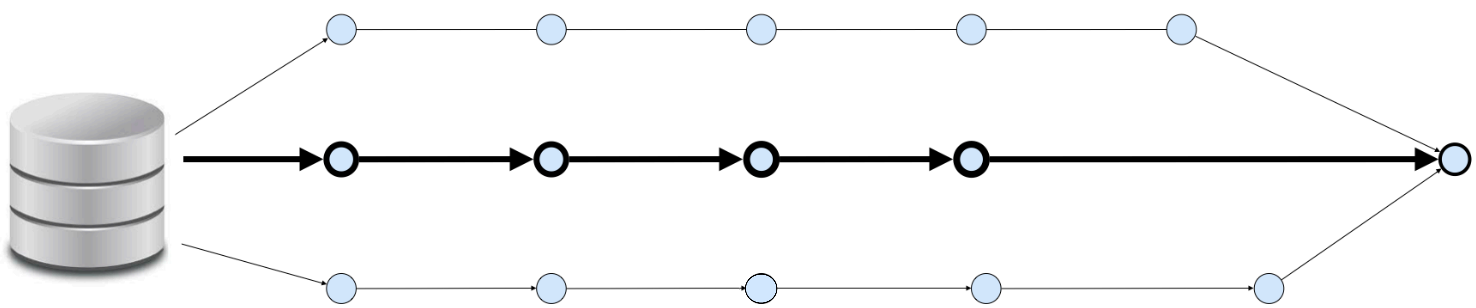
[ICDE 2011]

Data preprocessing is challenging



Optimization Problem

Can we help the user in composing the data preparation pipeline that maximizes the quality performance of the ML method ?



Optimization Problem

Can we help the user in composing the data preparation pipeline that maximizes the quality performance of the ML method ?

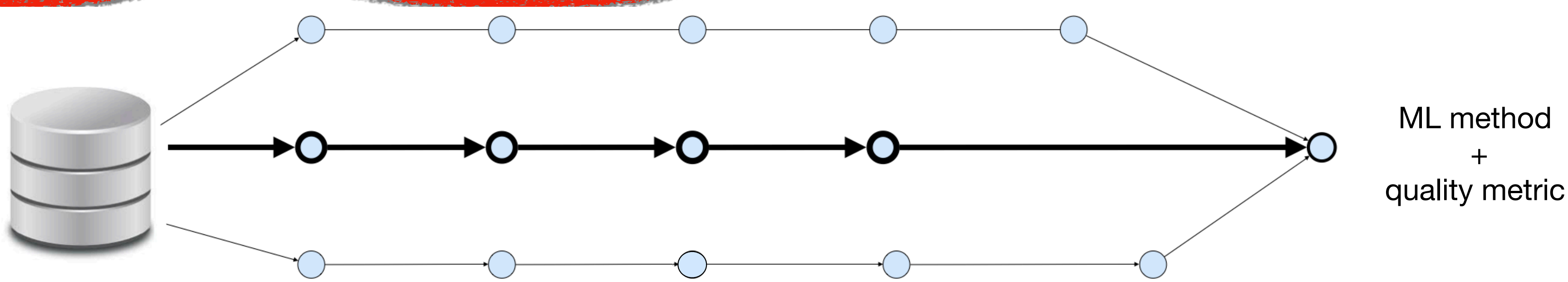
No training example for "good" data cleaning

