UTILIZING AI/ML METHODS FOR MEASURING DATA QUALITY

Bc. Michael Mikuš

Knowledge Engineering
Department of Applied Mathematics
Faculty of Information Technology
Czech Technical University in Prague

September 01, 2020



Supervisor: Ing. Tomáš Pajurek

MOTIVATION

MOTIVATION



- Current data quality measuring approaches:
 - expensive, expert & time-consuming work
 - $\bullet \ \ \text{manual effort} \to \text{prone to error}$
 - DQ issues we know that exist



CONCLUSION

MOTIVATION

MOTIVATION



- Current data quality measuring approaches:
 - expensive, expert & time-consuming work
 - $\bullet \ \ \text{manual effort} \to \text{prone to error}$
 - DQ issues we know that exist

"What are innovative ways to measure data quality?"



GOALS OF THE THESIS

- Theoretical framework (Data, Data quality & tools)
- Proposal Data Quality Measurement (DQM) Al
- Conduct experiments
- Propose directions Al in DQ



■ Data diversity & complexity:

- Abundant data types & complex data structures
- Makes automation of DQM methods challenging



Data diversity & complexity:

- Abundant data types & complex data structures
- Makes automation of DQM methods challenging

Review #21 DQ tools:

- Do not take full advantage of Al
- New categorization proposed (target group of users):
 - Regular users
 - Data engineering teams (+ AI \approx promising potential)

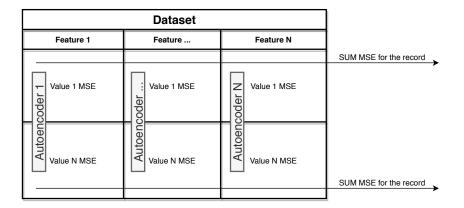


EXPERIMENTS

- Autoencoders
 - "Universal approach to measure DQ?"
- Association Rule Mining
 - "Why Association Rule Mining is not widely supported by general-purpose DQ tools?"



EXPERIMENT - AUTOENCODER - DESIGN



Input: tokenized text → numerical representation (Scaled)

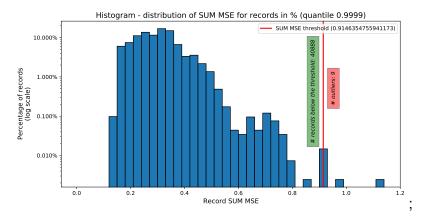


MOTIVATION

CONCLUSION

EXPERIMENT - AUTOENCODER - RESULTS

■ Dataset (e.g. E-Commerce) + synthetic DQ issues



EXPERIMENT - AUTOENCODER - RESULTS

Example – Detected DQ issues:

- Wrong currency
 - '£16.50' vs '\$16.50'
- Wrong name/category
 - 'Coca-Cola' vs Names of clothes
- Wrong language
 - German instead of English
- Values out of range
- Wrong URL domain
 - '.uk' vs '.com'
- Wrong datetime
 - '2017/07/26 18:27:10' vs
 - '2020-01-01T00:51:07Z'
- Wrong data types (string vs int)
- Wrong unit (gram vs liter)

Example – Not detected DQ issues:



■ Example – Detected DQ issues:

- Wrong currency
 - '£16.50' vs '\$16.50'
- Wrong name/category
 - · 'Coca-Cola' vs Names of clothes
- Wrong language
 - German instead of English
- Values out of range
- Wrong URL domain
 - '.uk' vs '.com'
- Wrong datetime
 - '2017/07/26 18:27:10' vs
 - '2020-01-01T00:51:07Z'
- Wrong data types (string vs int)
- Wrong unit (gram vs liter)

■ Example – Not detected DQ issues:

- Short product description
- Negative value
- Wrong color
 - 'blakc' vs 'black'
- Wrong price format
 - \$24,50 vs \$24.50
- Wrong hour value in datetime
 - '2019-10-15T72:21:10Z'
- Wrong file extension
 - '.jpg' vs '.txt'

EXPERIMENT - AUTOENCODER - RESULTS

Advantage:

- Promising universal nature of the approach
- 1 parameter (reconstruction error threshold)

Disadvantage:

- Does not detect all DQ issues
- Knowledge of max length of the encoded input in advance

Application potential:

- Preventive measurement of DQ → User notification
- Alternative non-Al approach:
 - Regular expression (flawless, task-dependent, expert knowledge, manual effort)



MOTIVATION

EXPERIMENT - ASSOCIATION RULE MINING

"Why Association Rule Mining is not widely supported by general-purpose DQ tools?"



EXPERIMENT - ASSOCIATION RULE MINING

"Why Association Rule Mining is not widely supported by general-purpose DQ tools?"

- Apriori algorithm
- **NLP for data preprocessing** (tokenization, lematization, stemming)

EXPERIMENT - ASSOCIATION RULE MINING

"Why Association Rule Mining is not widely supported by general-purpose DQ tools?"

- Apriori algorithm
- NLP for data preprocessing (tokenization, lematization, stemming)
- Result:
 - Rules were extracted
 - HOWEVER: the approach required significant preprocessing effort & focus on a specific question
 - Complex data processing



PROPOSED AI-BASED APPROACHES IN DOM

- A Deep Learning Approach to Semantic Data Type Detection
 - e.g. Location, Name, Year
 - Knowledge of feature data type → Adequately processed semantic information of values

- A Deep Learning Approach to Semantic Data Type Detection
 - · e.g. Location, Name, Year
 - Knowledge of feature data type → Adequately processed semantic information of values
- Automatically Generating Regular Expressions via Genetic Programming
 - Automatic data format check

- A Deep Learning Approach to Semantic Data Type Detection
 - e.g. Location, Name, Year
 - Knowledge of feature data type → Adequately processed semantic information of values
- Automatically Generating Regular Expressions via Genetic Programming
 - Automatic data format check
- Text Duplicates Detection via a ML Model with NLP Approaches
 - e.g. Word2Vec, Fuzzy string matching



CONCLUSION

- Comprehensive theory insight DQ & Al
- Review of #21 DQ tools
- Conducted experiments:
 - Autoencoder preventive measurement of DQ
 - Association Rule Mining using NLP challenging data preprocessing
- Additional innovative approaches in DQM were proposed
- Future work:
 - Extension of Autoencoder experiment
 - Advanced Autoencoders models (e.g. VAE)
 - Additional row metrics (e.g. inclusion # unique values in feature)
 - Semantic data types detection → Appropriately representation of semantic information in input value
 - Experiment with proposed DQM approaches



Thank you for your attention

Michael Mikuš

mikusmi1@fit.cvut.cz