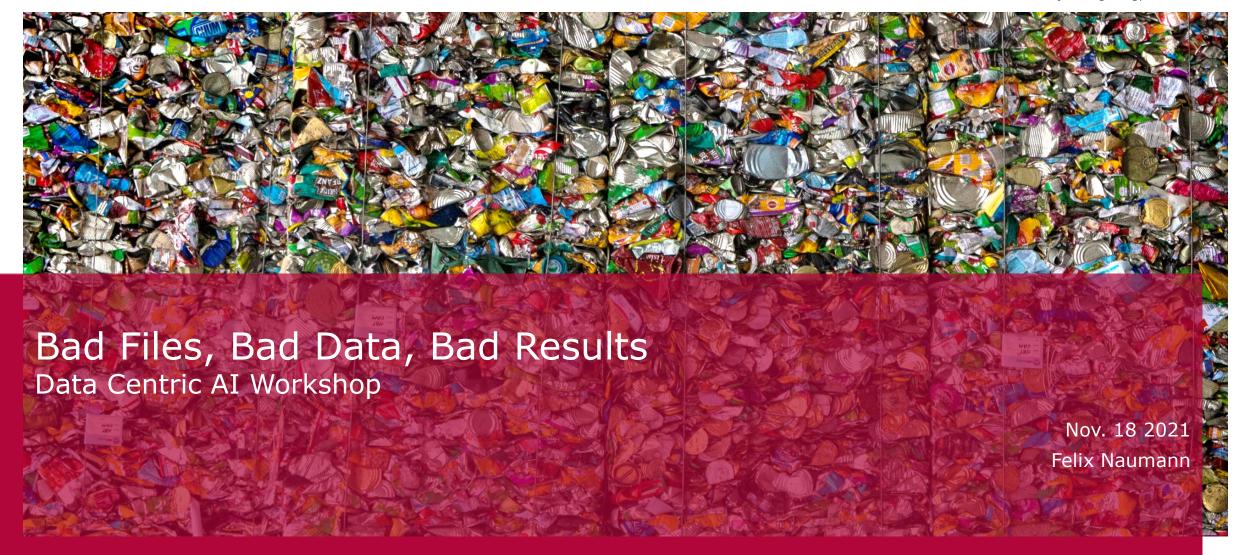


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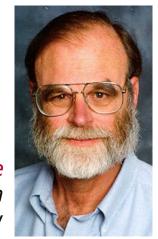


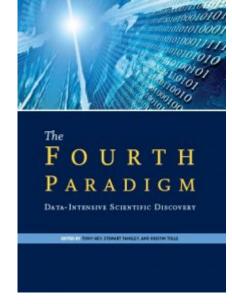


- 1. Empirical and experimental
- 2. Theoretical
- 3. Computational
- 4. Data-intensive

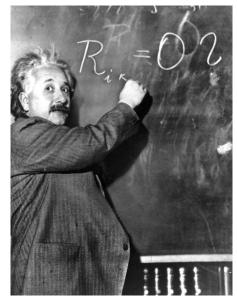
Enabling machine learning and AI

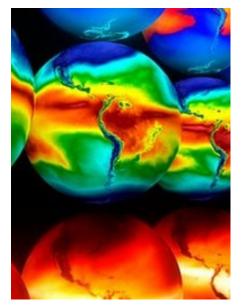
We have to do better producing tools to support the whole research cycle - from data capture and data curation to data analysis and data visualization. Jim Gray









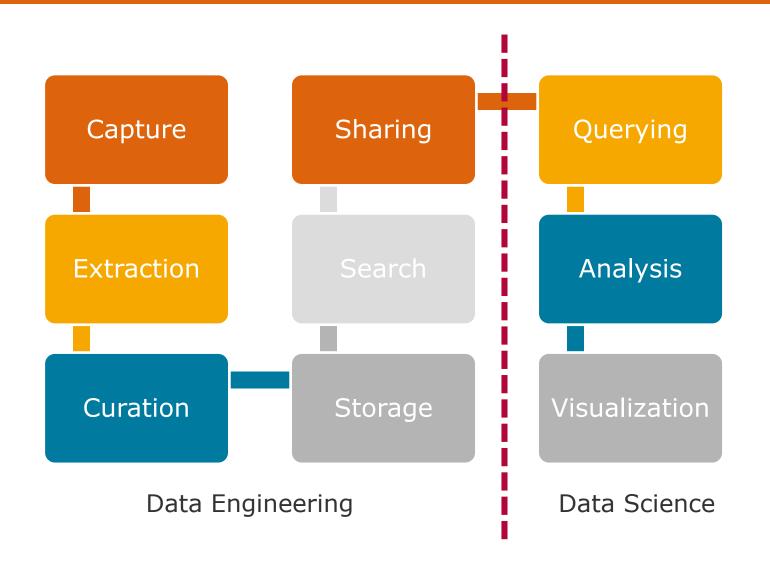




Felix Naumann Data Quality 2021



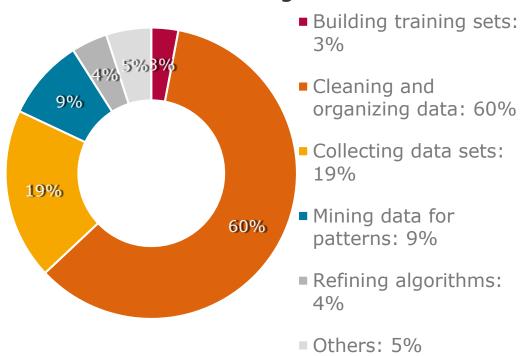
Data Science Pipeline



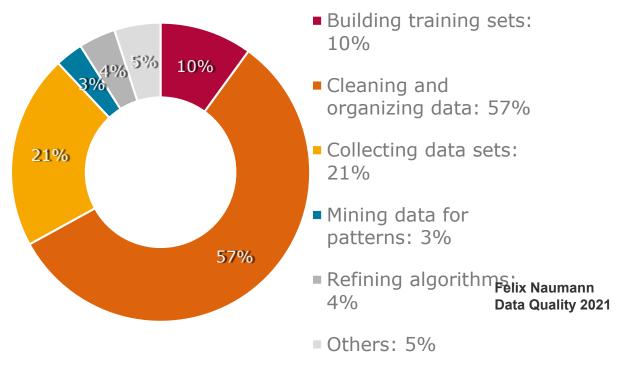


Data preparation and cleaning in reality

What data scientists spend the most time doing?



