

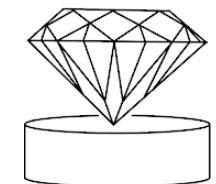
Machine Learning-Based Data Cleaning : Current Solutions and Challenges

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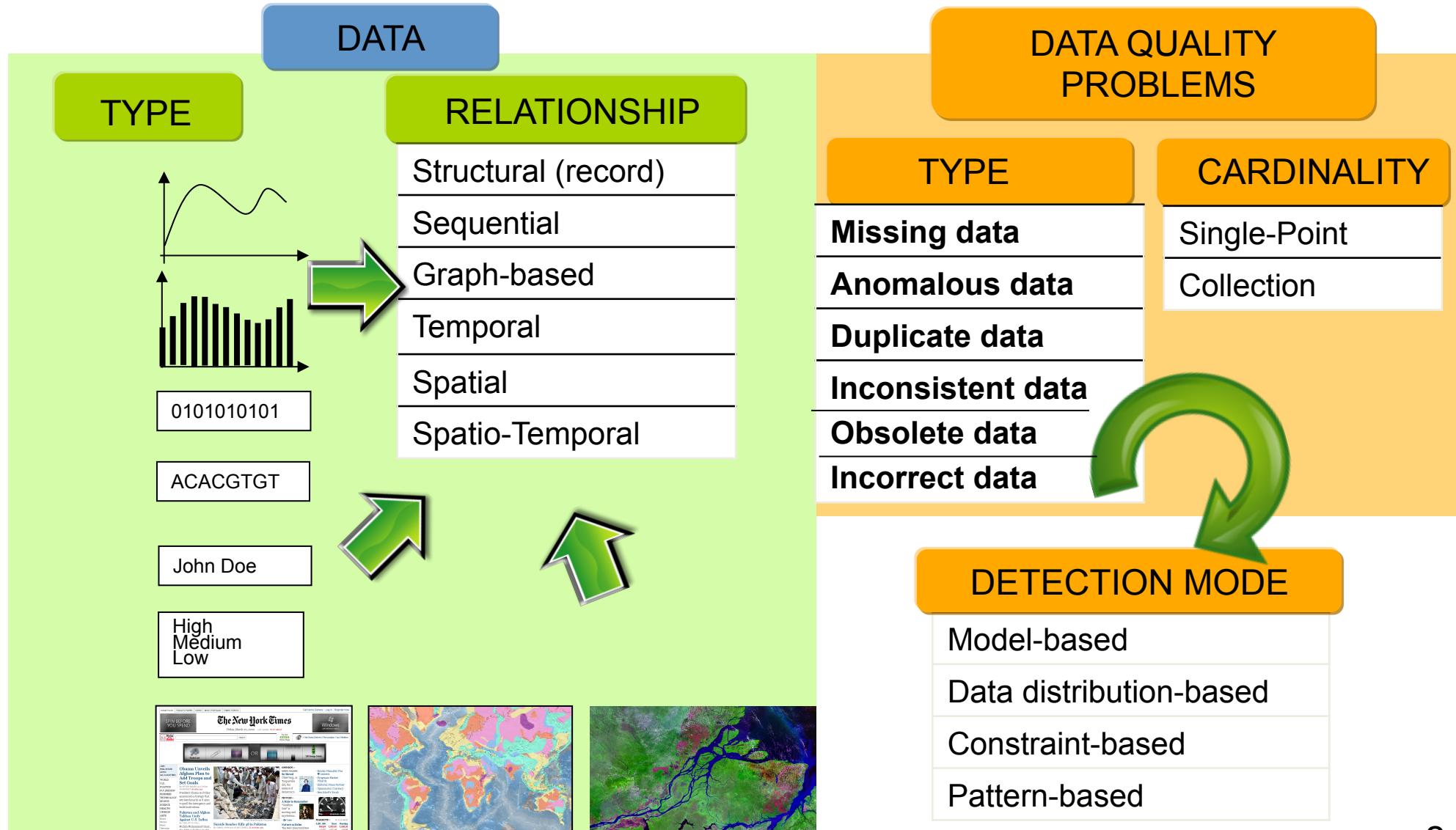
laure.berti@ird.fr

<http://pageperso.lif.univ-mrs.fr/~laure.berti/>



<https://diams.lis-lab.fr/>

Data Quality Problems



Example 1

Relational data : CiDE.21 committee

Nom	Etablissement	Ville	Tel
Prof. B. JACQUEMIN	Univ. Lille GERiiCO	Lyon	+33 (0) 3 20 41 66 38
Malek GHENIMA	ESC Tunis	Tunis	+216 71600615
Anis BEN MAMI	ESC Tunis	Tunis	74415567
M. GHENIHA	Tunis	Univ. de la Manouba	+216 71600615
Mehdi BEN GHANEM	NULL	Tunis	NULL
Hamida AMDOUN		ESEN-14009	00000000

Representation (points to the table structure)

Duplicates (points to the row for Malek GHENIMA and Anis BEN MAMI)

Typos (points to the name M. GHENIHA)

Misfielded Value (points to the phone number +33 (0) 3 20 41 66 38)

Inconsistencies (points to the row for Hamida AMDOUN, which contains an empty value in the Etablissement column)

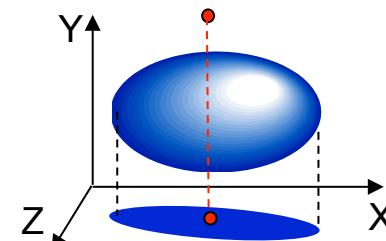
Obsolete Value (points to the phone number 74415567, which is likely obsolete)

Incorrect Values (points to the phone number 74415567, which is likely incorrect)

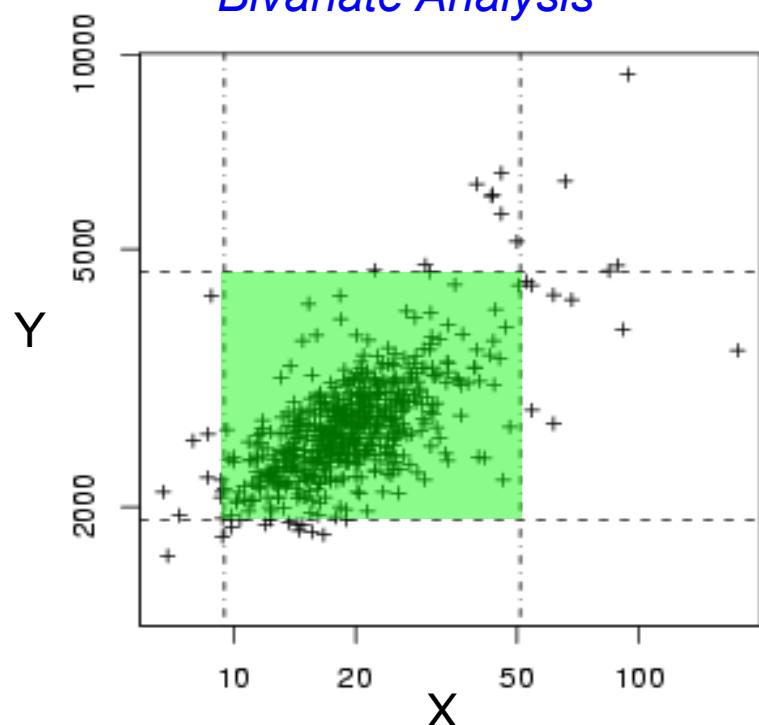
Missing Values (points to the empty values in the Etablissement and Tel columns for the last row)

Example 2

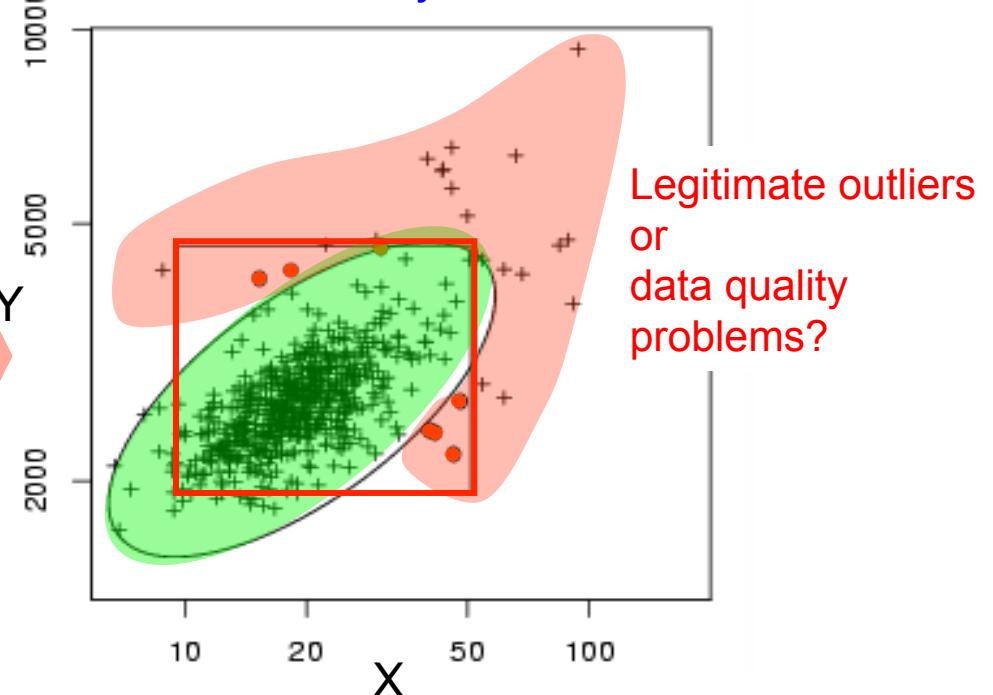
Outliers



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:
 $\text{Mahalanobis_dist}(\text{cov}(X,Y)) > \chi^2(.98,2)$

Example 3

Disguised missing data

Some are obvious...