Metric-dependent

No model a priori

AutoML-like approach

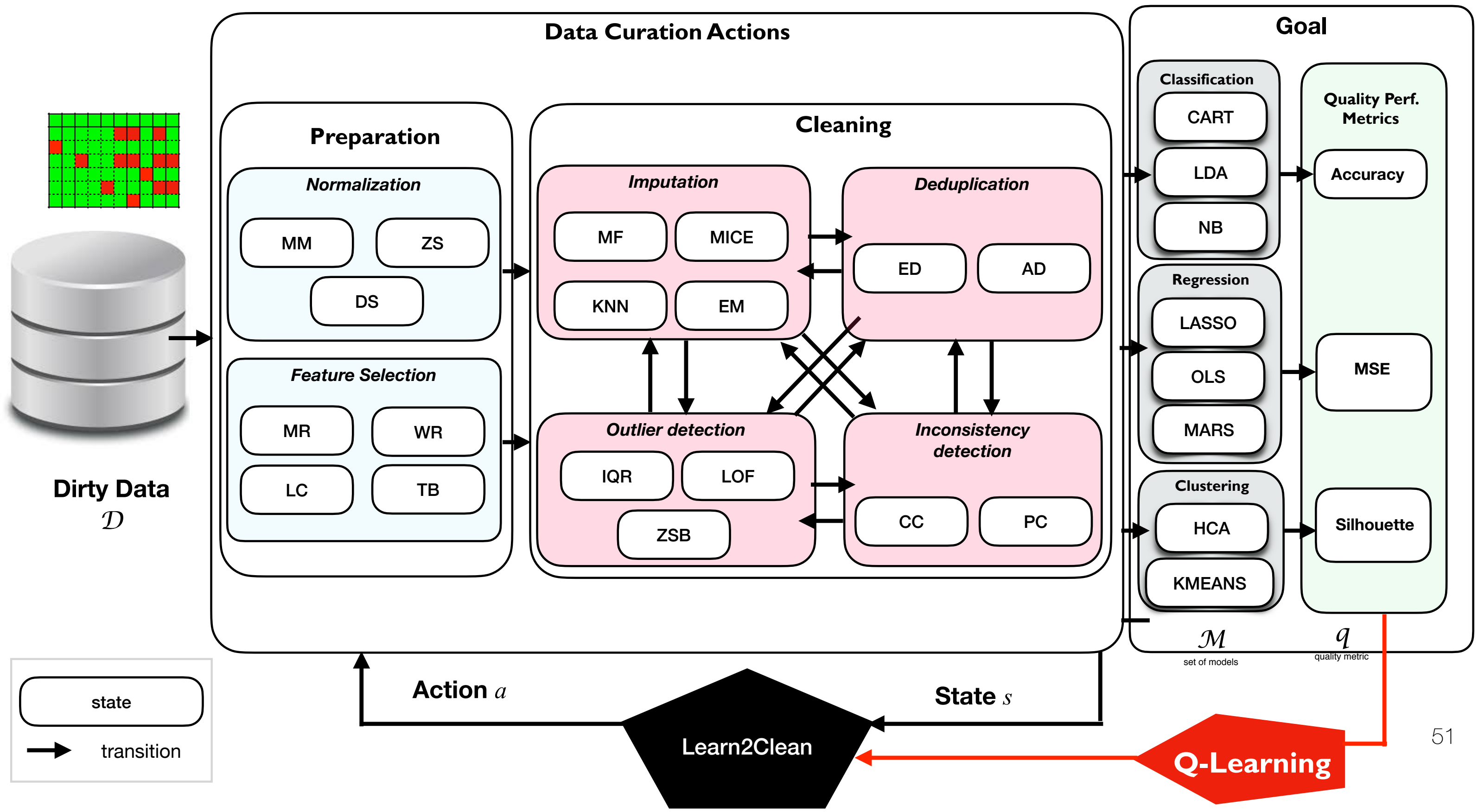
Human-In-The Loop



[The WebConf 2019]

First Solution: Learn2Clean

https://github.com/LaureBerti/Learn2Clean



AutoML-like approach for data curation

[The WebConf 2019]

Reinforcement Learning Framework

Markov Decision Process

State | Action | Transition | Reward

Learn2Clean

$D_s \circ \xrightarrow{p_q}$

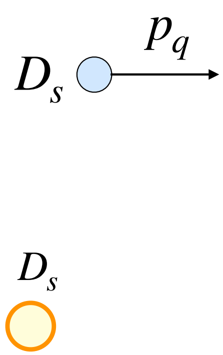
[The WebConf 2019]

Reinforcement Learning Framework

Markov Decision Process

State | Action | Transition | Reward

Learn2Clean



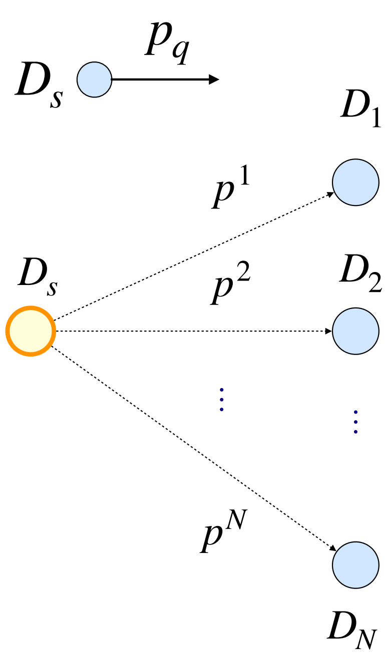
[The WebConf 2019]

Reinforcement Learning Framework

Markov Decision Process

State | **Action** | Transition | Reward

Learn2Clean



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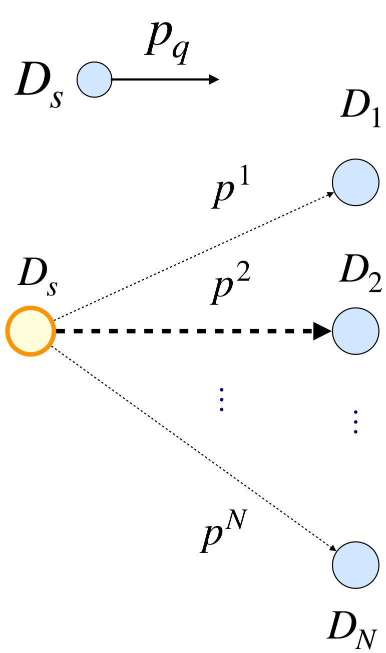
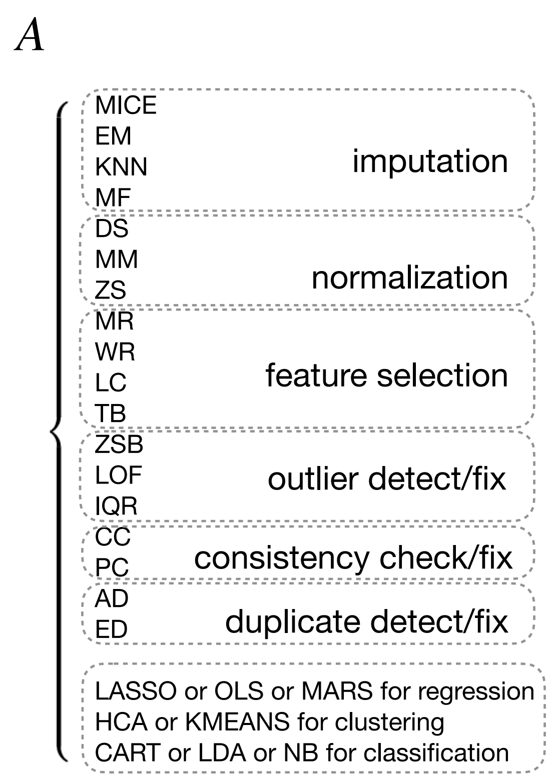
[The WebConf 2019]