What is the least enjoyable part of data science?





Data Preparation and Cleaning: Tasks and Tools

- Data discovery
- Data validation
- Data structuring
- Data enrichment
- Data filtering
- Data cleaning
- And for data scientists
 - □ Feature selection
 - □ Feature extraction

Categories	Available features			Data	prepar	ation too	ls	
		Altair	Paxata	SAP	SAS	Tableau	Talend	Trifacta
Data discovery	Locate missing values (nulls)	✓	√	√	√	✓	√	√
	Locate outliers		√		√			√
	Search by pattern	√	√	√	√	√	√	√
	Sort data	✓	√	√	✓	√	√	√
Data validation	Compare values (selection and join)	✓	√	√		√	√	√
	Check data range	√	√	√		√	√	√
	Check permitted characters							√
	Check column uniqueness	√	√	√		√	√	√
	Find type-mismatched data		√	√		√	√	√
	Find data-mismatched datatypes		√				√	√
Data structuring	Change column data type	1.	\	√	√	√	√	√
	Delete column	tal	1	√	√	√	√	√
	Detect & change encoding	-416	hd				√	√
	Pivot / unpivot	D,	ATA PRED		14	√		√
	Rename column		and ATA PREPARATIO	DN	+++	1	✓	√
	Split column	tair			++	+ 01	\	√
	Transform by example [13]	PADA		:		90/	0	\
Data enrichment	Split column Transform by example [13] Assign semantic data type	MATION	77	Pa)		+ 9 6 1	Gau	
	Calculate column using ex		SE	LF SEPIN	(215)		PREF	
	Discover & merge extern:			WICE	DATA PRO		1	
	Duplicate column				TEPA	RATION	00	
	Generate primary key colu.						SHO	
	Join & union	AGILE DATA	REPARATION	y -		ACTA WRANG	DA	3
	Merge columns	VIIA P	REPARATIO	- //	212		DATA PREPARA	1
	Normalize numeric values	1	MOV		11-7	10-	****	NON V
Data filtering	Delete/keep filtered rows	√	1	-		·C/A		\
	Delete empty and invalid rows	✓	√	1		WRANG		✓
	Extract value parts	√			1	., vG	LER	✓
	Filter with regular expressions							√
Data cleaning	Change date & time format	√	√	√	√	√	V	√
	Change letter case	√	√	√	√	√	√	√
	Change number format	√	√	√	√	√	√	√
	Deduplicate data	√	√	√	√		√	√
	Delete by pattern	√	√		√	√	√	√
	Edit & replace cell data	√	√	√	√	√	√	√
	Fill empty cells	√	√				√	√
	Remove extra whitespace	√	√	√	√	√	√	✓
	Remove diacritics			√				
	Standardize strings by pattern		√	√	√	√	√	✓
	Standardize values in clusters		<i>-</i>	1	1	<i></i>	<i>'</i>	<u> </u>