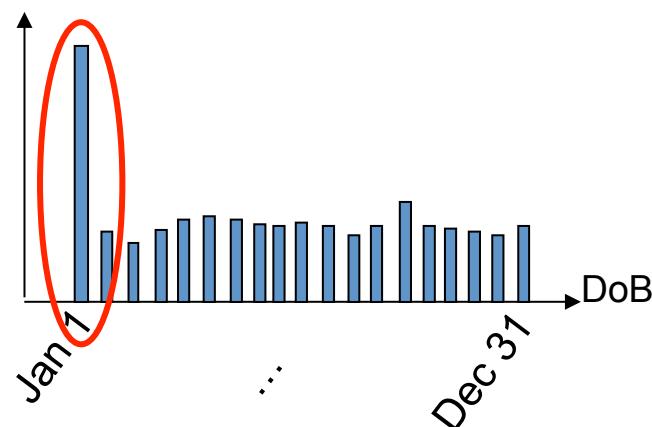
Detectable with syntactical or domain constraints

Phone number: 999-999-9999

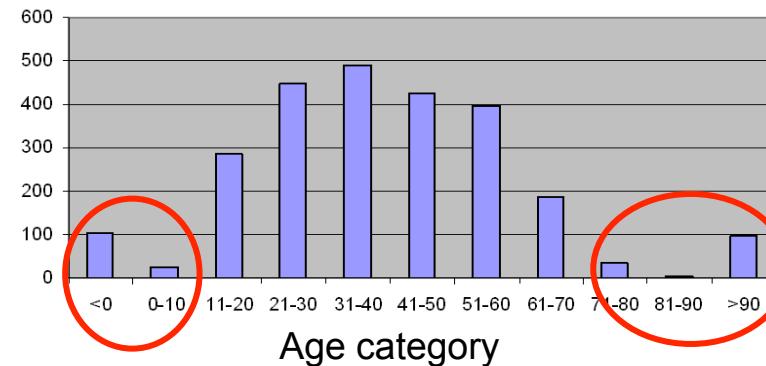
Others are not....

Could be suspected because the data distribution doesn't conform to the expected model

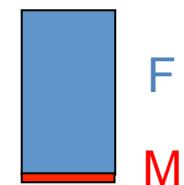
Histogram of DoBs per day of the year



Histogram of online shopping customers per age category



2% patients in the obstetrical emergency service are male...



Example 4

Are the information sources equally accurate, up-to-date, and trustworthy?

AFP apologises to French industrialist after death reported



February 28, 2015 2:42 PM



© REUTERS/ BENOIT TESSIER

[French TV Denies Reports of Bouygues Conglomerate CEO's Death](#)

AFP issued an apology to French industrialist Martin Bouygues, chairman and CEO of the conglomerate Bouygue...

Example 5

Rumors: Celebrity Death Hoaxes



成龙 Jackie Chan
June 21

Hi everybody! Yesterday, I got on a 3am flight from India to Beijing. I didn't get a chance to sleep and even had to clean my house when I got home. Today, everybody called to congratulate me on my rumored engagement. Afterward, everybody called me to see if I was alive.

If I died, I would probably tell the world! I took a photo with today's date, just in case you don't believe me! However, thank you all for your concern. Kiss kiss and love you all!

P.S. My dog is healthy, just like me! He doesn't need surgery! By the way, my dogs are golden retrievers, not Labradors.

Like Irene Ennenbach, Kimyong Fu Fu, Daniel K others like this.
10,816 shares
View previous comments
Damian Luko oже
See Translation
30 minutes ago
Rose Quayle Long live the hero for a thought u turned into chuck norris
16 minutes ago
Trevor Taylor add to circle



DWAYNE JOHNSON died while filming a dangerous stunt for FAST & FURIOUS 7

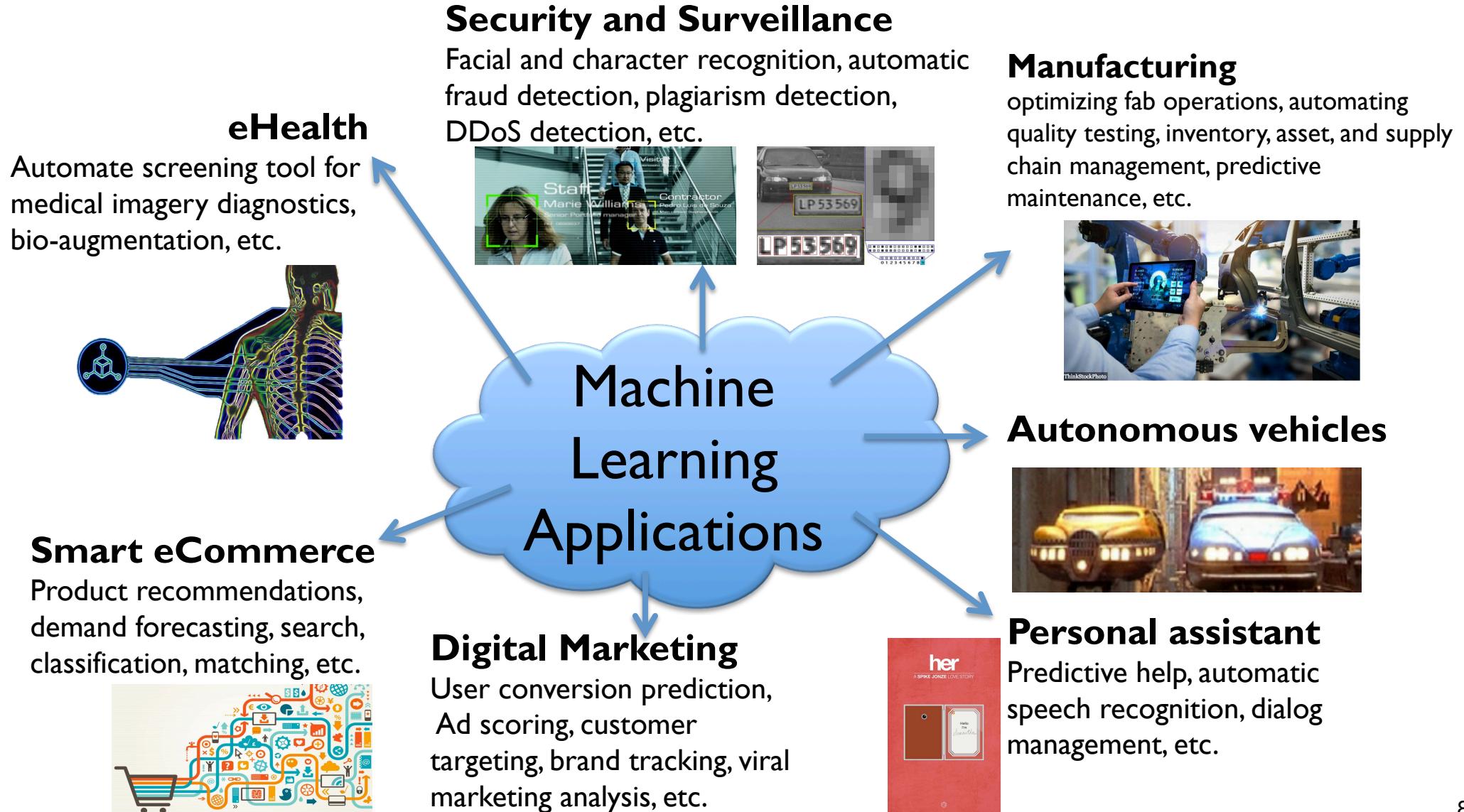


Community
At about 5 p.m. ET on Thursday, our beloved actor Morgan Freeman passed away due to a artery rupture. Morgan was born on June 1, 1937. He will be missed but not forgotten. Please show your sympathy and condolences by commenting on and liking this page.

About

Photos Likes
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ML Revolutionizes Industry



Hot Topic for DB community

[VLDB'17 Keynote]

Deep Learning (m)eats Databases

(shortened)

Jens Dittrich

Machine Learning and Databases: The Sound of Things to Come or a Cacophony of Hype?

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Categories and Subject Descriptors H.2.0 [Information Systems]: Database Management

General Terms

Database Research, Machine Learning

Keywords

Database Research, Machine Learning, Panel

1. INTRODUCTION

Machine learning is here to stay—the world with a new breed of machine learning applications in image analysis, search, voice recognition, mobile, and office productivity products. To paraphrase Mike Stonebraker, machine learning is “the new SQL.” As machine learning becomes a mainstay of high-value, data-driven applications for over four decades, a natural question for database researchers to ask is what role do databases play in this revolution? Is there now a new divide between data-driven machine-learning-based applications?

The last few years have seen increasing crossover between database research and machine learning. But is this crossover a wise move? What are the opportunities and the costs of this approach to industry, to the future of database research, and to academics? Do database researchers have a role to play in this revolution? These two areas have dissimilar traditions in both research, intellectually, and in industry, so bringing the gap between the fields is likely to require considerable effort. Is it worth the

2. QUESTIONS TO CONSIDER

We consider here what is at the core of the database community making major contributions at the intersection of machine learning and databases.

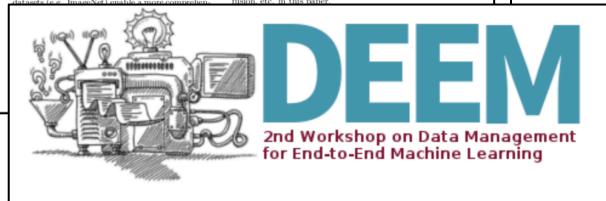
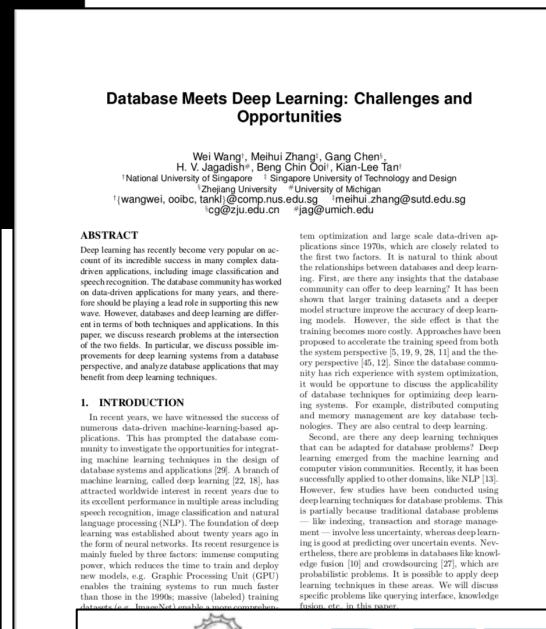
What are the research opportunities and pitfalls for database researchers in these machine-learning applications?