Reinforcement Learning Framework

Markov Decision Process | State | **Action** | Transition | Reward | Learn2Clean



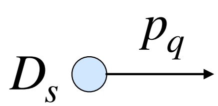


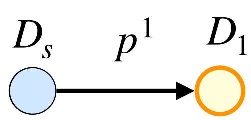
Reinforcement Learning Framework

Markov Decision Process

State | Action | **Transition** | Reward

Learn2Clean





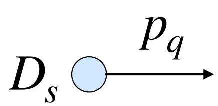
[The WebConf 2019]

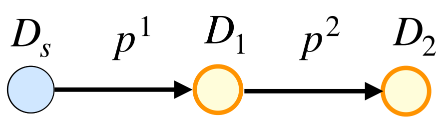
Reinforcement Learning Framework

Markov Decision Process

State | Action | **Transition** | Reward

Learn2Clean





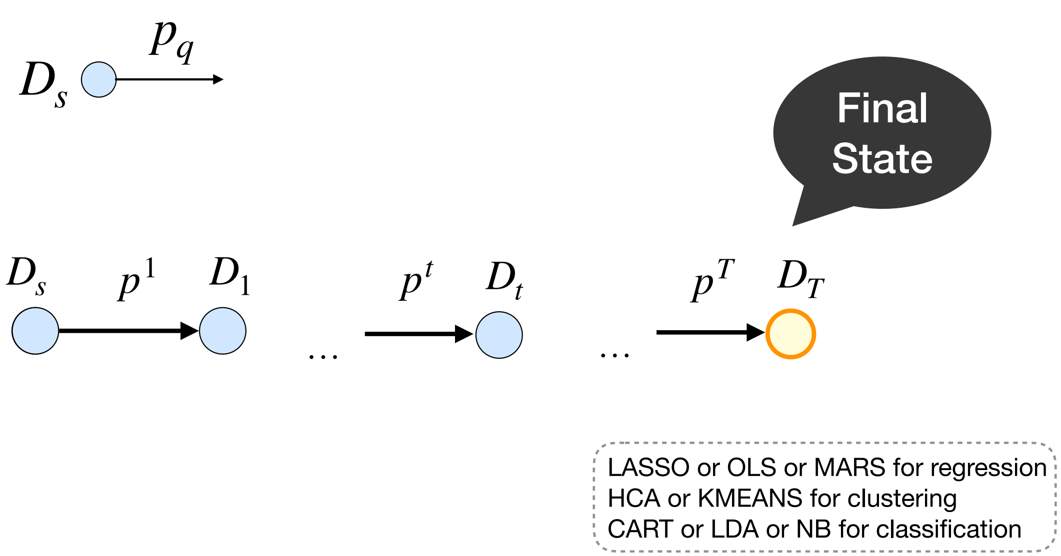
[The WebConf 2019]

Reinforcement Learning Framework

Markov Decision Process

State | Action | **Transition** | Reward

Learn2Clean



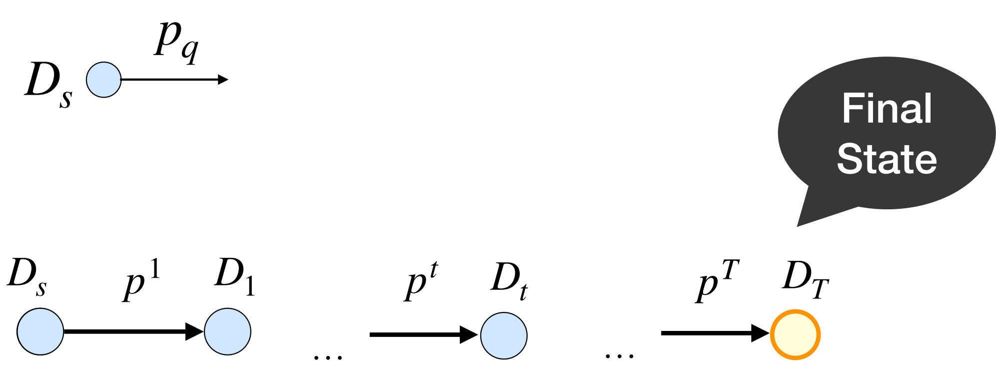
[The WebConf 2019]

Reinforcement Learning Framework

Markov Decision Process

State | Action | Transition | **Reward**

Learn2Clean



deterministic

$$R = \begin{array}{c} \begin{array}{ccccccccccccccccccc} \text{MICE} & \text{EM} & \text{KNN} & \text{MF} & \text{DS} & \text{MM} & \text{ZS} & \text{MR} & \text{WR} & \text{LC} & \text{TB} & \text{ZSB} & \text{LOF} & \text{IQR} & \text{CC} & \text{PC} & \text{AD} & \text{ED} & \text{LASSO} \end{array} \\ \begin{bmatrix}
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\end{bmatrix} \end{array}$$

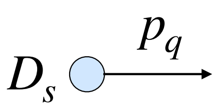
[The WebConf 2019]

Reinforcement Learning Framework

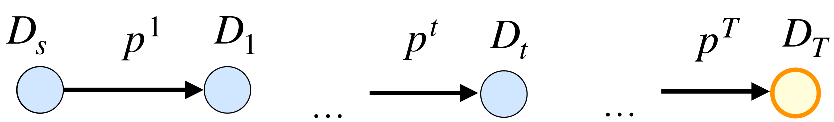
Markov Decision Process

State | Action | Transition | **Reward**

Learn2Clean



Final State



deterministic

$$R = \begin{array}{c} \text{MICE EM KNN MF DS MM ZS MR WR LC TB ZSB LOF IQR CC PC AD ED LASSO} \\ \begin{bmatrix} -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 100 \\ -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 100 \\ -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 100 \\ -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 100 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 100 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 100 \\ 0 & 0 & 0 & 0 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 100 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 100 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 100 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 100 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 100 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \end{bmatrix} \end{array}$$

