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Data Profiling

An ICDE 2016 Tutorial

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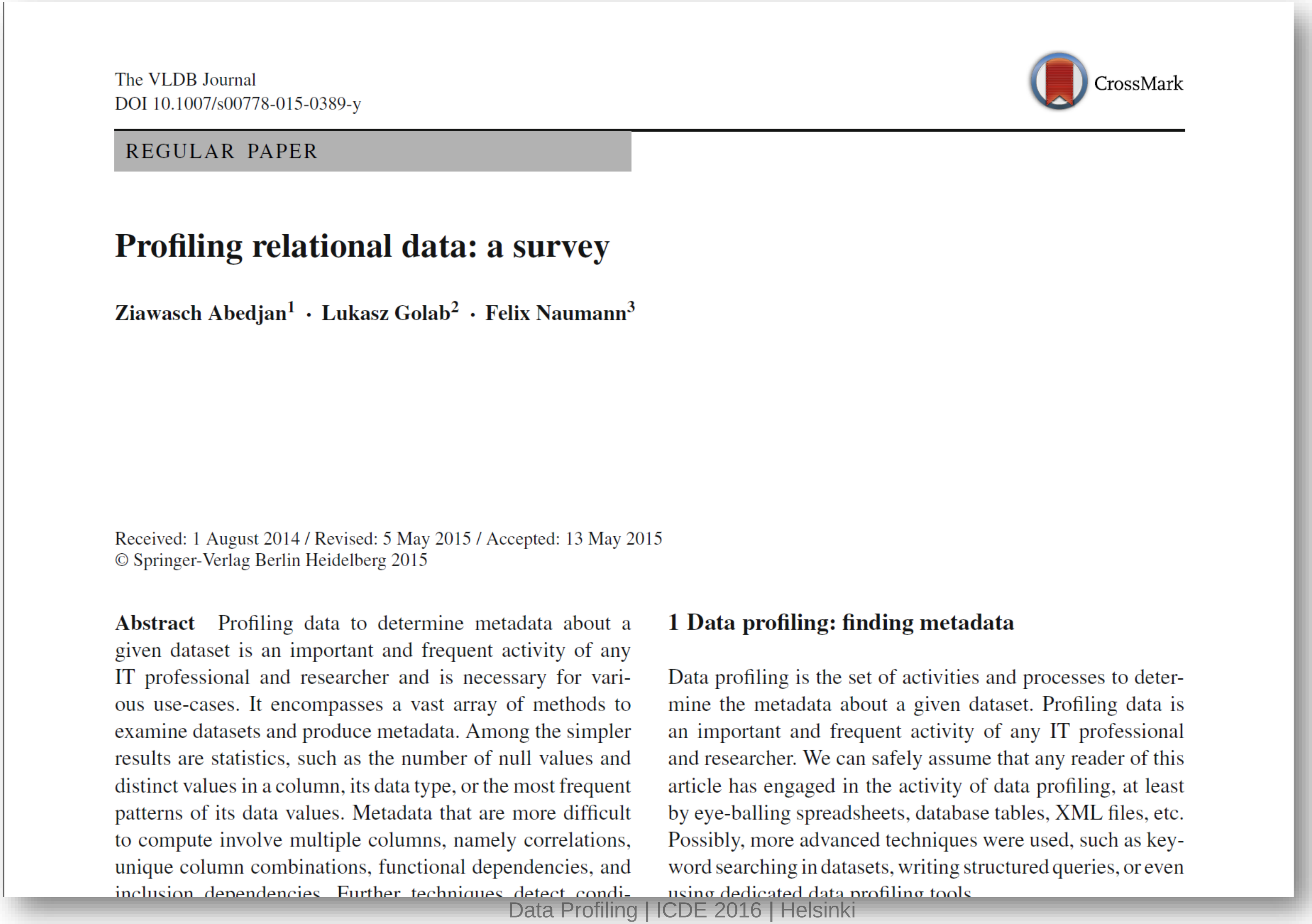
> “If we just have a bunch of data sets in a repository, it is unlikely anyone will ever be able to find, let alone reuse, any of this data. With adequate metadata, there is some hope, but even so, challenges will remain..