- What are the most interesting research problems at this intersection? Are there core intellectual problems in machine learning that can only be solved with research from the database community? Or is it more about data-journal work? If it is data-journal work, is it sufficiently interesting journal work to examine in research papers?
- Is there anything fundamentally different about building database systems that use machine learning or are developments in machine learning just a way to make these new systems just the same old thing rebranded with a new name?
- To attract partners in the machine learning side of the world, we need to be viewed as providing intellectual contributions. What do database people know that is useful to machine learning? In what ways is this knowledge useful? Should we regard machine learning as a black box? Or should we try to understand its inner workings? Should we build systems that make the black box happy? Where is the most benefit for the black box?
- Do we need to learn a new language? “Databases” or SIGMOD or KDD or the right place?
- What is the risk to the database community? If database people could make learning tools, could this lead to better “new” database systems? Or is this a danger rather than a leading—indicator? Or is this risk higher if we are to move away from traditional database design like other fields, notably NLP and Computer Vision?
- Can we teach old dogs new tricks? Does working at the intersection of machine learning and databases require that database researchers learn an entirely new set of skills? In contrast, while Database research is applied to and often driven by business, there are few

[SIGMOD Record 2016]

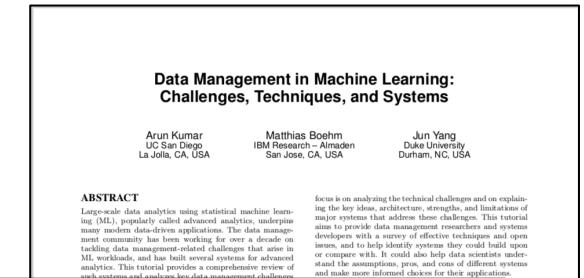
[ICDE'18 Tutorial]

[SIGMOD'17 Tutorial]



[workshop@SIGMOD]

[SIGMOD'15 Panel]



ABSTRACT
Large-scale data analytics using statistical machine learning (ML), popularly called advanced analytics, underpins many modern data-driven applications. The data management community has been working for over a decade on developing data management systems that arise in ML workloads and has proposed system-level primitives for such systems and analyses. This tutorial provides a comprehensive review of such systems and analyses, their data management challenges, and research directions.

COURTING ML: WITNESSING THE MARRIAGE OF RELATIONAL & WEB DATA SYSTEMS TO MACHINE LEARNING

Big Data , Databases , Machine Learning  No Comment

The web is an ever-evolving source of information, with data and knowledge derived from it powering a great range of modern applications. Accompanying the huge wealth of information, web data also introduces numerous challenges due to its size, diversity, volatility, inaccuracy, and contradictions. This year's [WebDB 2018](#) theme emphasizes the challenges and opportunities that arise at the intersection of web data and machine learning research. On one hand, a large portion of web data fuels ML, with novel applications such as predictive analytics, Q&A chat bots, and content generation. On the other hand, the new wave of ML technology found its way into traditional Web data challenges, with contributions such as web data extraction with deep learning, and using ML to optimize data processing pipelines.

To kick start the conversation on research at the cross hairs of ML and data, we interviewed **Luna Dong** (Amazon Research), **Alkis Polyzotis** (Google), **Jens Dittrich** (Saarland University), **Arun Kumar** (University of California, San Diego) and **Peter Bailis** (Stanford University). Below you will find their bios. We selected this diverse set of academic and industrial, systems and theoretical researchers to better understand the quickly evolving research field of Machine Learning and Database Systems. We asked them about their motivation for working in this field, their current work and their view on the future. We summarize our interviews along the following four questions.

[SIGMOD Blog, Feb. 2018]

Introduction : DB perspective

Many problems in data management need precise knowledge and reasoning about information content and linkage for tasks as:

- Information and structure extraction
- Data curation
- Data integration
- Querying & DB administration
- Privacy preservation
- Data storage

Our focus

Many DM tasks can be reformulated as a classification or an optimization problem.

Goals

- Offer an overview of ML applications to specific areas of data curation
- Analyze when and how ML might be leveraged for developing new areas of data management
- Analyze how data management could help ML workflows and data pipelines and contribute to ML advances
- Discuss about our ML journey in DB research community and how this can apply to yours

Disclaimer

- Not specific to ML pipelines, systems or techniques
→ [Kumar, Boehm, Yang, Tutorial SIGMOD'17]
[Polyzotis et al., Tutorial SIGMOD'17]
- Not trying to cover all domain-specific methods
- Not specific to data integration
→ [Dong, Rekatsinas, *coming* Tutorial SIGMOD'18]
- Not specific to “Deep Learning” nor “Big Data”
- Not exhaustive for the sake of conciseness

Outline

Introduction

- Motivations
- SWOT Analysis

ML-Powered Data Curation

- Record Linkage, Deduplication, Entity Resolution
- Error Repair and Pattern Enforcement
- Concluding Remarks and Open Issues

Outline

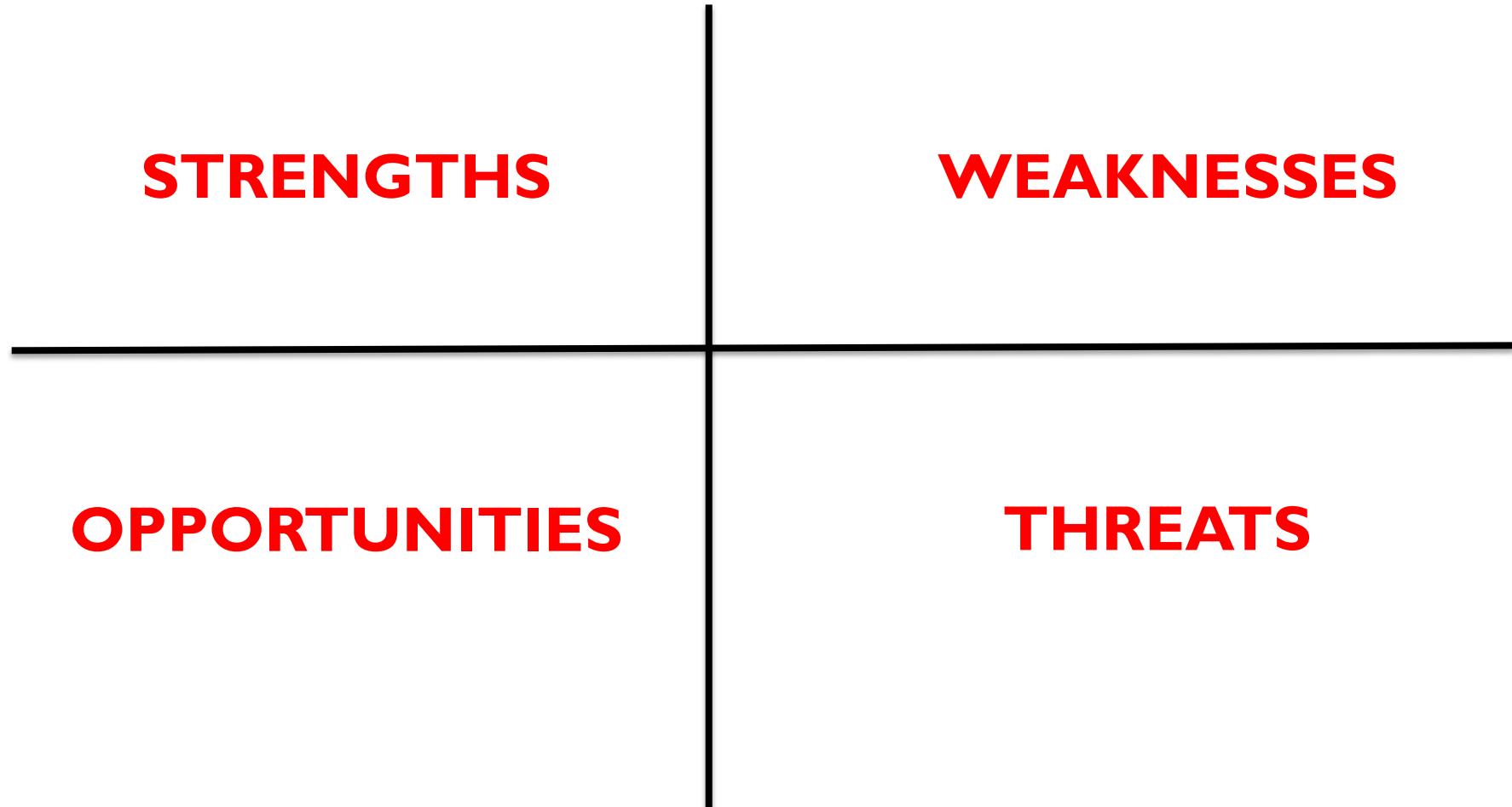
Introduction

- Motivations
- **SWOT Analysis**

Part I- ML-Powered Data Curation

- Record Linkage, Deduplication, Entity Resolution
- Error Repair and Pattern Enforcement
- Concluding Remarks and Open Issues

SWOT Analysis (I)



SWOT Analysis (2)

STRENGTHS

**I. Leverage diverse signals/
data with semantically
rich representations**

**2. Various techniques for
learning representations**

EXAMPLES

To manage multimedia and cross-modal data:

- Information extraction, Slot Filling, KB Construction [Shin et al., 2015][Wu et al., SIGMOD'18]
- Cross-modal information retrieval
- Complex event summarization
- Cross-modal synthesis of medical images
- Automatic image/video labeling

***Embeddings, multiple views, hierarchical
representations***

- Large-scale networks representation [Tang, KDD'17 tutorial]
- Text representation and classification
- Recommendation
- Link prediction
- Visualization

SWOT Analysis (3)