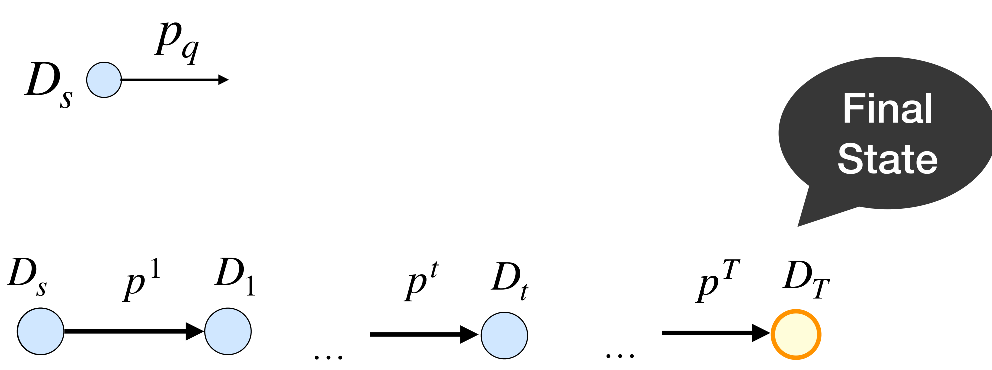
LASSO or OLS or MARS for regression $\longrightarrow$ MSE
HCA or KMEANS for clustering $\longrightarrow$ Silhouette
CART or LDA or NB for classification $\longrightarrow$ Accuracy

Quality metric

[The WebConf 2019]

Reinforcement Learning Framework

Markov Decision Process — State | Action | Transition | **Reward** — Learn2Clean



deterministic

$$R = \begin{array}{c}
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\begin{bmatrix}
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-1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 100 \\
-1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 100 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 100 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 100 \\
-1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1
\end{bmatrix}
\end{array}$$

LASSO or OLS or MARS for regression → MSE
HCA or KMEANS for clustering → Silhouette
CART or LDA or NB for classification → Accuracy

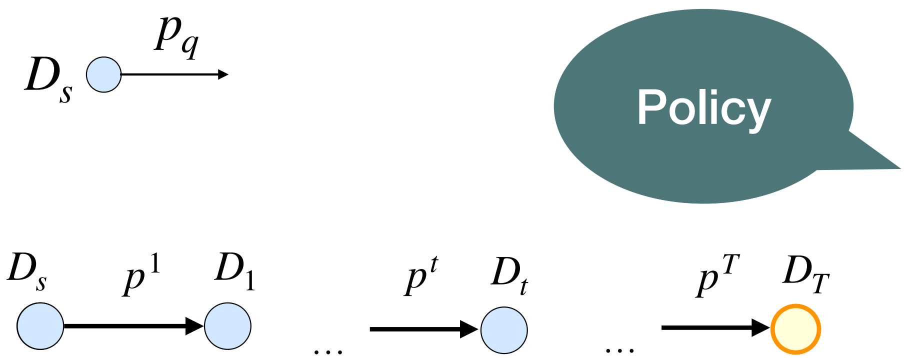
Quality metric

Learn2Clean selects the sequence of preprocessing actions that maximizes the quality metric (or minimizes the error)

[The WebConf 2019]

Reinforcement Learning Framework

Markov Decision Process — State | Action | Transition | **Reward** — Learn2Clean



Softmax action selection

$$\pi = P(a \mid s) = \frac{e^{Q(s,a)/k}}{\sum_j e^{Q(s,a_j)/k}}$$

Q-table

Value iteration update

$$\underbrace{Q^{\pi}(s,a)}_{\text{new value}} \leftarrow (1-\underbrace{\alpha}_{\text{learning rate}}) \, . \, \underbrace{Q(s,a)}_{\text{old value}} + \alpha \, . \, \overbrace{\Big(\underbrace{R(s,a)}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \, . \, \underbrace{\max_{a'} Q(s',a')}_{\text{optimal future value}}\Big)}^{\text{learned value}}$$

[The WebConf 2019]