Felix Naumann
Data Quality 2021

6

Tool nameURLAltair Monarch Data Preparationhttps://www.datawatch.com/in-action/monarch-draft/Alteryx Data Preparationhttps://www.alteryx.com/solutions/analytics-need/data-preparationBigGorilla Data Preparationhttps://www.biggorilla.org/Cambridge Semantics Anzohttps://www.cambridgesemantics.com/Datameerhttps://www.datameer.com/EasyMorph Data Preparation and Automationhttps://easymorph.com/Erwinhttps://erwin.com/FICOhttps://www.fico.com/Google Cloud Data Prep by Trifactahttps://cloud.google.com/dataprep/Hitachi-Pentaho Business Analyticshttps://www.hitachivantara.com/en-us/products/data-management-analytics.htmlIBM Data Refineryhttps://www.ibm.com/cloud/data-refinery
Alteryx Data Preparation BigGorilla Data Preparation https://www.biggorilla.org/ Cambridge Semantics Anzo https://www.cambridgesemantics.com/ Datameer https://www.datameer.com/ EasyMorph Data Preparation and Automation https://easymorph.com/ Erwin FICO https://erwin.com/ https://www.fico.com/ https://www.fico.com/ https://www.fico.com/ https://www.fico.com/ https://cloud.google.com/dataprep/ Hitachi-Pentaho Business Analytics https://www.hitachivantara.com/en-us/products/data-management-analytics.html
BigGorilla Data Preparation Cambridge Semantics Anzo https://www.biggorilla.org/ Datameer https://www.datameer.com/ EasyMorph Data Preparation and Automation https://easymorph.com/ Erwin https://erwin.com/ FICO https://www.fico.com/ Google Cloud Data Prep by Trifacta https://cloud.google.com/dataprep/ Hitachi-Pentaho Business Analytics https://www.hitachivantara.com/en-us/products/data-management-analytics.html
Cambridge Semantics Anzo https://www.cambridgesemantics.com/ Datameer https://www.datameer.com/ EasyMorph Data Preparation and Automation https://easymorph.com/ Erwin https://erwin.com/ FICO https://www.fico.com/ Google Cloud Data Prep by Trifacta https://cloud.google.com/dataprep/ Hitachi-Pentaho Business Analytics https://www.hitachivantara.com/en-us/products/data-management-analytics.html
Datameer https://www.datameer.com/ EasyMorph Data Preparation and Automation https://easymorph.com/ Erwin https://erwin.com/ FICO https://www.fico.com/ Google Cloud Data Prep by Trifacta https://cloud.google.com/dataprep/ Hitachi-Pentaho Business Analytics https://www.hitachivantara.com/en-us/products/data-management-analytics.html
EasyMorph Data Preparation and Automation https://easymorph.com/ Erwin https://erwin.com/ FICO https://www.fico.com/ Google Cloud Data Prep by Trifacta https://cloud.google.com/dataprep/ Hitachi-Pentaho Business Analytics https://www.hitachivantara.com/en-us/products/data-management-analytics.html
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Google Cloud Data Prep by Trifacta https://cloud.google.com/dataprep/ Hitachi-Pentaho Business Analytics https://www.hitachivantara.com/en-us/products/data-management-analytics.html
Hitachi-Pentaho Business Analytics https://www.hitachivantara.com/en-us/products/data-management-analytics.html
INFOGIX https://www.infogix.com/data3sixty/analyze/
Informatica Enterprise Data Preparation https://www.informatica.com/products/data-catalog/enterprise-data-prep.html
Looker https://looker.com/
Lore IO https://www.getlore.io/
Microsoft Power BI https://powerbi.microsoft.com/en-us/
MicroStrategy https://www.microstrategy.com/us/product/analytics/data-visualization
Modak-nabu https://modakanalytics.com/nabu.html
OpenRefine http://openrefine.org/
Oracle Analytics Cloud https://www.oracle.com/business-analytics/analytics-cloud.html
Paxata Self Service Data Preparation https://www.paxata.com/self-service-data-prep/
Qlik Data Catalyst https://www.qlik.com/us/products/qlik-data-catalyst
Quest Toad Data Point https://www.quest.com/products/toad-data-point/
Rapid Insight https://www.rapidinsight.com/solutions/data-preparation/
RapidMiner Turbo Prep https://rapidminer.com/products/turbo-prep/
SAP Agile Data Preparation https://www.sap.com/germany/products/data-preparation.html
SAS Data Preparation https://www.sas.com/en_us/software/data-preparation.html
Smarten Advanced Data Discovery https://www.smarten.com/self-serve-data-preparation.html
Solix Common Data Platform https://www.solix.com/products/solix-common-data-platform/
Sparkflows https://www.sparkflows.io/data-science
Tableau Prep https://www.tableau.com/products/prep
Talend Data Preparation https://www.talend.com/products/data-preparation/
Tamr https://www.tamr.com/
Teradata Vantage https://www.teradata.com/Products/Software/Vantage
TIBCO Spotfire Analytics https://www.tibco.com/products/tibco-spotfire
TMMData https://www.tmmdata.com/
Trifacta Wrangler https://www.trifacta.com/products/wrangler-editions/
Unifi Data Platform https://unifisoftware.com/platform/
Waterline Data https://www.waterlinedata.com/
Workday-Prism Analytics https://www.workday.com/en-us/applications/analytics/prism-analytics.html
Yellowfin Data Prep https://www.yellowfinbi.com/suite/data-prep
Zoho Analytics https://www.zoho.com/analytics/

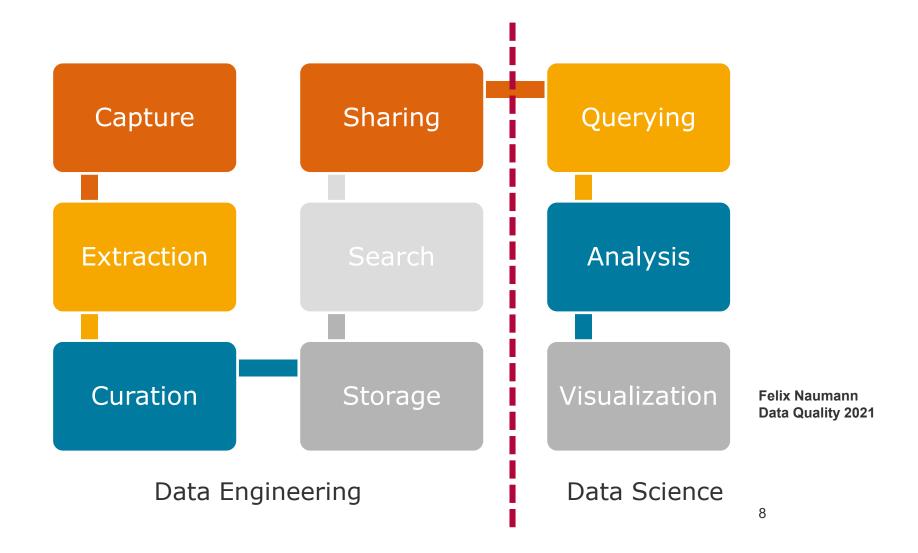




Overview

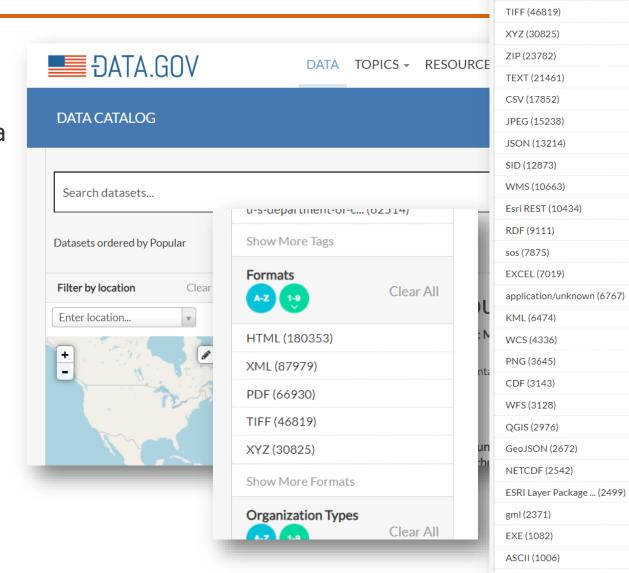
1. Bad Files

- 2. Bad Data
- 3. Bad Results



Data Sources – Data Formats

- Data lakes
- Open (government) data
- Instrumented processes
- Sensor data
- Experimental output
- Database exports
- Excel