STRENGTHS

3. Optimization

4. Cost reduction

5. Good alternative to heuristics

EXAMPLES

To deduplicate, repair, or fuse data:

- SCARE [Yakout et al., 2013]
- HoloClean [Rekatsinas et al., 2017]
- SLIMFast [Joglekar et al., 2017]

To build large-scale knowledge graph:

- ML-based relation extraction can automatically generate large amount of annotated data and extract features via distant supervision [Mintz et al., 2009] reducing annotating cost

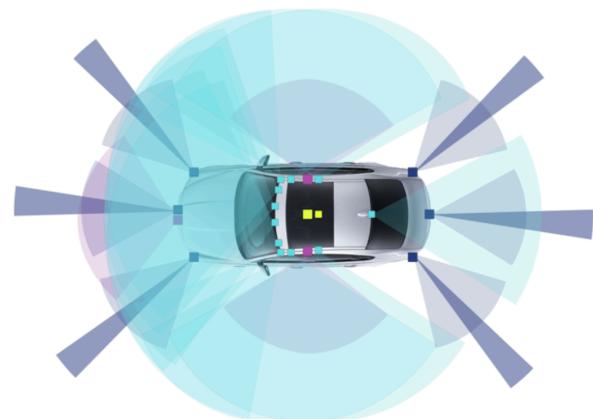
To optimize queries & tune DB:

- Complicated heuristics for estimating selectivity and query plan cost could be replaced and learn dynamically
- Regression-based automatic profiling/tuning (demo Dione [Zacheilas et al., ICDE'18])

SWOT Analysis (4)

WEAKNESSES

I. Obtaining training data is costly



EXAMPLES

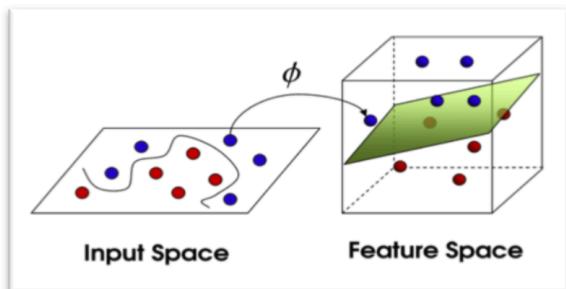
- **Data annotation and preprocessing bottlenecks:** For self-driving cars, 3 million miles of driving data have to be annotated.

Assumptions	Very Conservative estimate
Fleet size	100
Duration of data collection	1 working year / 8h
Volume of data generated by a single car	1TB / h
Data reduction due to preprocessing	0.0005
Research team size	30
Proportion of the team submitting jobs	20%
Target training time	7 days
Number of epochs required for convergence	50
Calculations	
Total raw data volume	203.1 PB
Total data volume after preprocessing	104 TB
Training time on a single DGX-1 Volta system (8 GPUs)	166 days (Inception V3) 113 days (ResNet 50) 21 days (AlexNet)
Number of machines (DGX-1 with Volta GPUs) required to achieve target training time for the team	142 (Inception V3) 97 (ResNet 50) 18 (AlexNet)

SWOT Analysis (5)

WEAKNESSES

1. **Obtaining training data is costly**
2. **Finding or coding evidences into features is hard**



3. **Scaling to Terabytes-size datasets with millions of variables is not easy**

4. **Model interpretability is limited**

EXAMPLES

- **Data annotation and preprocessing bottlenecks**
 - *Training data generation:* Snorkel [Ratner et al., NIPS'17]
 - *Crowdsourcing automation for labeling training data* suffers from inconsistent quality because expertise is hard to get.
 - *Data integration and curation* are required but generally ad-hoc to get clean training data with well-defined features relevant for the ML models.
- **Deep model training is computationally-expensive.** Techniques for “Learning to learn”, and hyper-parameter optimization can multiply training computation by 5-1000X. [Marcus, Arxiv, 2018]
- **Understand the decisions of Convolutional Neural Network is not straightforward**

Human beings usually cannot fully trust a network, unless it can explain its logic for decisions (NIPS 2017 Interpretable ML Symposium: <http://interpretable.ml/>)

SWOT Analysis (6)

OPPORTUNITIES

- I. **Revisit DBMS design, techniques and the whole “DBMS abstraction”** [Dittrich, Keynote VLDB’17]

“ML hardware is at its infancy.”

[Dean, NIPS 2017]

<http://learningsys.org/nips17/assets/slides/dean-nips17.pdf>

What about ML DBMS?

2. **Apply core-DB technologies to ML workloads**

EXAMPLES

To **improve components of a DB system**:

- Learned Index structure [Kraska et al., 2017]
- NoDBA project [Sharma et al., 2018]
using reinforcement learning to tune a database as a virtual database administrator

Automated testing of DB applications:

ETL regression testing [Dzakovic, XLDB’18]

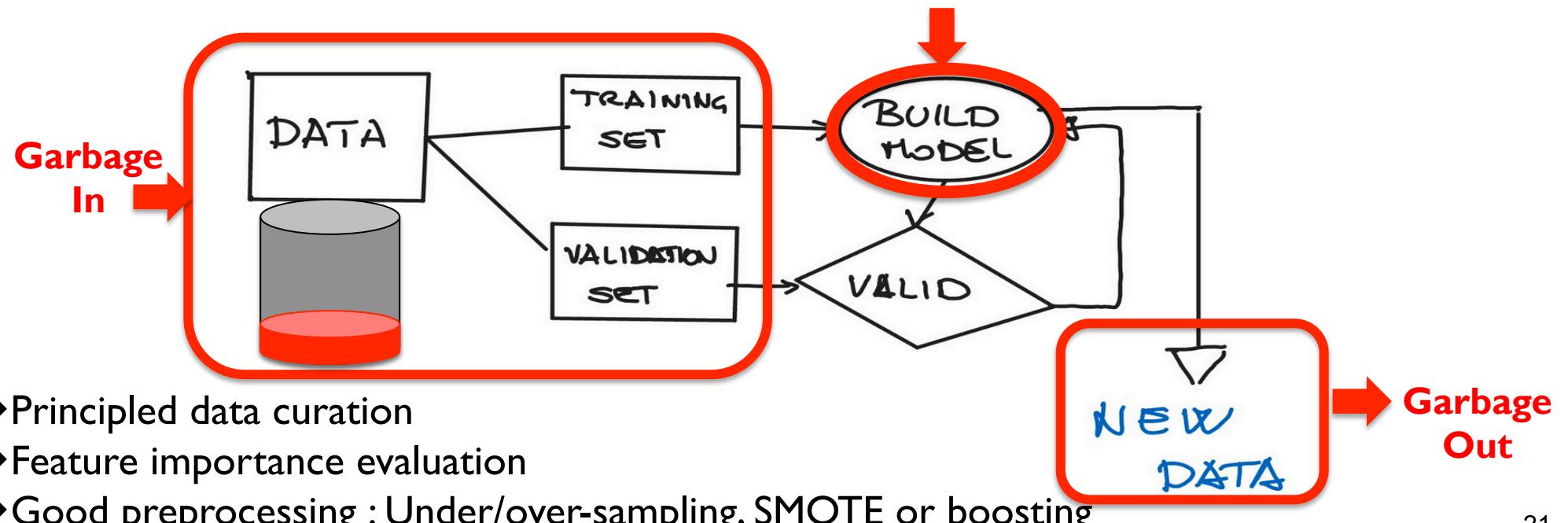
When releasing ETL upgrades, the stakes are high: a single defect can spoil the data in the DB, and the worst-case recovery from a backup would take days

Principled data curation and preprocessing for ML

SWOT Analysis (7)

THREATS

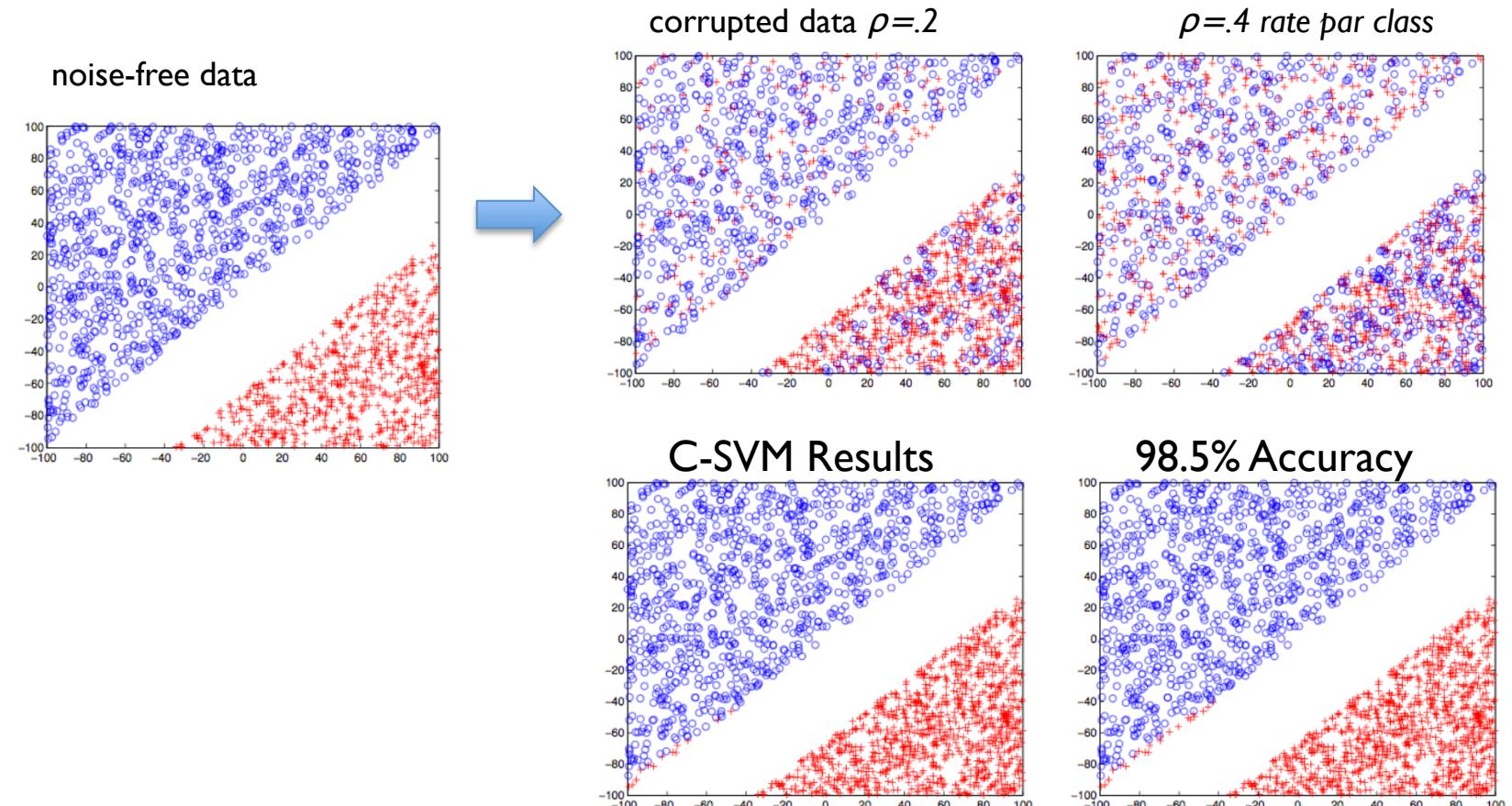
1. Learning from dirty data is risky
2. Bad feature engineering
3. Minority class problem in unbalanced dataset