[D. Agrawal, P. Bernstein, E. Bertino, S. Davidson, U. Dayal, M. Franklin, J. Gehrke, L. Haas, A. Halevy, J. Han, H. V. Jagadish, A. Labrinidis, S. Madden, Y. Papakonstantinou, J. M. Patel, R. Ramakrishnan, K. Ross, C. Shahabi, D. Suciu, S. Vaithyanathan, and J. Widom. Challenges and opportunities with Big Data. Technical report, Computing Community Consortium, http://cra.org/ccc/docs/ init/bigdatawhitepaper.pdf, 2012.]



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REGULAR PAPER

Profiling relational data: a survey

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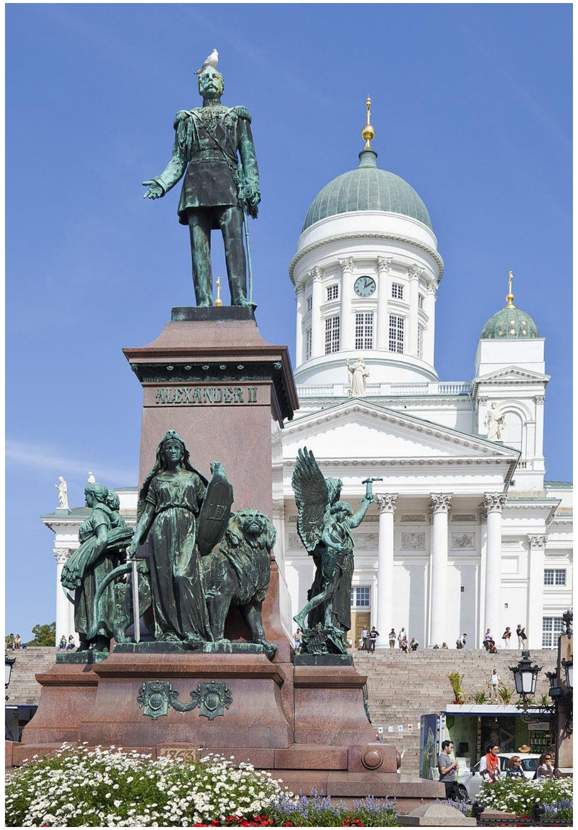
Abstract Profiling data to determine metadata about a given dataset is an important and frequent activity of any IT professional and researcher and is necessary for various use-cases. It encompasses a vast array of methods to examine datasets and produce metadata. Among the simpler results are statistics, such as the number of null values and distinct values in a column, its data type, or the most frequent patterns of its data values. Metadata that are more difficult to compute involve multiple columns, namely correlations, unique column combinations, functional dependencies, and inclusion dependencies. Further techniques detect condi-