CONTACT

Formats

A-Z 1-9

HTML (180353)

XML (87979)

PDF (66930)

Clear All

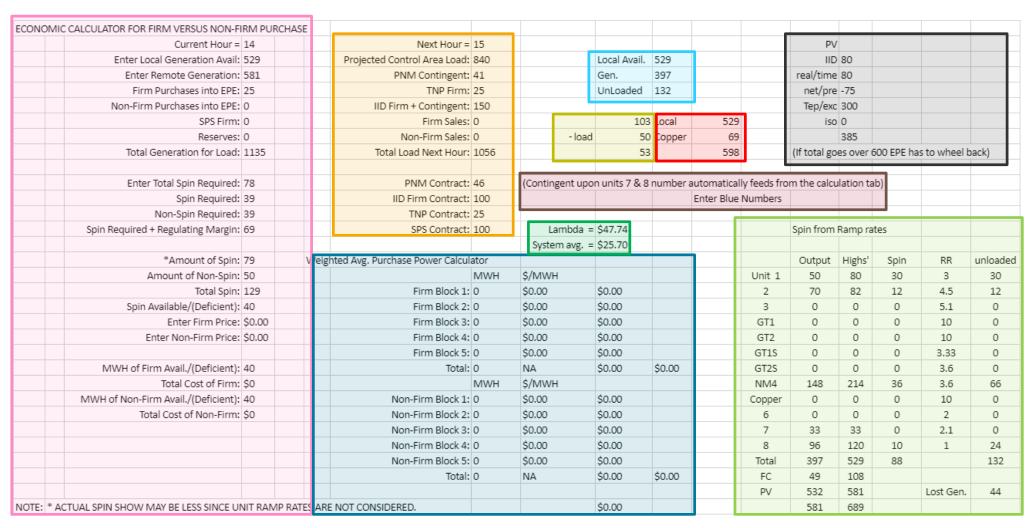
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r	TAR (785)
	GeoTIFF (697)
ı	OGC WMS (509)
	Digital Data (508)
	application/html (507)
	application/vnd.geo (372)
	data (294)
	Export (294)
S	rest (265)
ı	ARCE (245)
ı.	ARCG (239)
	BIN (226)
	Undefined (209)
	comma-delimited text (207)
	chemical/x-mdl-sdfile (198)
	nc (197)
	MGD77t (192)

1	1 Table rv.03.q: Removals and voluntary departures by country of nationality and type															
		Geographical		Total enforced	Total Refused entry at port and subsequentl	Total voluntary	asylum	Non-asylum cases: Refused entry at port and subsequenti	Total non- asylum voluntary	Non-asylum cases: Assisted Voluntary	Non-asylum cases: Notified voluntary	cases: Other confirmed	Total asylum	_		
2			Country of nationality	removals	y departed	departures	removals	y departed	departures	Returns	departures					
			Turkey	48	39	79	22	39	74	0	23	· · · · · · · · · · · · · · · · · · ·	26		0	
238	2011 Q1	Europe	Turkmenistan	2	3	10	1	3	9	0	0	9	1	1	0	
239	2011 Q1	Americas	Turks and Caicos Islands (British)	0	0	0	0	0	0	0	0	0	0	(0	
			Tuvalu	0	0	0	0	0	0	0	0	_			0	
			Uganda	24	3	58	7	3	50	4	8					
			Ukraine	53	63	39	46	63	36	0	12				_	
			United Arab Emirates	0	1	5	0	1	5	0	0	_	_		0	
			United States	14	472	91	14	472	88	0	35				3	
			Uruguay	1	3	0	0	3	0	0	0	_			0	
		•	Uzbekistan	22	1	46	20	1	46	0	8				0	
			Vanuatu	0	0	0	0	0	0	0	0	_	-			
			Vatican City	0	0	0	0	0	0	0	0	_	_			
			Venezuela	2	45	5	0	45	5	0	3		_		-	
			Vietnam	249	24	77	190	24	72	2	10				5 3	
			Virgin Islands (British)	0	0	0	0	0	0	0	0	_	_		-	
			Virgin Islands (US)	0	0	0	0	0	0	0	0		-		0	
		Oceania	Wallis and Futuna	0	0	0	0	0	0	0	0		-			
			Western Sahara	2	0	0	2	0	0	0	0	_			-	
			Yemen	2	0	2	2	0	2	0	2				0	
			Zambia	3 7	3	27	3	3	26	5	6					
			Zimbabwe	•	3 000	73	3	3	35	1	4.525			•		
		Total	*Total	3.456	3.963	5.156	2.130	3.963	4.488	154	1.525					
		Africa	*Total Africa	703	611	970	377	611	811	28	357					
		Americas	*Total Americas	343	1.367	652	301	1.367	643	55	194				0	
		Asia	*Total Asia	1.790	888	2.892	1.006	888	2.526	61 9	812					
		Europe Middle Fact	*Total Europe	512		356	418	638	318	9	92 47					
		Middle East Oceania	*Total Middle East *Total Oceania	98 4	192 153	240 38	22 3	192 153	144 38	0	16				39 0 0	
		Other	*Total Other	6	114	8	3	114	36 8	0	7				0	
			Afghanistan	296	70	69	17	70	4	0	3		_			
			Albania	100	187	25	53	187	19	0					5 2	
		•	Algeria	49	32	42	17	32	21	0	11	_				
			American Samoa	0		0	0	0	0	0	0	-			0	
	2011 Q2 2011 Q2		Andorra	0	0	0	0	0	0	0		-				
	2011 Q2 2011 Q2		Angola	7	19	12	1	19	4	0	0	_			3 4	
	2011 Q2		Anguilla (British)	0	0	0	0	0	0	0	0		_		0	
	2011 Q2		Antigua and Barbuda	0		1	0	6	1	0		_			0	
	2011 Q2		Argentina	4	30	4	4	30	4	1	2				0	
	2011 Q2		Armenia	2		1	1	3	0	0	0		_			
	2011 Q2 2011 Q2		Aruba	0	0	0	0	0	0	0	0				0	
	2011 Q2		Australia	1	120	24	1	120	24	0	8				0	
	2011 Q2		Austria	2		0	2		0	0					0	