SWOT Analysis (8)

Learning from noisy labels is a hot topic in ML

[Natarajan et al., NIPS'13]

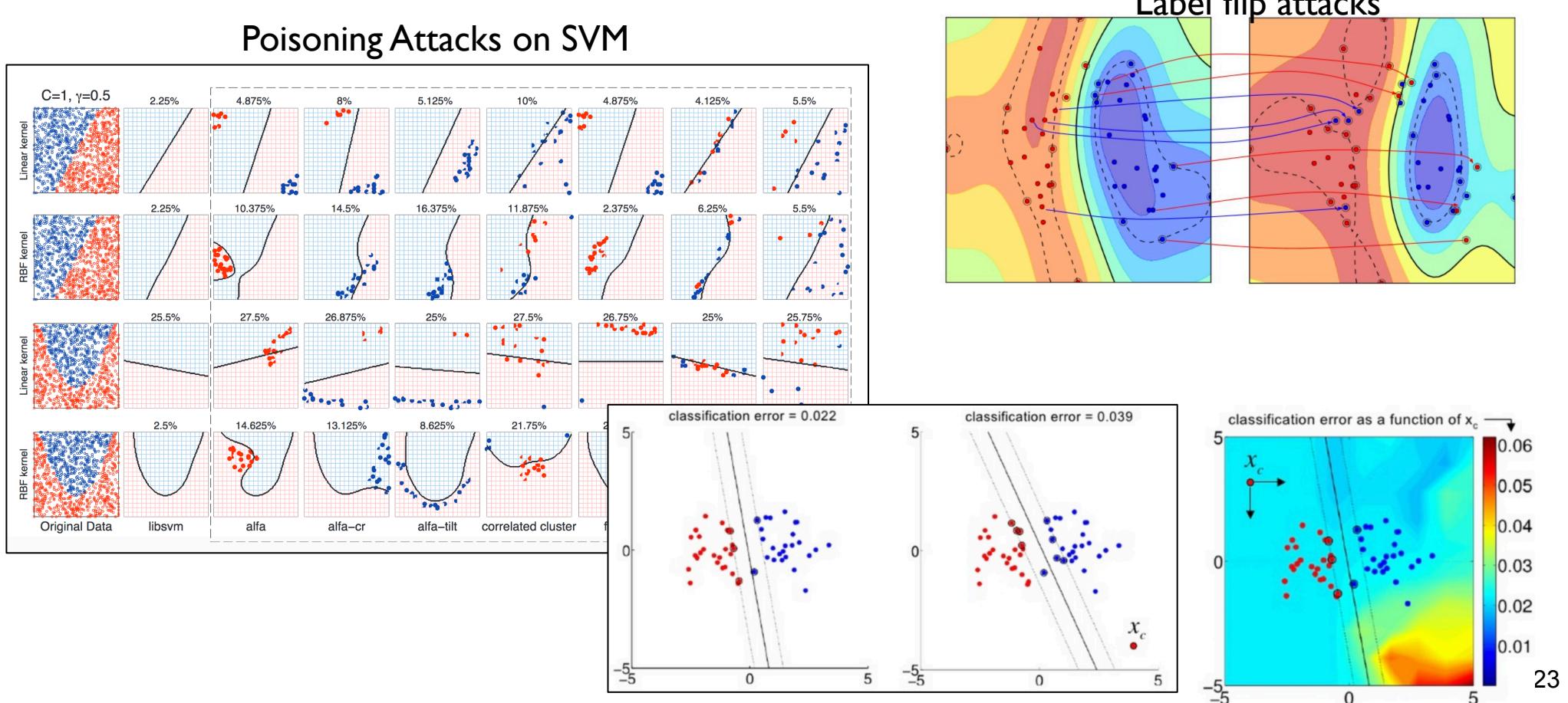


SWOT Analysis (9)

THREATS

4. Adversarial Learning

[Xiao et al., Neurocomputing 2014][Biggio et al., ICML'12]



SWOT Analysis: A Summary (10)

STRENGTHS

- 1. Leverage diverse signals/data with semantically rich representations
- 2. Various techniques for learning representations
- 3. Good alternative to heuristics
- 4. Optimization with objective functions
- 5. Reduction of annotating cost

WEAKNESSES

- 1. Training data annotation and preprocessing is costly
- 2. Finding/coding evidences into features is hard
- 3. Scaling to TB-size datasets with millions of variables is challenging
- 4. Model interpretability can be limited

OPPORTUNITIES

- 1. Revisit design, techniques, and “DBMS abstraction”
- 2. Apply core-DB technologies to ML workloads

THREATS

- 1. Learning from dirty data is risky
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- 4. Adversarial Learning

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Record Linkage (RL): Generic Workflow

Database R



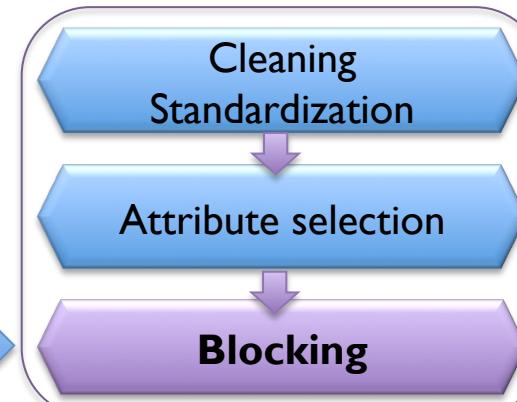
Name	SSN	Addr
Will Forth	354-564-339	Ada Bd
Jacky Khan	435-232-129	Marple Street
Dom Hack	235-575-689	Main Street
...

Database S



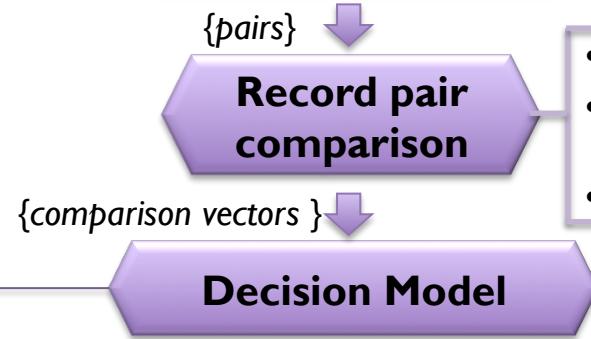
Name	SSN	Addr
Jack Khan	435-223-129	Marple St
Hans Ford	354-564-339	Clover Bd
Tom Hack	235-557-689	Main St
...

R X S



[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

$$\text{Linkage decision: } RL(pair) = \frac{P(\text{vector} \mid \text{pair} \in \text{Match})}{P(\text{vector} \mid \text{pair} \in \text{Non Match})}$$

L

U

→ RL(pair)

Non Match

Potential Match

Match

Pioneer ML-based Deduplication

[Sarawagi, Bhamidipaty, KDD'02]

[Koudas, Srivastava, Sarawagi, Tutorial SIGMOD'06]

Training examples

Customer 1 D

Customer 2

Customer 1 N

Customer 3

Customer 4 D

Customer 5

f_1	f_2	\dots	f_n	
1.0	0.4	...	0.2	1
0.0	0.1	...	0.3	0
0.3	0.4	...	0.4	1

← *Similarity distance functions*

Classifier

Unlabeled list

Customer 6

Customer 7

Customer 8

Customer 9

Customer 10

Customer 11

0.0	0.1	...	0.3	?
1.0	0.4	...	0.2	?
0.6	0.2	...	0.5	?
0.7	0.1	...	0.6	?
0.3	0.4	...	0.4	?
0.0	0.1	...	0.1	?