Experiments

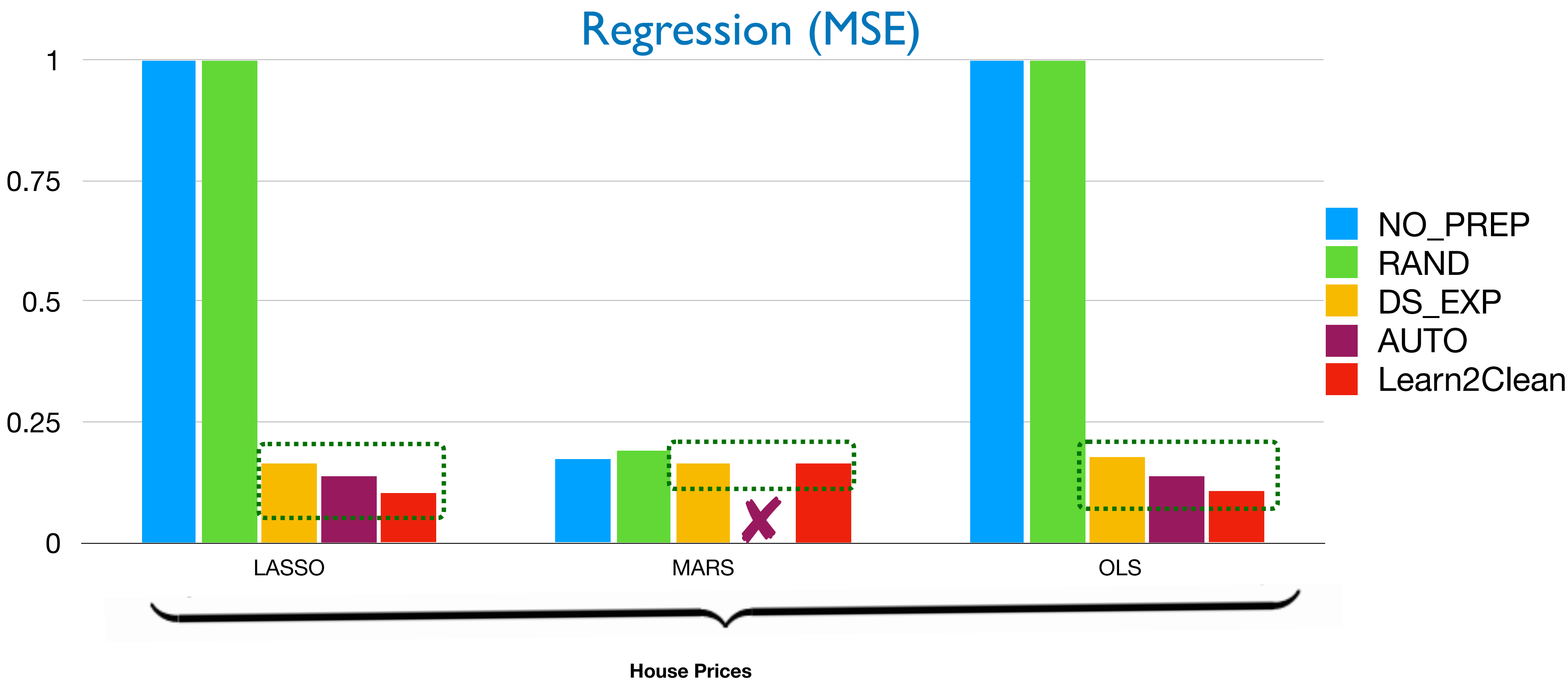
Datasets

Name	# Att.	# Rows	Clustering	Regression	Classification
House Prices	81	1.46k	✓	✓	✓
Google Playstore Users	5	64.3k	✓		
Google Playstore Apps	13	10.8k	✓		✓

Evaluation : Silhouette for Clustering
MSE for Regression
Accuracy for Classification

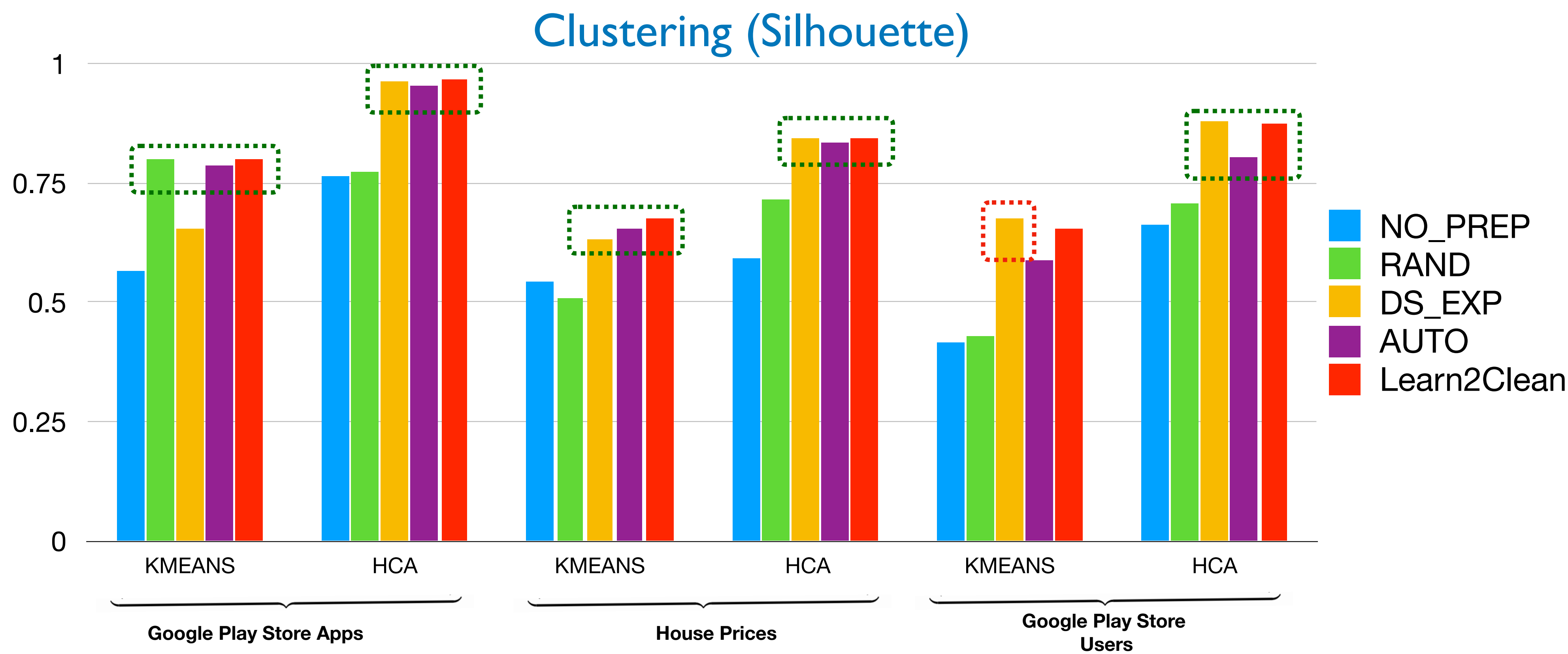
[The WebConf 2019]

Experimental Results



[The WebConf 2019]