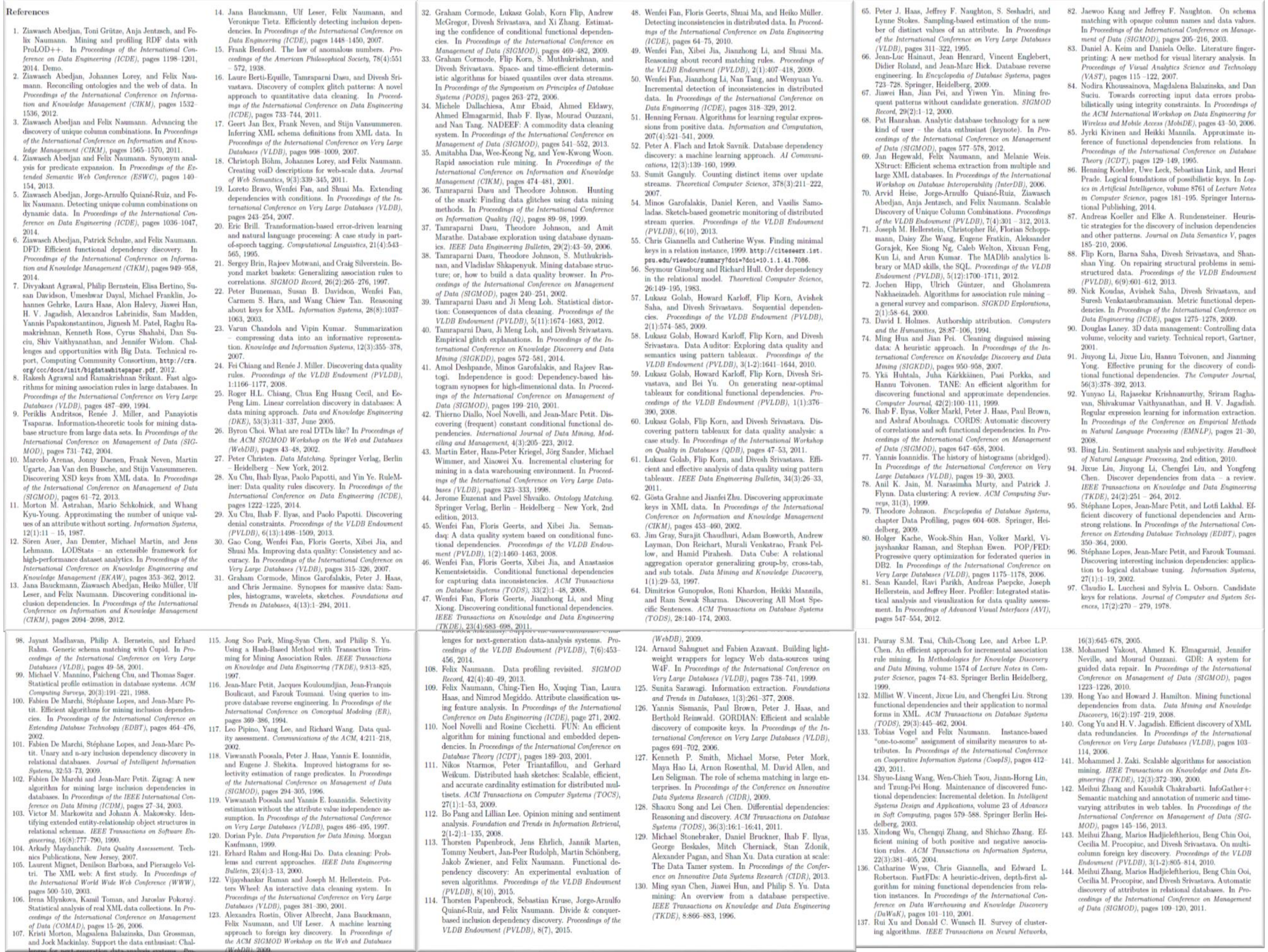
1 Data profiling: finding metadata

Data profiling is the set of activities and processes to determine the metadata about a given dataset. Profiling data is an important and frequent activity of any IT professional and researcher. We can safely assume that any reader of this article has engaged in the activity of data profiling, at least by eye-balling spreadsheets, database tables, XML files, etc. Possibly, more advanced techniques were used, such as keyword searching in datasets, writing structured queries, or even using dedicated data profiling tools.