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126
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      Oct-12, *, 9, 60, 43, 19, 122, 58, 1270, 212, 793, 27, 0, 21, 17, 3, 41, 7, 142, 3, 50, 0, 1, 19, 11, 5, 36, 14, 53, 4, 162, 0
     Nov-12,,7,48,36,15,100,49,912,147,672,21,0,16,14,2,33,6,119,2,27,0,1,13,10,4,28,11,41,3,133,0
      Dec-12, 6, 40, 30, 12, 82, 35, 917, 152, 628, 17, 0, 15, 14, 2, 31, 5, 104, 2, 23, 0, 0, 12, 10, 4, 26, 9, 32, 3, 115, 0
```

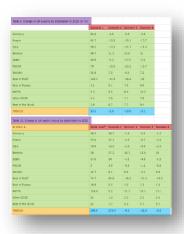


Multitable Spreadsheets



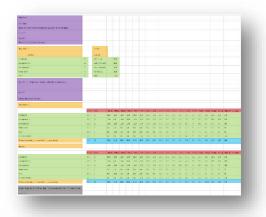


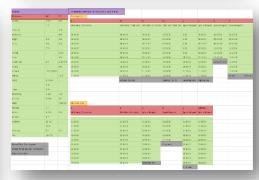




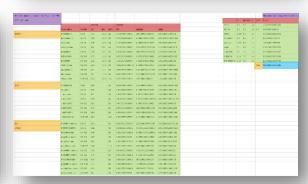












Metadata

Header

Group header

Data

Aggregation

Notes



ExtracTable: Bad Files – Worse Files

min	max	num	dist
1.8	1.8	1	0
20	60	40	1
0	0	1	0
0	1	10	2
0.01	0.01	1	0
0.009	0.009	1	0
0.2	7	40	1
-0.35	-0.35	1	2
-0.15	-0.15	1	0
0.5	0.5	1	0
0.2	0.2	1	0
0.01	0.01	1	0
27.947	27.947	1	0
7.04345	7.04345	1	0
146.691	146.691	1	0
1	1	1	0

mean	std	comment	
1.5	0	N	
40	15	cab	

OBIA4RTM config file for setting up Prospect4SAIL

Typical values (taken from J Gomez-Dans on https://pypi.org/project/prosail/)

Parameter	Description of parameter	Units	Typical min	Typical max	ļ
N	Leaf structure parameter	N/A	0.8	2.5	
cab	Chlorophyll a+b concentration	ug/cm2	0	80	İ
caw	Equivalent water thickiness	cm	0	200	İ
car	Carotenoid concentration	ug/cm2	0	20	ĺ
cbrown	Brown pigment	NA	0	1	ĺ
cm	Dry matter content	g/cm2	0	200	ĺ
lai	Leaf Area Index	N/A	0	10	ĺ
lidfa	Leaf angle distribution	N/A	j -	ĺ -	ĺ
lidfb	Leaf angle distribution	N/A	j -	ĺ -	ĺ
psoil	Dry/Wet soil factor	N/A	0	1	
rsoil	Soil brigthness factor	N/A	-	-	
hspot	Hotspot parameter	N/A	-	-	l
tts	Solar zenith angle	deg	0	90	ĺ
tto	Observer zenith angle	deg	0	90	
phi	Relative azimuth angle	deg	0	360	
typelidf	Leaf angle distribution type	Integer	-	-	

You can enter your values held

You can enter your values below -> make sure not to alter the overall structure of this template -> otherwise bad things might happen

Further Explainations:

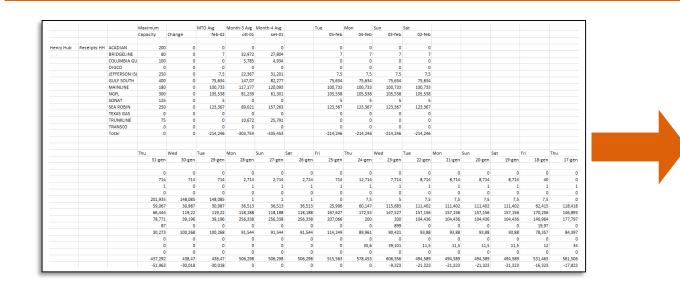
min: Minimum Value of Parameter

max: Maximum Value of Parameter (in case min=max, the parameter will not be retrieved)

num: in case min!=max, the number of samples to be drawn for the specific parameter



Automatic Table Recognition



- 1. Render spreadsheet as image
- 2. Recognize elements
- 3. Cluster elements into tables
- 4. Cluster files into templates

Gerardo Vitagliano, Lan Jiang, Felix Naumann: Detecting Layout Templates in Complex Multiregion Files. PVLDB vol 15 (accepted)



Pollock: Benchmarking Ingestion Ability

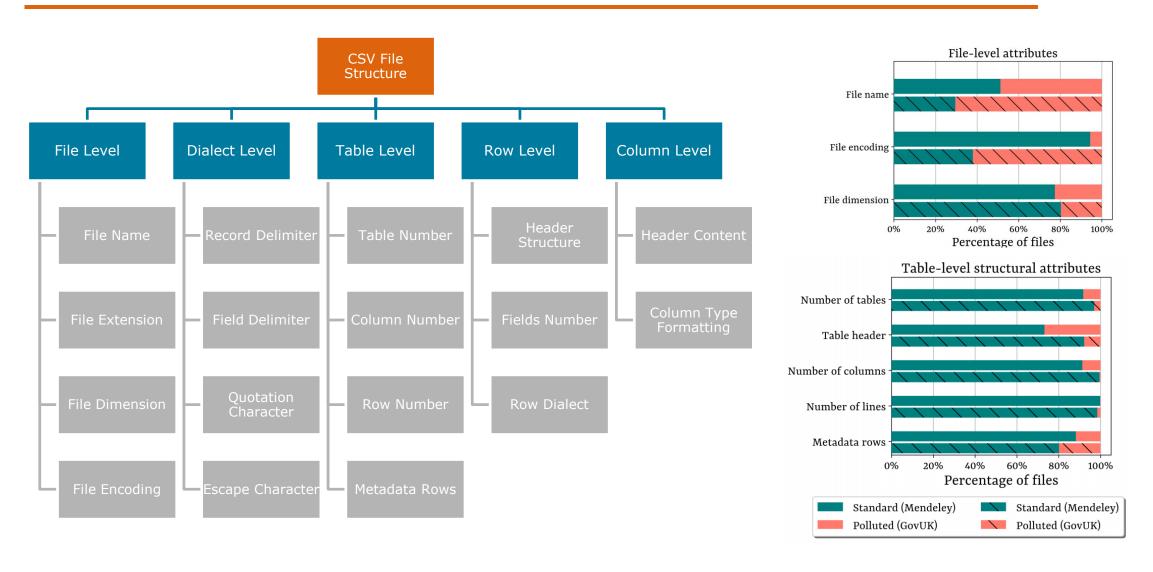
```
    Programming framework (Pandas)

