Using databases for social scientists

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Computational Social Science Amsterdam
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Today

Günther, Elisabeth; Trilling, Damian; van de Velde, Bob: But how do we store it? Data architecture in the social-scientific research process. In: Stuetzer, C.M. (Hrsg.); Welker, M. (Hrsg.); Egger, M. (Hrsg.): Computational social science in the age of Big Data. Concepts, methodologies, tools, and applications. Cologne: Herbert von Halem, 2018, pp. 161–187

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When and why databases?

The "traditional" approach

Example: Analysis of a couple of thousands articles/speeches/reports/...

- Store as seperate `.txt` files

If metadata (beyond what can be inferred from filename and location) are important

- Store as tabular dataset (`.csv` or proprietary format)
- (possibly: store as seperate `.json` files)

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- easy to understand
- no dependencies
- works on all platforms, also in the future $\rightarrow$ good fallback/backup option

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- requires loading whole dataset into memory *or* reading all files from disk to query/aggregate/etc.
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Databases: because you want to

- You do not want to take care of I/O yourself
- Because it allows you to do better searches and queries
- Because you can easily aggregate your data
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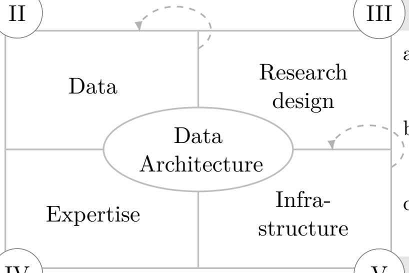
I *Do you need pre-processing / cleaning?*

II *What's your input?*

a) Technical properties (data types)
b) Source properties (static vs. dynamic)
c) Corpus properties (quantity, messiness homogeneity)

III *What's your goal?*

a) Project setup (set up an archive vs. specific research interest)
b) Project priorities (availability, consistency, performance)
c) Scientific standards (accessibility, sustainability)



IV *What are your skills?*

a) Previous experiences
b) External support (collaboration vs. contracting)
c) Future demands

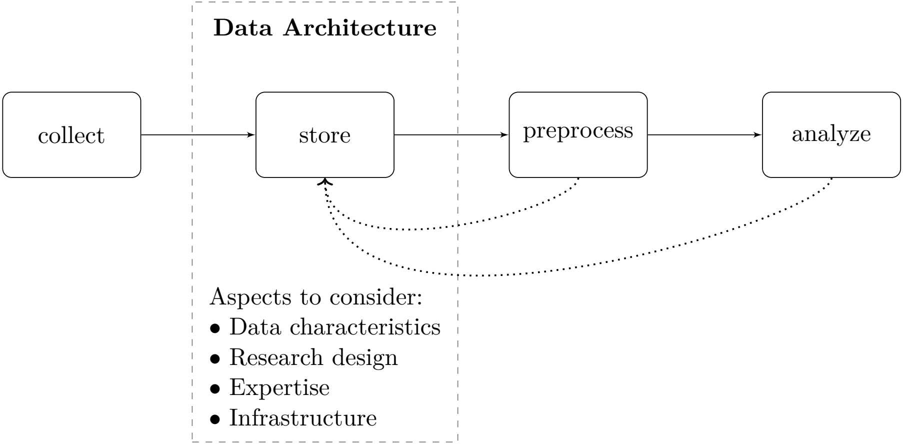
V *What else do you use?*

a) Software compatibility (technical interface)
b) Hardware scalability (vertical vs. horizontal)

Data architecture

Data architecture

- File formats
- Linkage
- Internal structure


Data Architecture
collect
store
preprocess
analyze
Aspects to consider:
• Data characteristics
• Research design
• Expertise
• Infrastructure

Database types

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Relational databases

- Tabular data structure
- Relational: tables are linked by keys
- Well-defined data types per column
- Good at joining and aggregating

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Relational databases

itemid	orderid	item	amount
5	1	Chair	200.00
6	1	Table	200.00
7	1	Lamp	123.12

customerid	name	email
5	Rosalyn Rivera	rosalyn@adatum.com
6	Jayne Sargent	jayne@contoso.com
7	Dean Luong	dean@contoso.com

orderid	customerid	date	amount
1	4	11/1/17	523.12
2	3	11/15/17	32.99
3	1	11/21/17	23.99