Tutorial Overview

- Motivation
  - Task classification
  - Use cases
- Tools
  - Research and industry
  - Shortcomings
- Single and Multiple Column Analysis
  - Cardinalities and datatypes
  - Co-occurrences and summaries
- Dependencies
  - UCCs, INDs, FDs
  - and their discover algorithms
- Outlook
  - Functionality
  - Semantics





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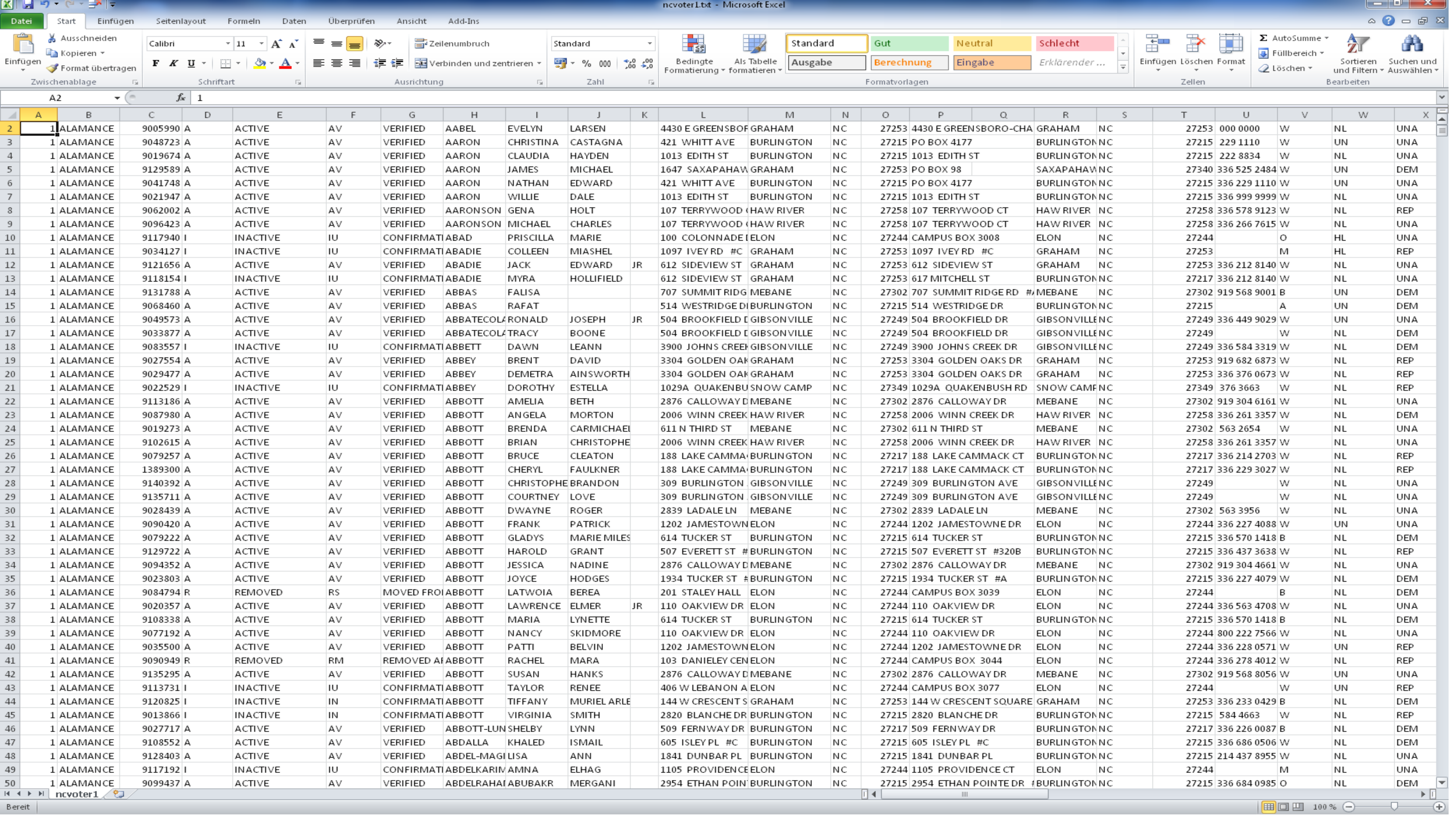