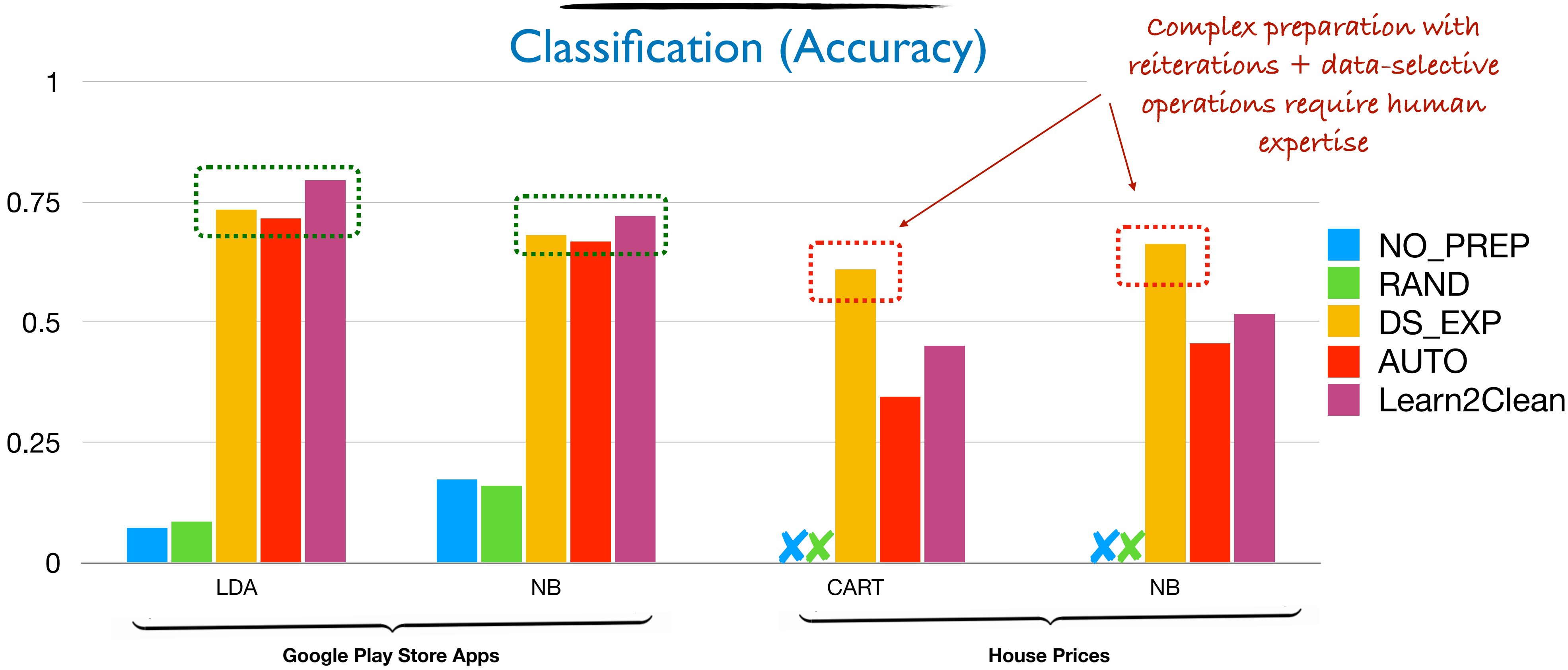
Experimental Results



[The WebConf 2019]