Python 3.8.5 (default, Sep 3 2020, 21:29:08) [MSC v.1916 64 bi
                                                                  Spreadsheet software (Libreoffice)
Type "help", "copyright", "credits" or "license" for more infor
                                                                  Database tool (MySQL)
>>> import pandas as pd
                                                                  Data Visualization (Tableau)
>>> pd.read csv("11-708-data-nlss-2009-1.csv")
Traceback (most recent call last):
 File "<stdin>", line 1, in <module>
 File "C:\Users\User\miniconda3\envs\pollution\lib\site-packages\pandas\io\parsers.py", line 686, in read csv
   return read(filepath or buffer, kwds)
 File "C:\Users\User\miniconda3\envs\pollution\lib\site-packages\pandas\io\parsers.py", line 458, in read
   data = parser.read(nrows)
  File "C:\Users\User\miniconda3\envs\pollution\lib\site-packages\pandas\io\parsers.py", line 1196, in read
   ret = self. engine.read(nrows)
 File "C:\Users\User\miniconda3\envs\pollution\lib\site-packages\pandas\io\parsers.py", line 2155, in read
   data = self. reader.read(nrows)
 File "pandas\ libs\parsers.pyx", line 847, in pandas. libs.parsers.TextReader.read
 File "pandas\_libs\parsers.pyx", line 862, in pandas._libs.parsers.TextReader._read_low_memory Quality 2021
 File "pandas\ libs\parsers.pyx", line 918, in pandas. libs.parsers.TextReader. read rows
  File "pandas\ libs\parsers.pyx", line 905, in pandas. libs.parsers.TextReader. tokenize rows
 File "pandas\ libs\parsers.pvx", line 2042, in pandas, libs.parsers.raise parser error
pandas.errors.ParserError: Error tokenizing data. C error: Expected 25 fields in line 97, saw 27
```

Systems under test:



Pollock: Benchmark Dimensions





Data Aggregation Errors in CSV Files

MICROS Systems, Inc.			% Change	e 2003 vs. 20	$002 = \frac{\text{FY20}}{}$	003 – FY200 FY2002)2		
Financial Summary						11200			
,	% Change								
Income Statement Data	2003 vs. 20 02	FY2003	FY2002	FY2001	FY2000	FY1999	FY1998	FY1997	
Hardware Revenue	2.2%	\$137,013	\$134,121	\$116,058	\$152,186	\$155,237	\$126,974	\$102,816	
Software Revenue	17.8%	\$71,251	\$60,484	\$55,873	\$66,290	\$63,317	\$57,744	\$45,985	
Service Revenue	11.2%	\$191,927	\$172,558	\$154,845	\$143,378	\$118,525	\$97,200	\$79,368	
Total Revenue						Э	\$281,918	\$228,169	