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
2	1	ALAMANCE	9005990	A	ACTIVE	AV	VERIFIED	AABEL	EVELYN	LARSEN		4430 E GREENSBOF	GRAHAM	NC	27253	4430 E GREENSBORO-CHA		GRAHAM	NC	27253	000 0000	W	NL	UNA
3	1	ALAMANCE	9048723	A	ACTIVE	AV	VERIFIED	AARON	CHRISTINA	CASTAGNA		421 WHITT AVE	BURLINGTON	NC	27215	PO BOX 4177		BURLINGTON	NC	27215	229 1110	W	UN	UNA
4	1	ALAMANCE	9019674	A	ACTIVE	AV	VERIFIED	AARON	CLAUDIA	HAYDEN		1013 EDITH ST	BURLINGTON	NC	27215	1013 EDITH ST		BURLINGTON	NC	27215	222 8834	W	NL	UNA
5	1	ALAMANCE	9129589	A	ACTIVE	AV	VERIFIED	AARON	JAMES	MICHAEL		1647 SAXAPAHAW	GRAHAM	NC	27253	PO BOX 98		SAXAPAHAW	NC	27340	336 525 2484	W	UN	DEM
6	1	ALAMANCE	9041748	A	ACTIVE	AV	VERIFIED	AARON	NATHAN	EDWARD		421 WHITT AVE	BURLINGTON	NC	27215	PO BOX 4177		BURLINGTON	NC	27215	336 229 1110	W	UN	UNA
7	1	ALAMANCE	9021947	A	ACTIVE	AV	VERIFIED	AARON	WILLIE	DALE		1013 EDITH ST	BURLINGTON	NC	27215	1013 EDITH ST		BURLINGTON	NC	27215	336 999 9999	W	NL	UNA
8	1	ALAMANCE	9062002	A	ACTIVE	AV	VERIFIED	AARONSON	GENA	HOLT		107 TERRYWOOD (	HAW RIVER	NC	27258	107 TERRYWOOD CT		HAW RIVER	NC	27258	336 578 9123	W	NL	REP
9	1	ALAMANCE	9096423	A	ACTIVE	AV	VERIFIED	AARONSON	MICHAEL	CHARLES		107 TERRYWOOD (	HAW RIVER	NC	27258	107 TERRYWOOD CT		HAW RIVER	NC	27258	336 266 7615	W	NL	UNA
10	1	ALAMANCE	9117940	I	INACTIVE	IU	CONFIRMATI	ABAD	PRISCILLA	MARIE		100 COLONNADE I	ELON	NC	27244	CAMPUS BOX 3008		ELON	NC	27244		O	HL	UNA
11	1	ALAMANCE	9034127	I	INACTIVE	IU	CONFIRMATI	ABADIE	COLLEEN	MIASHEL		1097 IVEY RD #C	GRAHAM	NC	27253	1097 IVEY RD #C		GRAHAM	NC	27253		M	HL	REP
12	1	ALAMANCE	9121656	A	ACTIVE	AV	VERIFIED	ABADIE	JACK	EDWARD	JR	612 SIDEVIEW ST	GRAHAM	NC	27253	612 SIDEVIEW ST		GRAHAM	NC	27253	336 212 8140	W	NL	UNA
13	1	ALAMANCE	9118154	I	INACTIVE	IU	CONFIRMATI	ABADIE	MYRA	HOLLIFIELD		612 SIDEVIEW ST	GRAHAM	NC	27253	617 MITCHELL ST		BURLINGTON	NC	27217	336 212 8140	W	NL	UNA
14	1	ALAMANCE	9131788	A	ACTIVE	AV	VERIFIED	ABBAS	FALISA			707 SUMMIT RIDG	MEBANE	NC	27302	707 SUMMIT RIDGE RD #/		MEBANE	NC	27302	919 568 9001	B	UN	DEM