Learnt Rule: All-Ngrams*0.4
+ CustomerAddressNgrams*0.2
– 0.3EnrollYearDifference
+ 1.0*CustomerNameEditDist
+ 0.2*NumberOfAccountsMatch – 3 > 0

Learners:

SVMs: high accuracy with limited data [Christen, 2008]

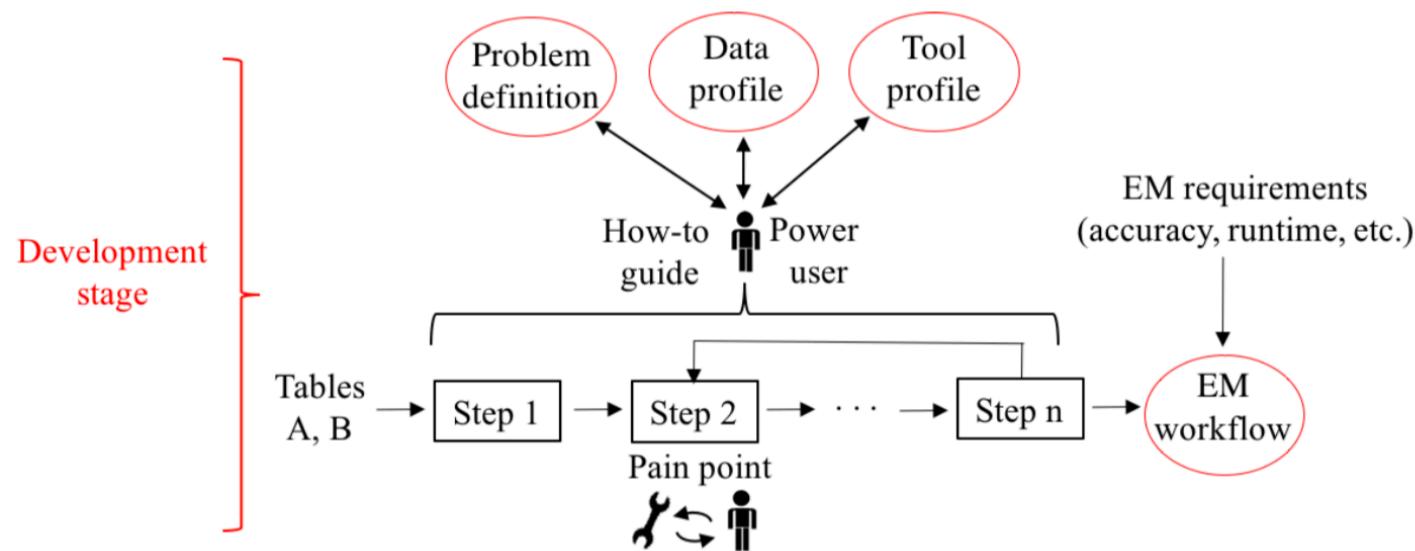
Decision trees: interpretable, efficient to apply

Perceptrons: efficient incremental training
[Bilenko et al., 2005]

Human-In-The Loop for Entity Matching

[Doan et al., HILDA@SIGMOD'17]

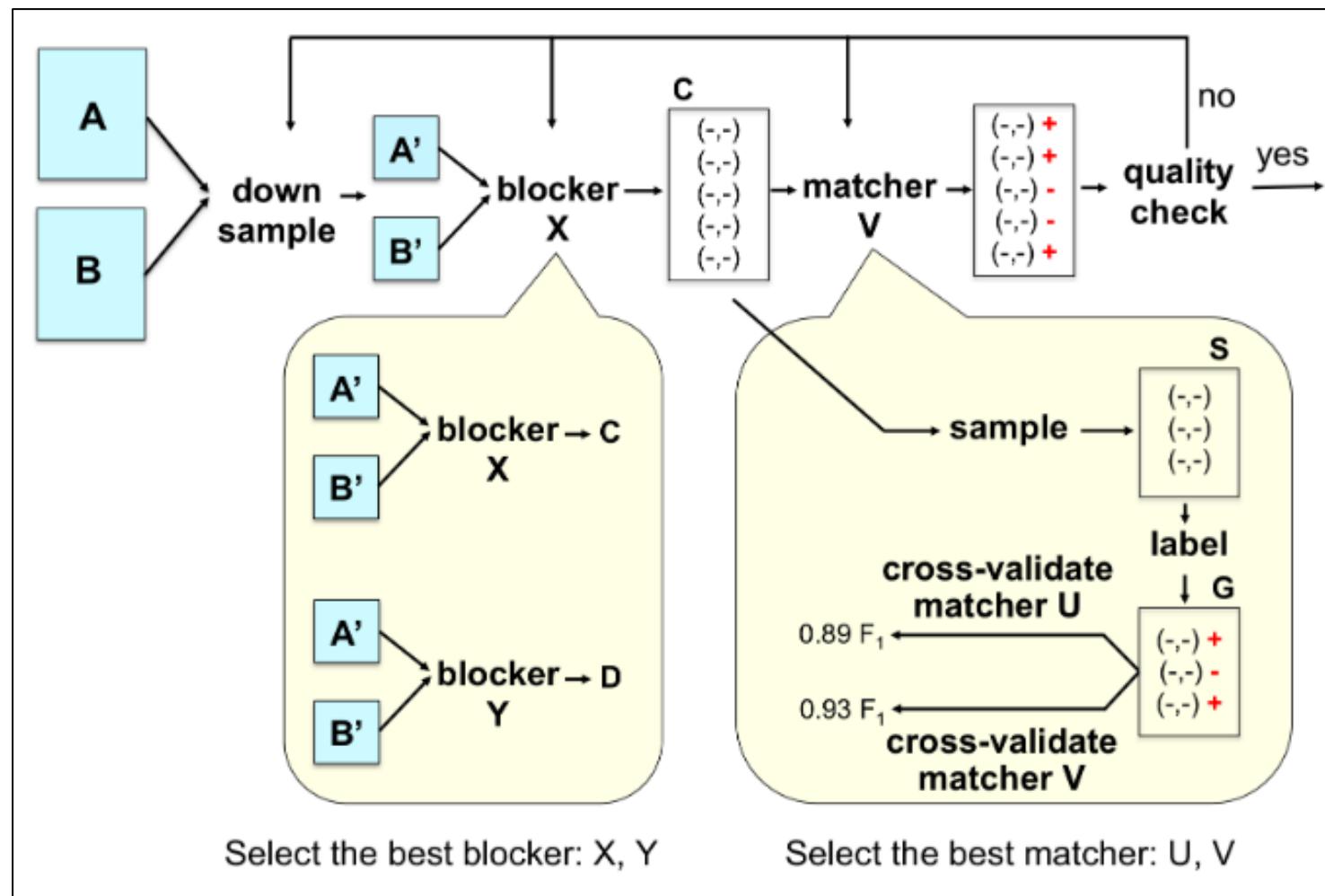
Magellan project: Lessons learnt for How-to Guide for EM



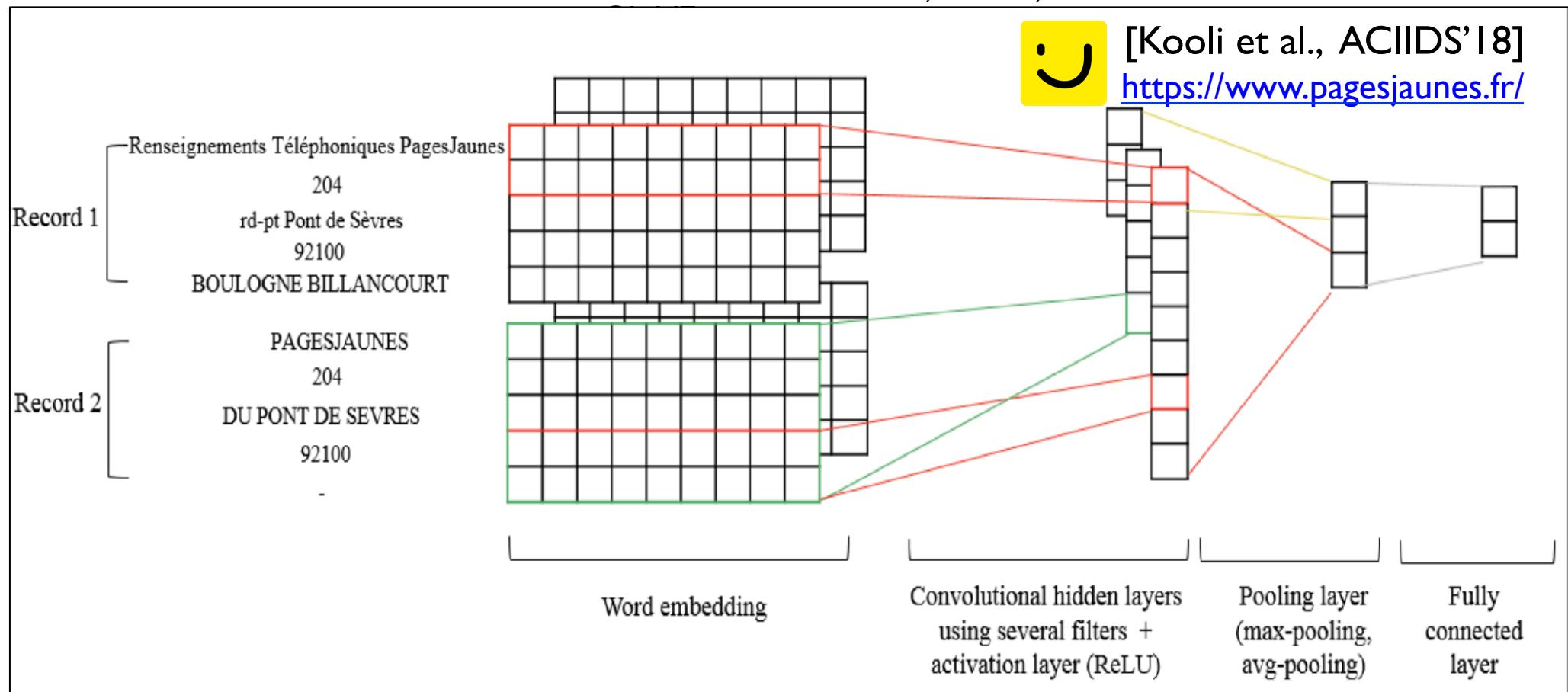
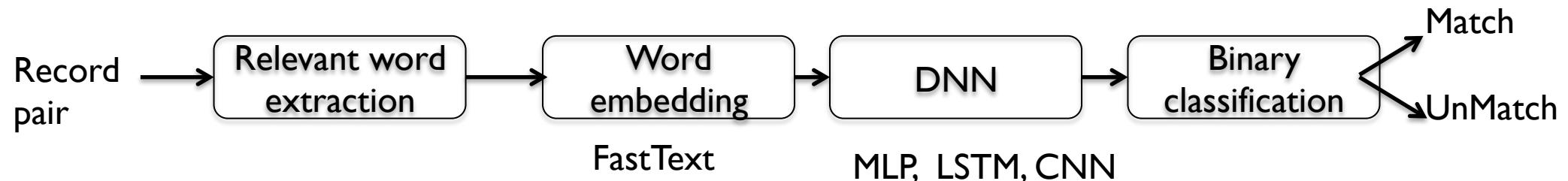
Human-In-The Loop for Entity Matching

