Business Intelligence and Analytics applied to Public Housing

Doctoral Consortium @ ADBIS 2019

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Introduction

Context

A business issue

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- **Public Housing** : dwellings, occupants, overdue, patrimony, ...

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Three main thematics

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- **Business Intelligence** (BI) : ETLs, data warehouses, OLAP, ...

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- **Business Intelligence** (BI) : ETLs, data warehouses, OLAP, ...
- **Data Science** (DS) : knowledge extraction, Machine Learning, ...

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- **Business Intelligence** (BI) : ETLs, data warehouses, OLAP, ...
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- **Big Data** : Volume, Variety, Velocity, ...

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- **Big Data** : Volume, Variety, Velocity, ...

$\rightarrow$ How does all this blend ?

What data ?

Several data sources

What data ?

Several data sources

1. Internal data

What data ?

Several data sources

1. Internal data
   - Landlord's data
   - Dwellings, occupants, overdue, ...
   - Mostly relational data
   - BI analyses, simple DS analyses

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    - BI analyses, simple DS analyses
2. **External data**

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1. **Internal data**
    - Landlord's data
    - Dwellings, occupants, overdue, ...
    - Mostly relational data
    - BI analyses, simple DS analyses
2. **External data**
    - Open data (+ social networks)
    - Environment
    - (possibly) Big Data
    - Advanced DS analyses

Table of contents

Data storage and management

Business Intelligence and Analytics

Business Intelligence (BI)

Methods and tools for collecting, storing, organizing and analyzing data to support decision-making

[Chen et al., 2012, Larson and Chang, 2016, Mortenson et al., 2015, Baars and Ereth, 2016, Gröger, 2018]

Business Intelligence and Analytics

Business Intelligence (BI)

Methods and tools for collecting, storing, organizing and analyzing data to support decision-making

Business Analytics (BA)

The use of Data Science methods on a company's data

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What about BI ?

- BI&A

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- BI & BA
- BI $\rightarrow$ BA

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Run BI and BA analyses...

Data Intelligence

Run BI and BA analyses...

- Separately

Run BI and BA analyses...

- Separately
- Together

Data Intelligence

Run BI and BA analyses...

- Separately
- Together
- (possibly) on Big Data

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Data Intelligence

Perform analyses, simple or advanced, on all types of data

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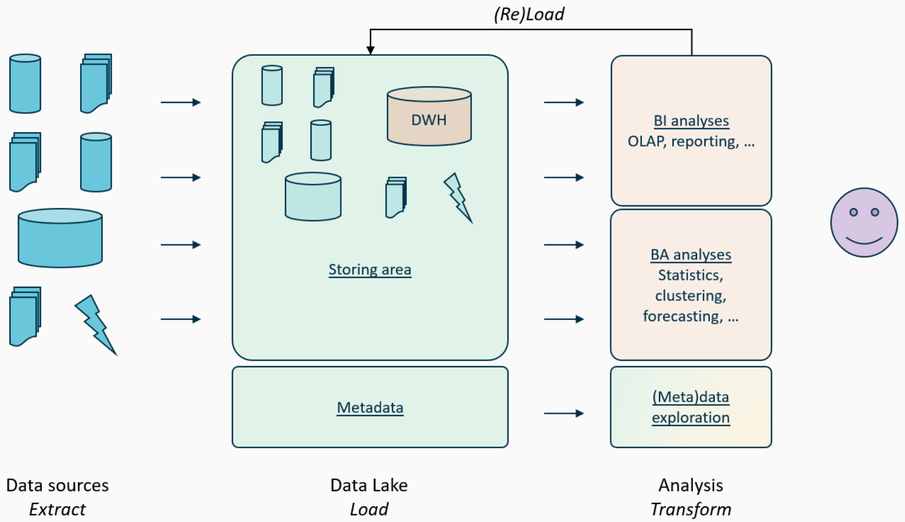
Data Intelligence

Perform analyses, simple or advanced, on all types of data

$\rightarrow$ How ?

Data Intelligence in practice



Data Lakes

Data Lake [Dixon, 2010]

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Two main characteristics

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[Miloslavskaya and Tolstoy, 2016]

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→ Need for a metadata system

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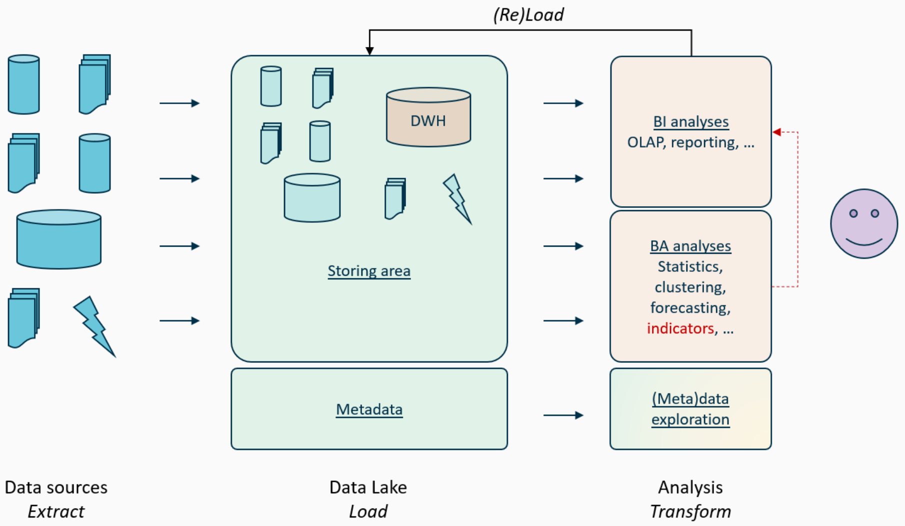
Big research field

[Miloslavskaya and Tolstoy, 2016]

Attractiveness

Data Intelligence in practice



Defining attractiveness

Attractiveness of what ?

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1. Dwelling

Defining attractiveness

Attractiveness of what ?

1. Dwelling
2. Residency

Defining attractiveness

Attractiveness of what ?

1. Dwelling
2. Residency
3. Neighborhood

Defining attractiveness

Attractiveness of what ?

1. Dwelling (internal)
2. Residency
3. Neighborhood

Defining attractiveness

Attractiveness of what ?

1. Dwelling (internal)
2. Residency (internal - external)
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$\rightarrow$ Strategic Patrimony Plan

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Advanced indicators

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Advanced indicators

- Machine Learning algorithms

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Advanced indicators

- Machine Learning algorithms
- Back-feeding the lake

Defining attractiveness

Attractiveness of what ?

1. Dwelling (internal)
2. Residency (internal - external)
3. Neighborhood (external)

→ Strategic Patrimony Plan

Advanced indicators

- Machine Learning algorithms
- Back-feeding the lake
- Enrich BI analyses

First results and future outcomes

First contribution

Work done with P. N. Sawadogo [Sawadogo et al., 2019, Scholly et al., 2019]

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Work done with P. N. Sawadogo [Sawadogo et al., 2019, Scholly et al., 2019]

- Our definition of a Data Lake
- Key features for metadata systems
- Metadata typology in three categories
- MEtadata model for DAta Lakes (MEDAL)

Presented at 4 PM in this room !

What's next ?

Work in progress

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- Implementation(s) of MEDAL

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- Retrieve all data

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- Implementation(s) of MEDAL
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What's next ?

Work in progress

- Implementation(s) of MEDAL
- Retrieve all data
- Development of a complete data lake
- Tests and comparisons

Thank you for your attention!

Questions?

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