	29% of all a	agrega	tions h	ave sor	ne erro	r.			Hardware GP
Mama Itam:	The highest							Hardw	$Vare GP \% = \frac{1100 \text{ GeV}}{\text{Hardware Revenue}}$
Maintenance Revenue (included in Service Revenue)	The mynest	onsei v	eu en o	i ievei	15 37.3	70.	\$45,908	\$37,38	
Hardware Gross Profit	2.3%	\$38,977	\$38,116	\$40,683	\$51,462	\$50,670	\$43,947	\$39,267	
Hardware Gross Profit %	-	28.4%	28.4%	35.1%	33.8%	32.6%	34.6%	38.2%	
Software Gross Profit	11.5%	\$54,045	\$48,457	\$46,875	\$51,349	\$52,138	\$47,235	\$37,464	
Software Gross Profit %	-4.2 Points	75.9%	80.1%	83.9%	77.5%	82.3%	81.8%	81.5%	Felix Naumann
Service Gross Profit	16.5%	\$105,538	\$90,564	\$76,472	\$71,741	\$61,367	\$46,455	\$39,447	Data Quality 2021
Service Gross Profit %	+2.5 Points	55.0%	52.5%	49.4%	50.0%	51.8%	47.8%	49.7%	Data Quality 2021
					1474 550	¢164 17E	\$137,637	4116 170	
Total Gross Profit	12.1%	\$198,560	\$177,137	\$164,028	\$174,552	\$164,175	\$137,037	\$116,178	
						\$104,175			
Total Gross Profit Gross Profit %	12.1% +1.4 Points	\$198,560 49.6%	\$177,137 48.2%	\$164,028 50.2%	48.2%	\$104,175	48.8%	50.9%	

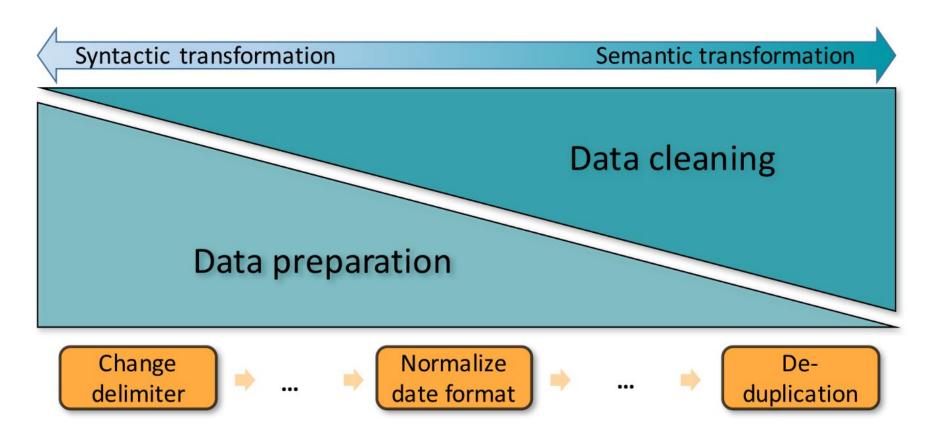
Service GP % = FY2003 - FY2002

Total Gross Profit = Hardware GP + Software GP + Service GP



Data Preparation vs. Data Cleaning

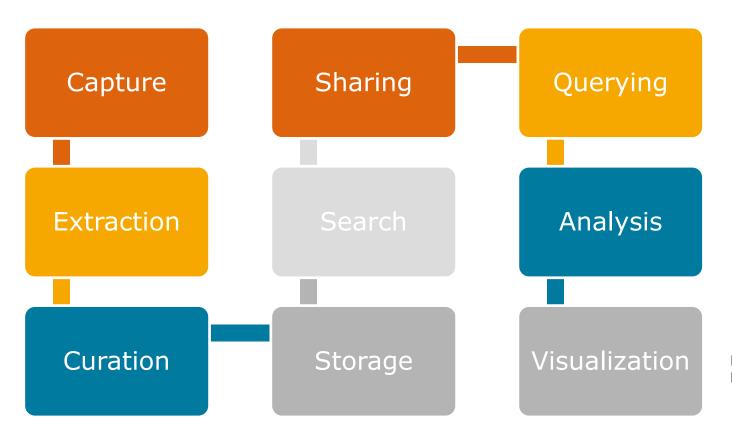
- Data preparation adds syntactic and structural value
- Data cleaning adds semantic value





Overview

- 1. Bad Files
- 2. Bad Data
- 3. Bad Results





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Real-world data is raw and dirty

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40134	brittany spears
36315	brittney spears
24342	britany spears
7331	britny spears
6633	briteny spears
2696	britteny spears
1807	briney spears
1635	brittny spears
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b However, each time	the serial	population		

population

offender was stopped he managed to evade justice by giving a different address.

But then his cover was blown.

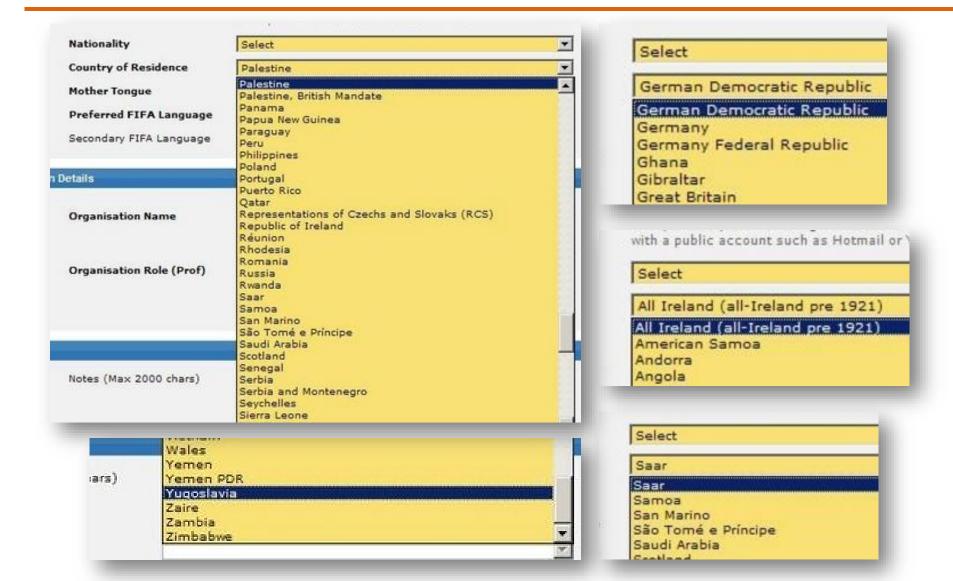
4 britnewy spears

It was discovered that the man every member of the Irish police's britneuv spears

2 barittany spears 2 bbbritney spears 2 britneyh spears 2 britneym spears



FIFA registration form (2010)







Fitness for use?

	Feld						· u
	Name1	Name2	Name3	City	District	Street	Sum
Mobile phone	41	501	10	0	2677	297	3526