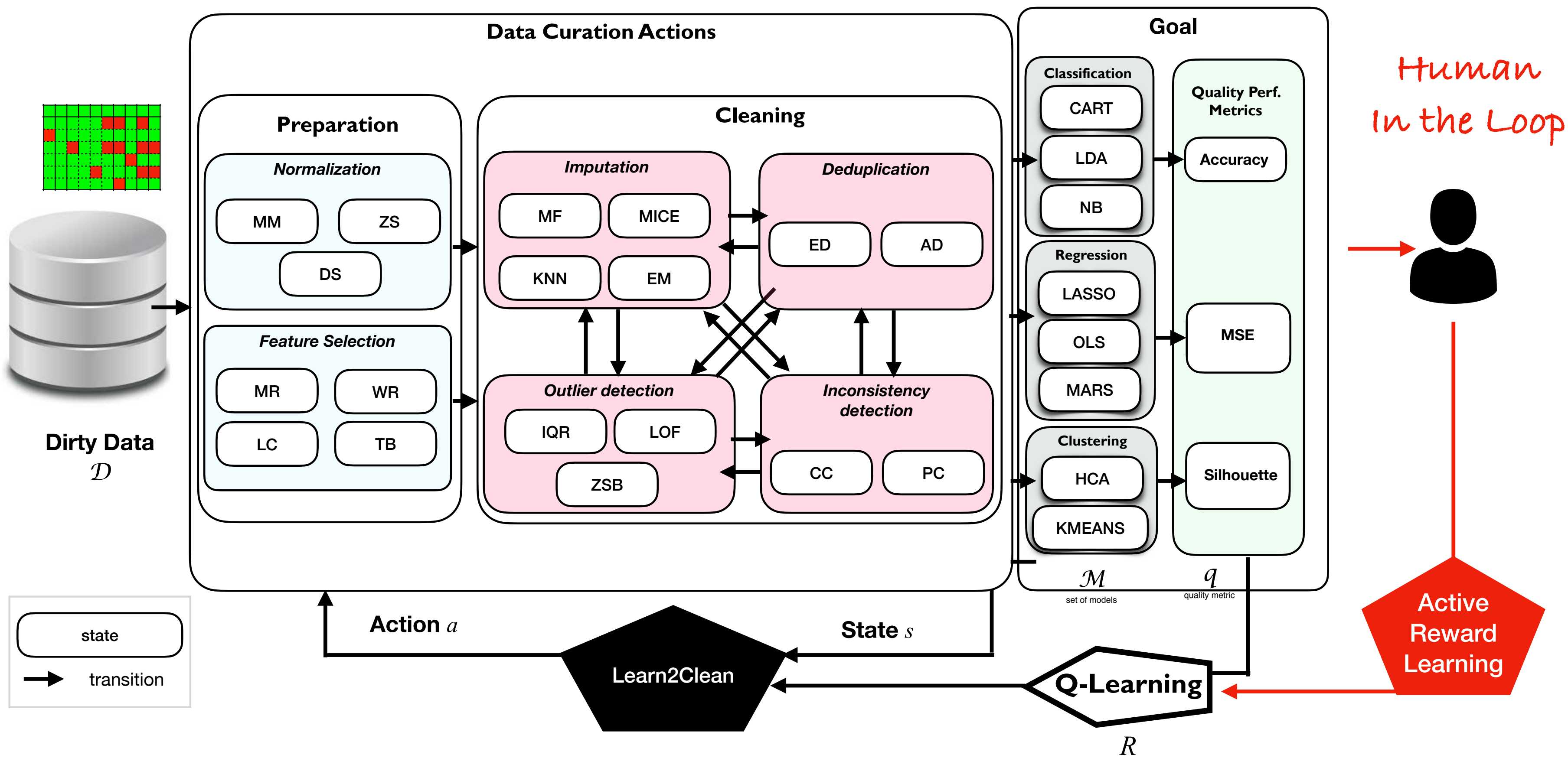
Experimental Results

Classification (Accuracy)



[HILDA@SIGMOD2019]

HIL with Active Reward Learning

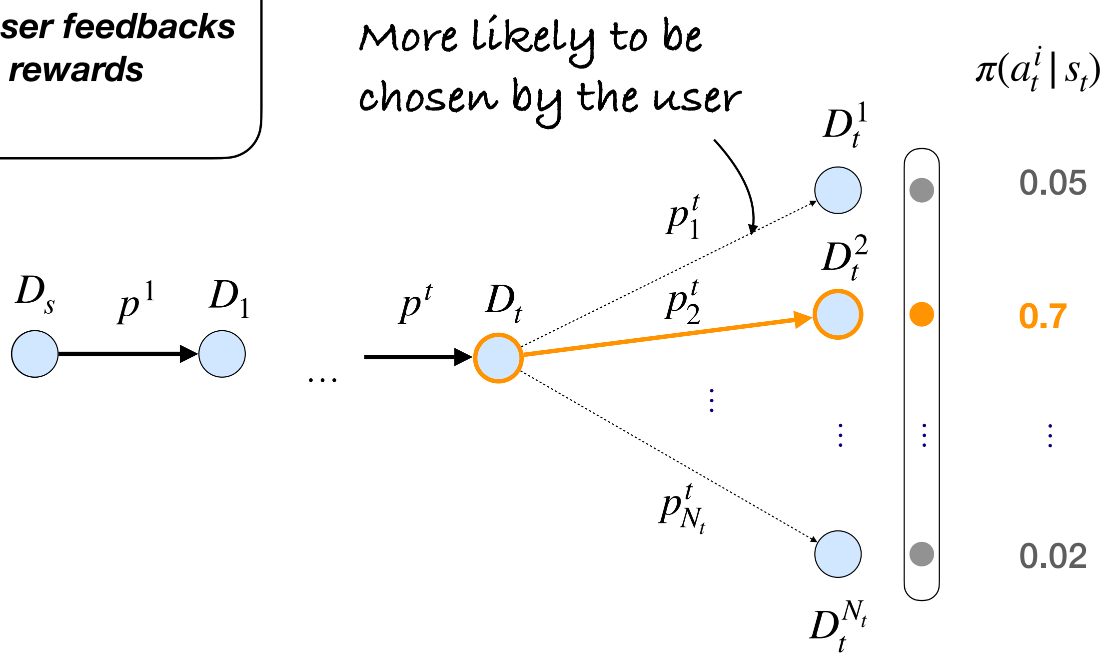


[HILDA@SIGMOD2019]

Active Reward Learning

Learn2Clean
+
HIL

Goal: ***learn from user feedbacks to adapt the rewards***

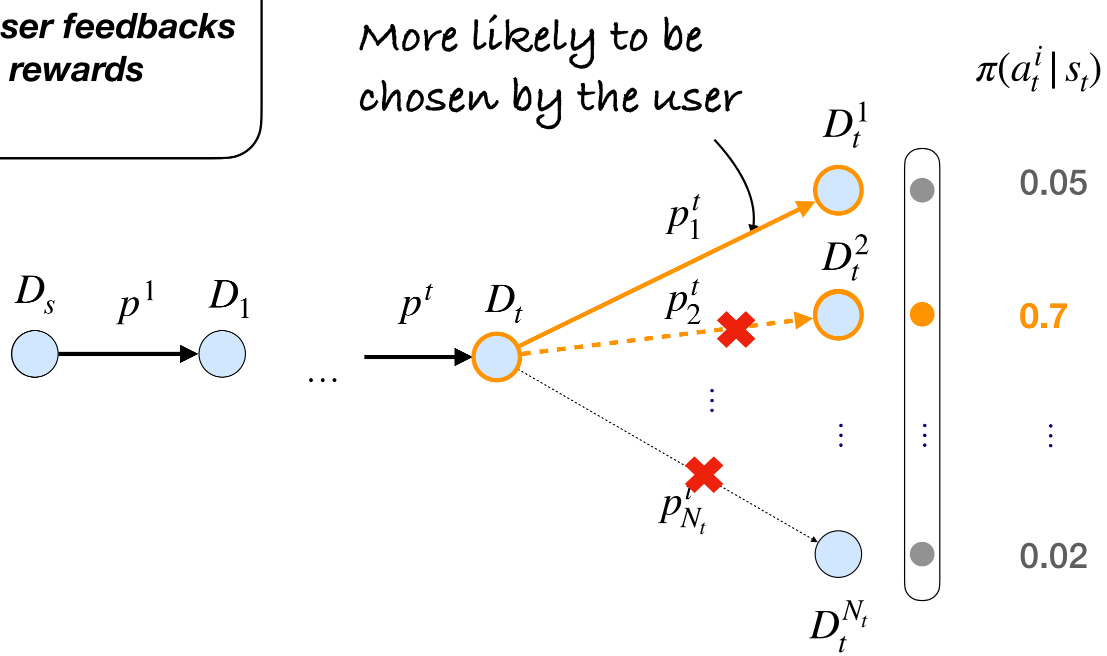


[HILDA@SIGMOD2019]