[Doan et al., HILDA@SIGMOD'17]

Magellan project: Lessons learnt for How-to Guide for EM



Deep learning for ER



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ML-Based Repairing

Semi-automatic techniques for:

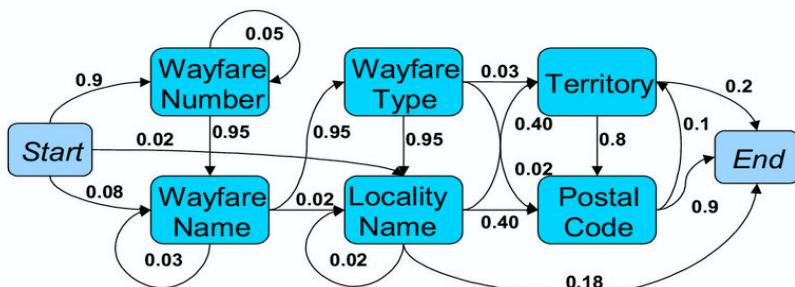
- **Pattern enforcement**
 - Syntactic patterns (date formatting)
 - Semantic patterns (name/address)
- **Value update** to satisfy a set of rules, constraints, FDs, CFDs, Denial Constraints (DCs), Matching Dependencies (MDs) with minimal number of changes. [Ilyas, Chu, 2015]
- **Value imputation** with statistical methods to replace outliers or missing values
- **Data fusion**

Febrl: Data standardization with HMM

[Churches et al., 2002]

[Christen et al., 2002]

HMM for Address Standardization



	To state								
From state	Start	Wayfare Number	Wayfare Name	Wayfare Type	Locality Name	Territory	Postal Code	End	
Start	0	0.9	0.08	0	0.02	0	0	0	
Wayfare Number	0	0.05	0.95	0	0	0	0	0	
Wayfare Name	0	0	0.03	0.95	0.02	0	0	0	
Wayfare Type	0	0	0	0	0.95	0.03	0.02	0	
Locality name	State								
Observation Symbol	Start	Wayfare Number	Wayfare Name	Wayfare Type	Locality Name	Territory	Postal Code	End	
NU	-	0.9	0.01	0.01	0.01	0.01	0.1	-	
WN	-	0.01	0.5	0.01	0.1	0.01	0.01	-	
WT	-	0.01	0.01	0.92	0.01	0.01	0.01	-	
LN	-	0.01	0.1	0.01	0.8	0.01	0.01	-	
TR	-	0.01	0.07	0.01	0.01	0.94	0.01	-	
PC	-	0.04	0.01	0.01	0.01	0.01	0.85	-	
UN	-	0.02	0.31	0.03	0.06	0.01	0.01	-	

Selection of representative training data
"17 Epping St Smithfield New South Wales 2987"

Tokenization based on Look-up Tables
['17', 'epping', 'street', 'smithfield', 'nsw', '2987']

Tagging
['NU', 'LN', 'WT', 'LN', 'TR', 'PC']
number-locality name-wayfare type-locality name-territory-postal code

Frequency-based Maximum Likelihood Estimates

$$8^6 = 262,144 \text{ possible combinations of hidden states}$$

- *Start* -> Wayfare Name (NU) -> Locality Name (LN) -> Postal Code (WT) -> Territory (LN) -> Postal Code (TR) -> Territory (PC) ->*End*

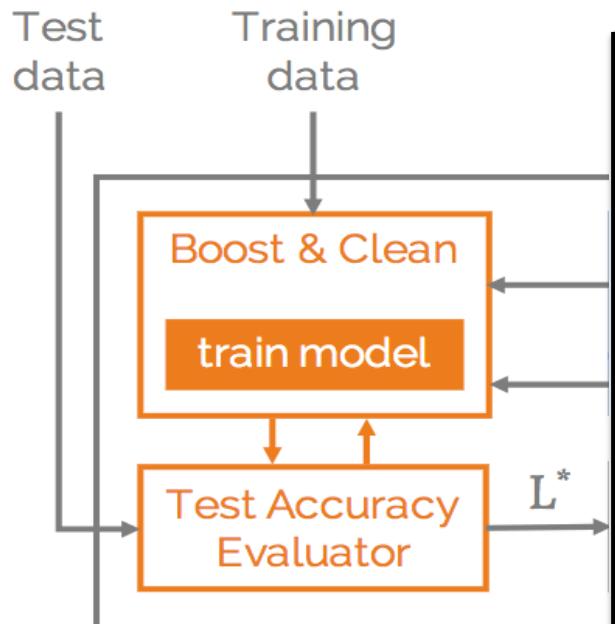
$$0.08 \times 0.01 \times 0.02 \times 0.8 \times 0.4 \times 0.01 \times 0.1 \times 0.01 \times 0.8 \times 0.01 \times 0.1 \times 0.01 \times 0.2 = 8.19 \times 10^{-17}$$
- *Start* -> Wayfare Number (NU) -> Wayfare Name (LN) -> Wayfare Type (WT) -> Locality (LN) -> Territory (TR) -> Postal Code (PC) ->*End*

$$0.9 \times 0.9 \times 0.95 \times 0.1 \times 0.95 \times 0.92 \times 0.95 \times 0.8 \times 0.4 \times 0.94 \times 0.8 \times 0.85 \times 0.9 = 1.18 \times 10^{-2}$$

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 2: Boost-and-Clean Algorithm

Data: (X, Y)

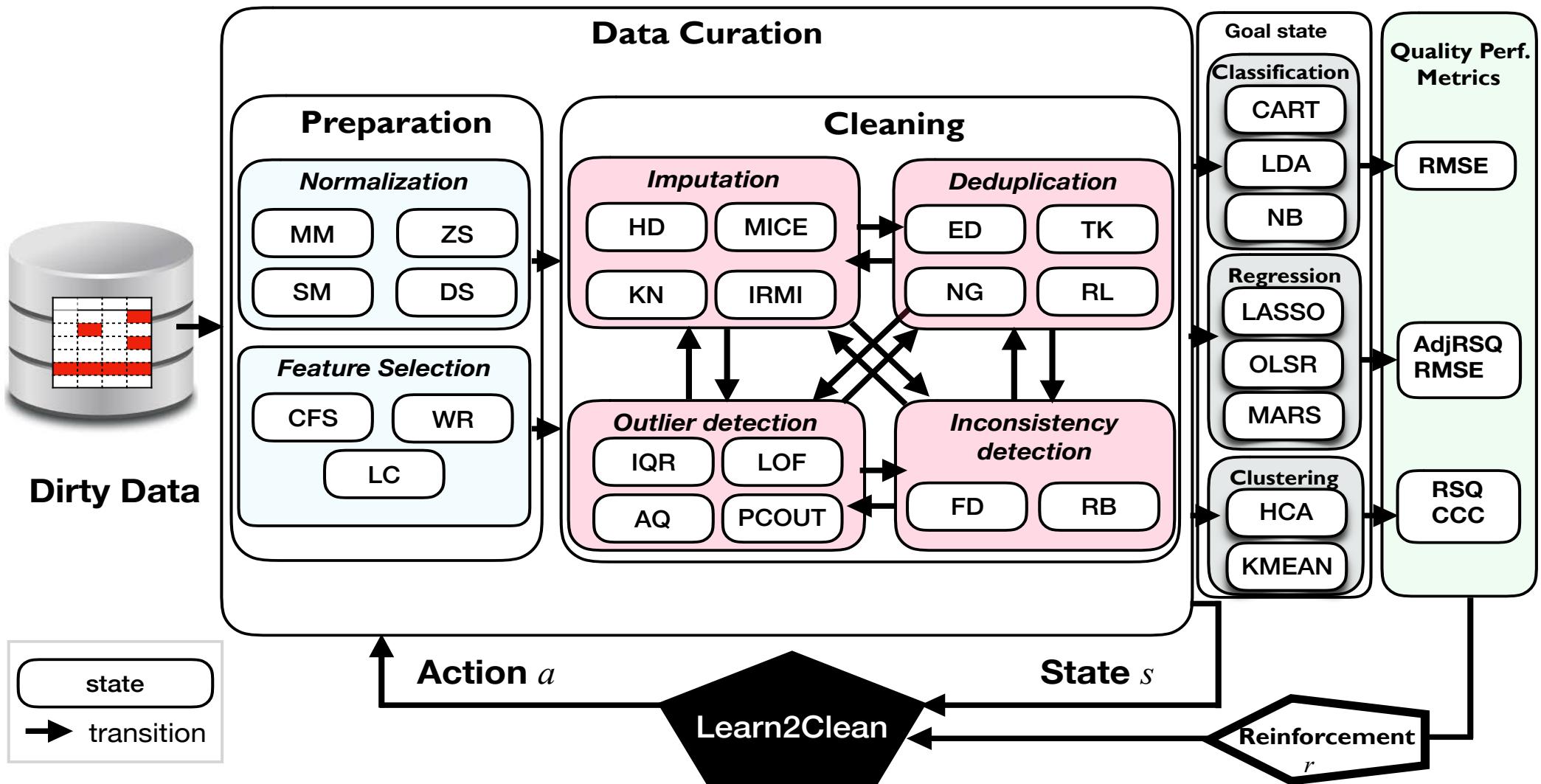
- 1 Initialize $W_i^{(1)} = \frac{1}{N}$
- 2 \mathcal{L} generates a set of classifiers $\mathcal{C}\{C^{(0)}, C^{(1)}, \dots, C^{(k)}\}$ where $C^{(0)}$ is the base classifier and $C^{(1)}, \dots, C^{(k)}$ are derived from the cleaning operations.
- 3 **for** $t \in [1, T]$ **do**
- 4 $C_t = \text{Find } C_t \in \mathcal{C} \text{ that maximizes the weighted accuracy}$
 on the test set. $\epsilon_t = \text{Calculate weighted classification}$
 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.
- 5 **return** $C(x) = \text{sign}(\sum_t^T \alpha_t C_t(x))$