Relational databases and text

- You can store text
- In fact, often used as backend for for instance tweets and sometimes news articles
- BUT (1): Not optimized for searching in text
- BUT (2): Not good for messy data
- BUT (3): Hard to add extra columns or change specifications of existing ones

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NoSQL databases

- optimized for messy data
- can be schema-free ⇒ we do not have to enforce a specific format at insertation time
- new entries do not necessarily have to follow the specifications of old ones
- Allow you to just throw in an arbitrary JSON object
- CAP-theorem: we trade consistency for availability and performance

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We can store retrieved web pages (1) together with some first roughly parsed extracted data (2), and do some cleaning and enrichment (3,4) later.

1. Retrieved →

```
<div>
<span id='author'
class='big'>
Author: John
Doe </span>
<span id='viewed'>
seen 42 times
</span>
</div>
```

2. Structured →

```
{
"author":
"Author: John Doe",
"viewed":
"seen 42 times"
}
```

3. Cleaned →

```
{
"author":
"john doe",
"viewed":
42,
}
```

4. Enriched

```
{
"author":
"john doe",
"author_gender":
"M",
"viewed":
42,
}
```

NoSQL databases and text

- Often optimized for indexing text
- Internal preprocessing ("analysis") under the hood: e.g., search based on stemmed text
- Nested data: e.g., comments within articles
- Texts can have additional keys that others don't (e.g., online news have urls, offline news have page numbers; some may have)
- You may have even different language versions of the same text (and all having analyzed accordingly)

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SQL vs NoSQL in one slide

(for storing (textual) social-scientific data)

SQL

- strucutre known in advance

NoSQL

- full-text search may be relevant

MongoDB and Elastic Search

Use case

- Scrape and store articles ($\approx$ 20M)
- We first used Mongo and later switched to ES (because of better performance for full-text search)

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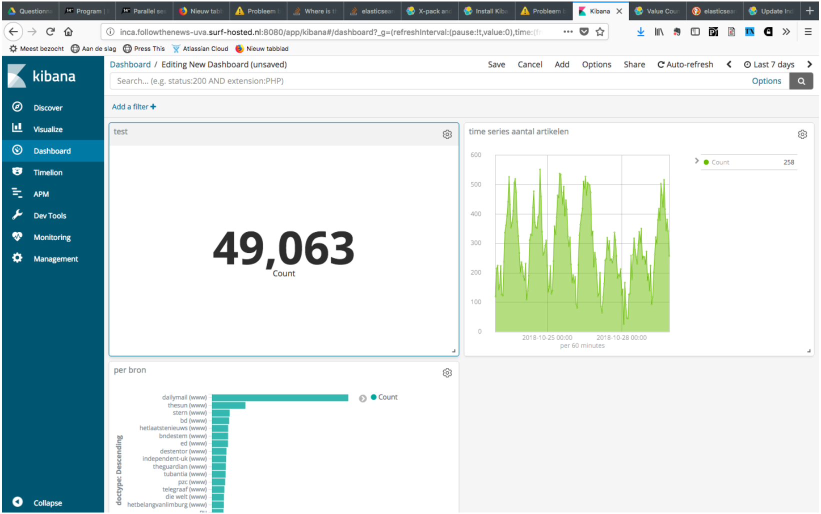
Interacting with ES via http requests

```
packer-ubuntu-16:~$ curl http://localhost:9200/inca6/_count?pretty
{
  "count" : 19054530,
  "_shards" : {
    "total" : 5,
    "successful" : 5,
    "skipped" : 0,
    "failed" : 0
  }
}
```

Interacting with ES via Kibana



Interacting with ES via Python

```
In [1]: from elasticsearch import Elasticsearch

In [2]: client = Elasticsearch()

In [3]: client.count('inca6')
Out[3]:
{'_shards': {'failed': 0, 'skipped': 0, 'successful': 5, 'total': 5},
 'count': 19054530}
```

Practical example (Jupyter Notebook)

Questions?

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