Learn2Clean
+
HIL

Active Reward Learning

Goal: ***learn from user feedbacks to adapt the rewards***

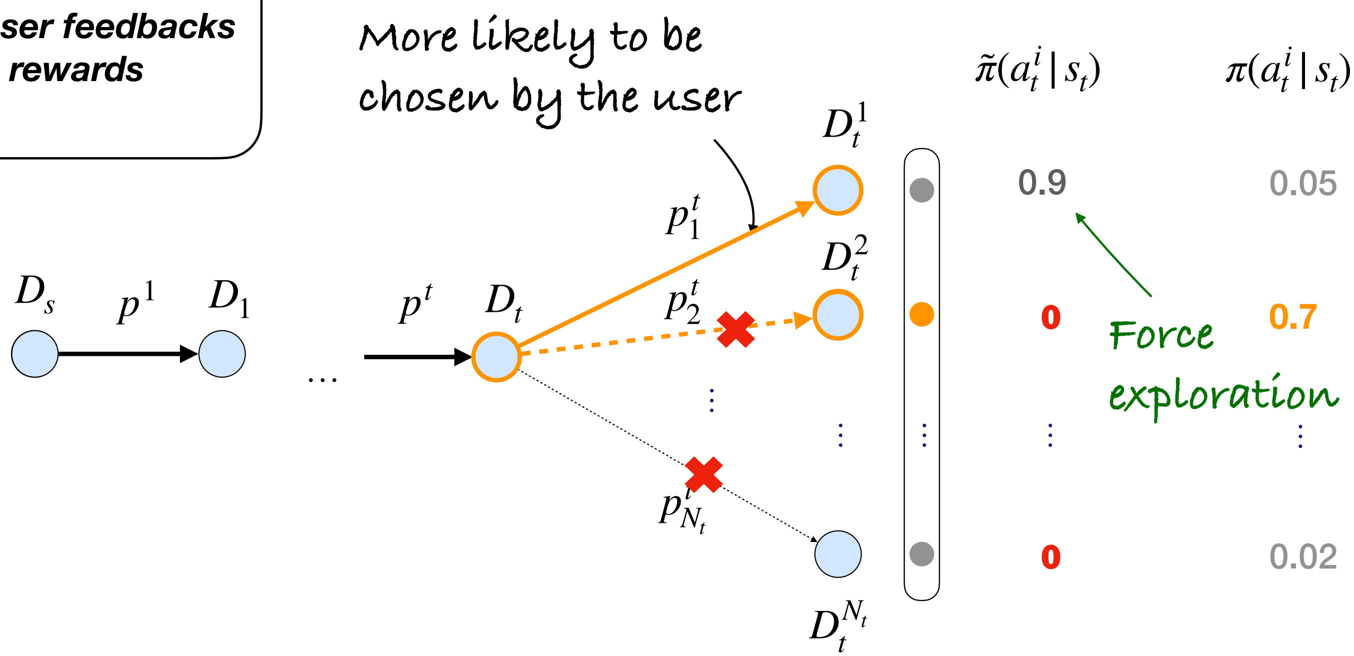


[HILDA@SIGMOD2019]

Learn2Clean
+
HIL

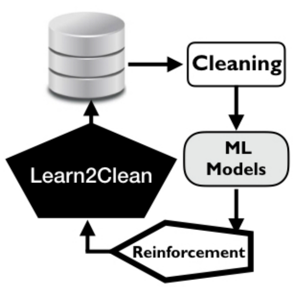
Active Reward Learning

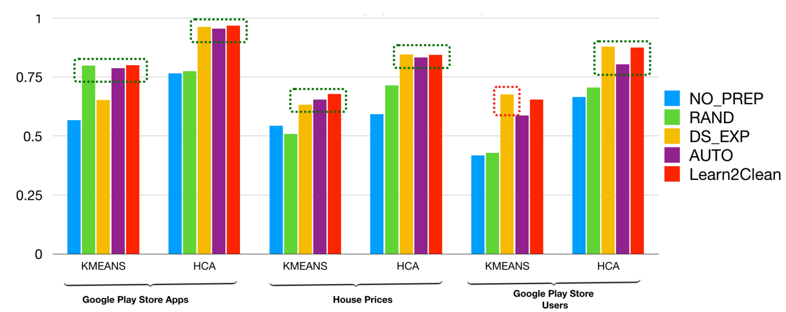
Goal: ***learn from user feedbacks to adapt the rewards***



Ongoing work

- New version of Learn2Clean with deep RL agents
- Combine AutoML, AutoCuration, and HIL
- Learn better reward functions
- Extend the library of ML and data preparation methods
- Extend experiments with more intricate data glitches and various glitch distributions





Code: https://github.com/LaureBerti/Learn2Clean

Concluding Remarks

- ML crucially needs principled data curation and preparation, adequate tooling, and user assistance
- The impact of data preprocessing variability is largely underestimated in ML
- Many data preprocessing tasks require seamless integration of Human-in-the-Loop and automated ML-based solutions
- Perfect timing for many R&D opportunities:
  - Manage and orchestrate human/machine resources
  - Challenge and transfer research ideas to operational and very large-scale contexts

Thank you!