Phone	15	98	6	0	221	9579	9919
Cost center	283	1112	73	2	87	16	1573
Registration ID	11	583	1	1	0	3	599
Delivery ID	55	390	9	0	212	15	681
Department	3711	9997	115	60	439	175	14497
Embargo flag	129	143	2	0	66	9	349
Deletion flag	1028	442	5	36	113	10	1634
Legal form	131700	66136	187	6	64	57	198150
Credit info	0	100	11	0	18	0	129
Commission	216	352	1	2	36	10	617
Construction site	2013	3452	42	5	124	222	5858
Loading point	2923	3808	94	1503	958	3065	12351
Administration	13410	12461	172	19	295	7075	33432
Summe	155535	99575	728	1634	5310	20533	

Felix Naumann Data Quality 2021

23

From Data Errors (aka. Data Quality) to Data Problems (aka. Information Quality)



■ Incorrect data: Accuracy

■ Missing data: Completeness

■ Poor formatting: Representational consistency

■ Old data: Timeliness

■ Unknown data source: Trustworthiness

■ Hard to reach data: Accessibility

■ Slow connection: Latency

And many more information quality dimensions



IQ Classification of Wang and Strong

- Intrinsic IQ
 - □ Believability, Accuracy, Objectivity, Reputation
- Contextual IQ
 - □ Value-added, Relevancy, Timeliness, Completeness, Amount
- Representational IQ
 - □ Interpretability, Understandability, Repr. Consistency, Repr. conciseness
- Accessibility IQ
 - Accessibility, Security



 Customer support, documentation, reliability, latency, price, response time, verifiability



Wang & Strong
Beyond Accuracy: What
data quality means to
data consumers
Management of
Information Systems,
1996, 12(4), 5-34

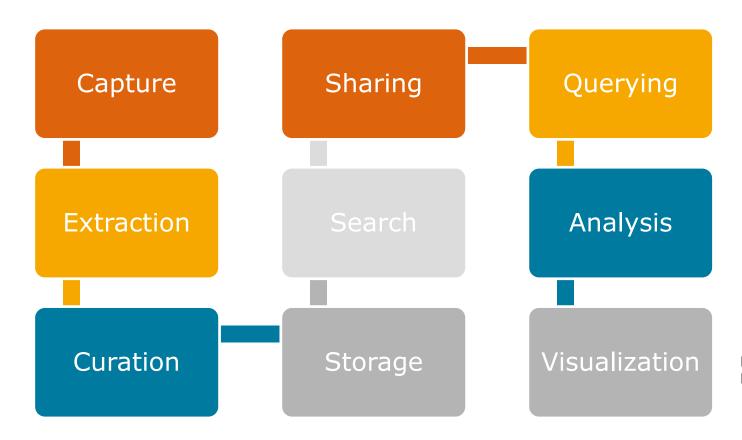
Felix Naumann
Data Quality 2021

Data scientists (might) choose the path of least resistance.



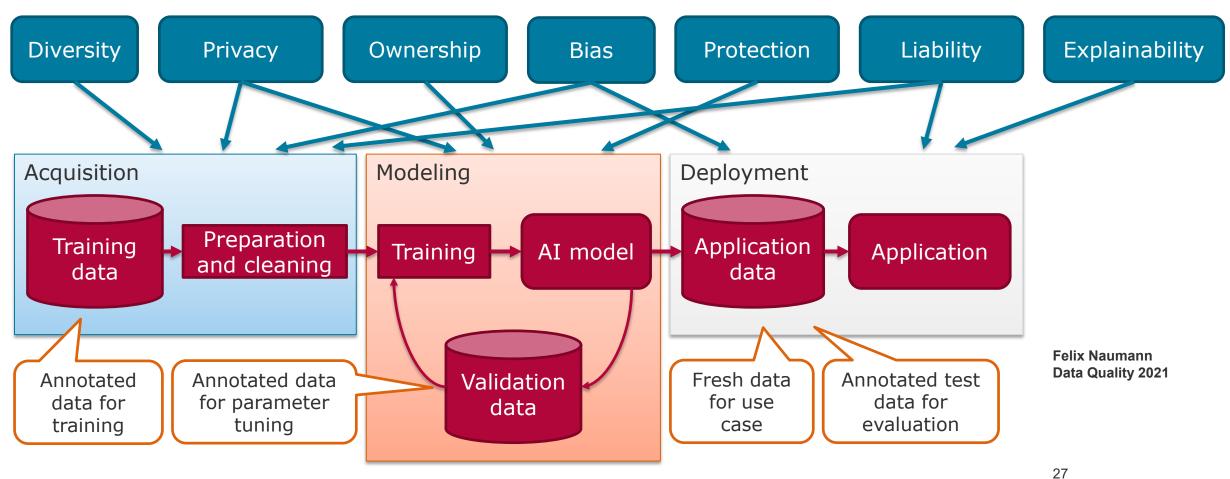
Overview

- 1. Bad Files
- 2. Bad Data
- 3. Bad Results





New AI-specific Data Quality Dimensions and Where to Find Them





Open Research Questions

- Data quality dimensions
 - □ Which established dimensions are relevant?
 - Learning task, pipeline stage, domain
 - □ Which new dimensions are needed?
 - Which are cross-dataset dimensions?
- Assessment and explanation of data quality
 - Which dimensions are (automatically) assessable/testable?
 - □ Can we efficiently measure data quality?
 - Automatically, manually, domain knowledge
 - Can we correlate model errors with data quality problems
- What are the legal and ethical aspects of data quality?