A Condensed View

Repair System	ML Approach	Goal
Febrl [Churches et al., 2002]	HMM and MLE	Standardizing loosely structured texts (e.g., name/address) based on the probabilistic model learnt from training data
SCARE [Yakout, Berti-Equille, Elmagarmid, SIGMOD'13]	Multiple ML models used to capture data dependencies across multiple data partitions	Find the candidate repair that maximizes the likelihood repair benefit under a cost threshold of the update
Continuous Cleaning [Volkovs et al., ICDE'14]	Logistic classifiers	Learning from past user repair preferences to recommend next more accurate repairs
Lens [Yang et al., VLDB'15]	Various ML models encoded in Domain Constraints	Declarative on-Demand ETL with prioritized curation tasks based on probabilistic query processing and PC-Tables
HoloClean [Rekatsinas et al., VLDB 2017]	Probabilistic inference on factor graphs with SGD and Gibbs sampling	Mixing statistical and logical rules, DCs, MDs, etc. to infer candidate repairs in a scalable way with domain pruning and constraint relaxation
BoostClean [Krishnan et al., 2017]	AdaBoost	Mixing statistical and logical rules, domain constraints for detection and repair combinations to maximize the predictive accuracy over test data

Reinforcement learning for data cleaning

Learn2Clean: Optimizing the Sequence of Tasks for Data Preparation
[The Web Conference 2019]



Outline

Introduction

- Motivations
- SWOT Analysis

ML-Powered Data Curation

- Record Linkage, Deduplication, Entity Resolution
- Error Repair and Pattern Enforcement
- Data and Knowledge Fusion
- **Concluding Remarks and Open Issues**

Concluding Remarks

- ML provides a principled framework and efficient tools for optimizing many Data Management tasks
- ML crucially needs principled data curation
- However, some tasks require **Humans in the loop**
- There are many opportunities for:
 - Cool ML applications to data management
 - Revisiting DB technology **with** and **for** ML
 - Managing and orchestrating human/machine resources

Open Issues

- **Usability:**
 - To consider Humans as resources
 - To be understood, interpreted, and trusted by Humans
 - To ease/self-adapt the design, tuning, and use
- **Efficiency:**
 - Runtime
 - Incremental
- **Accuracy:**
 - Reduce impact of dirty data
 - Augmenting the training set
 - Ensembling

Usability (I): Humans as Resources

Challenge I: Adjusting “Human-in-the-Loop”

- Seamless integration of humans as resources for ML-powered DM
- “Taskify” and minimize the amount of interactions with the users while, at the same time, maximize the potential “ML benefit” for selecting/cleaning/labeling training data and other data management tasks



- **Current efforts: Crowdsourcing and active learning**

- Data cleaning with oracle crowds [Bergman et al., SIGMOD’15]
- Entity resolution: CrowdER [Wang et al., VLDB’12], Corleone [Gokhale, et al., SIGMOD’14]
- Data fusion and truth inference [Zheng et al., VLDB’17]

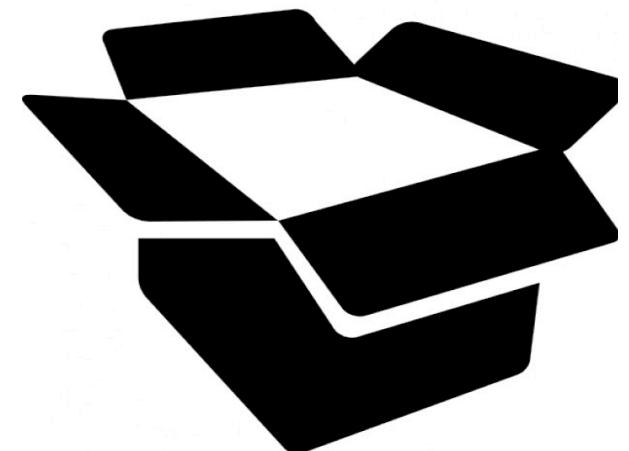
- **Direction:**

- Adaptive and quality-driven orchestration of Humans and Tools for ML-powered DM

Usability (2): Building trust

Challenge 2: Open the “Black-Box” and customize it

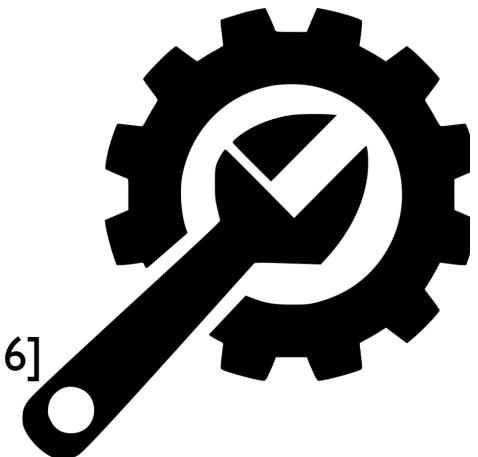
- Improve the interpretability of ML-based decisions
 - Build the trust: ML-based decisions should be interpretable, explainable, reproducible to be trusted
 - Adapt ML-based DM to on-demand, incremental, progressive tasks
- **Current efforts:**
 - Trusted Machine Learning [Ghosh et al., AAAI'17]
 - Model-Agnostic Explanations [Ribeiro et al., KDD'16]
 - On-demand ETL [Yang et al., VLDB'15]
 - ActiveClean [Krishnan et al., VLDB'16]
 - Continuous cleaning for considering incremental changes to the data and to the constraints [Volkovs et al., ICDE'14]
 - **Directions:**
 - Causality and explanations in ML-based DM and their effective representation
 - Reversibility and repeatability
 - Data privacy/security: What if adversarial learning is applied ?



Usability (3) : Easy to build, tune, and test

Challenge 3: Engineering ML-based DM applications

- Model building and feature selection
- Model interoperability and model selection
- **Current efforts:**
 - Systematizing/optimizing model selection
[Kumar, Boehm, Yang, SIGMOD'17 Tutorial],
MSMS [Kumar et al., SIGMODRec'15], Zombie [Anderson et al., 2016]
 - Declarative ML tasks
 - Interactive model building: Ava [John et al., CIDR'17], Vizdom [Crotty et al., VLDB'15]
 - Meta-learning, bandit techniques
 - PMML, ONNX, PFA for model interoperability
- **Directions:**
 - Analysis of dependability of models
 - Model debugging, versioning, and management (e.g., for large models)
 - Managing ML model provenance and elicitation
 - Transfer pre-trained models from task-/domain-agnostic to *-specific DM



Efficiency

- **Challenge 4: Incremental ML application to DM**
 - When we have more training data or refresh/delete some data (obsolete), shall we retrain ML model from scratch? Can we do incremental training/learning? For what cost/trade-off?
- **Challenge 5: Runtime ML-based DM**
 - Could we orchestrate and optimize data annotation and preprocessing tasks? Design cost models, candidate plans?
 - To what extent could we use transfer learning to reduce training data collection/preprocessing cost ?



Accuracy (I)

- **Challenge 6: Reduce the impact of dirty data**

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

- How could we capture the good, the bad and the ugly combinations?
- Should we robustify the ML algorithms or/and the data curation? Would both be inevitably better/necessary?
 - **Find optimal data cleaning strategies for a given ML-based DM application**
 - Can we predict the $\pm\delta$ elta in ML accuracy that a given data curation strategy brings to the model?



Accuracy (2)

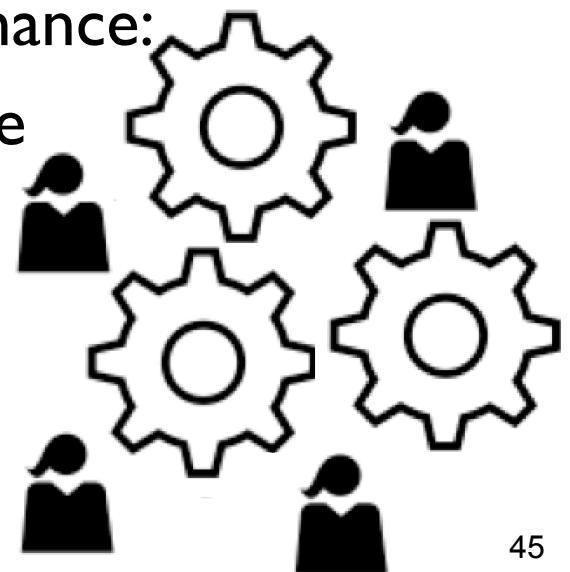
- **Challenge 7: Synthetic training data generation**

Copy/Transform existing labeled data to augment the training set
[Ratner et al., NIPS'17]

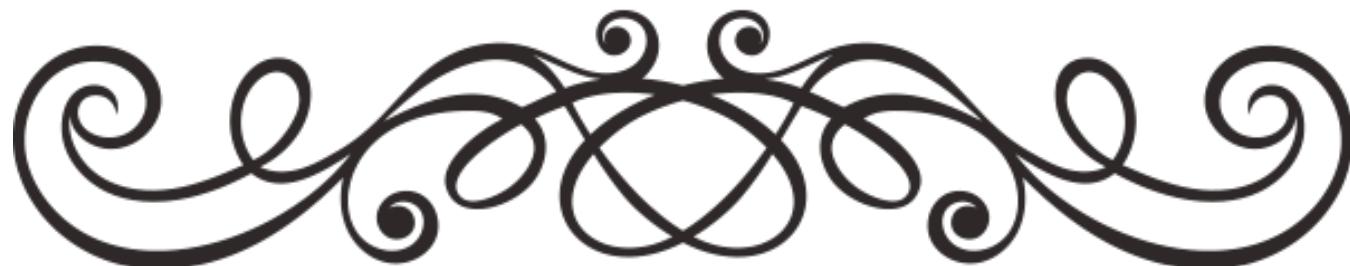
- **Challenge 8: Model/Feature recommendation and ensembling**

Many ML models can be parameterized, applied and combined in different ways leading to various quality performance:

- Could we define a predictive scoring of the models and their ensembles ?
- Would ensembling be (inevitably) better?



Thanks!



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