15	1	ALAMANCE	9068460	A	ACTIVE	AV	VERIFIED	ABBAS	RAFAT			514 WESTRIDGE DI	BURLINGTON	NC	27215	514 WESTRIDGE DR		BURLINGTON	NC	27215		A	UN	DEM
16	1	ALAMANCE	9049573	A	ACTIVE	AV	VERIFIED	ABBATECOL/	RONALD	JOSEPH	JR	504 BROOKFIELD D	GIBSONVILLE	NC	27249	504 BROOKFIELD DR		GIBSONVILLE	NC	27249	336 449 9029	W	UN	UNA
17	1	ALAMANCE	9033877	A	ACTIVE	AV	VERIFIED	ABBATECOL/	TRACY	BOONE		504 BROOKFIELD D	GIBSONVILLE	NC	27249	504 BROOKFIELD DR		GIBSONVILLE	NC	27249		W	NL	DEM
18	1	ALAMANCE	9083557	I	INACTIVE	IU	CONFIRMATI	ABBETT	DAWN	LEANN		3900 JOHNS CREEI	GIBSONVILLE	NC	27249	3900 JOHNS CREEK DR		GIBSONVILLE	NC	27249	336 584 3319	W	NL	DEM
19	1	ALAMANCE	9027554	A	ACTIVE	AV	VERIFIED	ABBEY	BRENT	DAVID		3304 GOLDEN OAI	GRAHAM	NC	27253	3304 GOLDEN OAKS DR		GRAHAM	NC	27253	919 682 6873	W	NL	REP
20	1	ALAMANCE	9029477	A	ACTIVE	AV	VERIFIED	ABBEY	DEMETRA	AINSWORTH		3304 GOLDEN OAI	GRAHAM	NC	27253	3304 GOLDEN OAKS DR		GRAHAM	NC	27253	336 376 0673	W	NL	REP
21	1	ALAMANCE	9022529	I	INACTIVE	IU	CONFIRMATI	ABBEY	DOROTHY	ESTELLA		1029A QUAKENBU	SNOW CAMP	NC	27349	1029A QUAKENBUSH RD		SNOW CAMF	NC	27349	376 3663	W	NL	REP
22	1	ALAMANCE	9113186	A	ACTIVE	AV	VERIFIED	ABBOTT	AMELIA	BETH		2876 CALLOWAY D	MEBANE	NC	27302	2876 CALLOWAY DR		MEBANE	NC	27302	919 304 6161	W	NL	UNA
23	1	ALAMANCE	9087980	A	ACTIVE	AV	VERIFIED	ABBOTT	ANGELA	MORTON		2006 WINN CREEK	HAW RIVER	NC	27258	2006 WINN CREEK DR		HAW RIVER	NC	27258	336 261 3357	W	NL	DEM
24	1	ALAMANCE	9019273	A	ACTIVE	AV	VERIFIED	ABBOTT	BRENDA	CARMICHAEI		611 N THIRD ST	MEBANE	NC	27302	611 N THIRD ST		MEBANE	NC	27302	563 2654	W	NL	UNA
25	1	ALAMANCE	9102615	A	ACTIVE	AV	VERIFIED	ABBOTT	BRIAN	CHRISTOPHE		2006 WINN CREEK	HAW RIVER	NC	27258	2006 WINN CREEK DR		HAW RIVER	NC	27258	336 261 3357	W	NL	UNA
26	1	ALAMANCE	9079257	A	ACTIVE	AV	VERIFIED	ABBOTT	BRUCE	CLEATON		188 LAKE CAMMA(	BURLINGTON	NC	27217	188 LAKE CAMMACK CT		BURLINGTON	NC	27217	336 214 2703	W	NL	REP
27	1	ALAMANCE	1389300	A	ACTIVE	AV	VERIFIED	ABBOTT	CHERYL	FAULKNER		188 LAKE CAMMA(	BURLINGTON	NC	27217	188 LAKE CAMMACK CT		BURLINGTON	NC	27217	336 229 3027	W	NL	REP
28	1	ALAMANCE	9140392	A	ACTIVE	AV	VERIFIED	ABBOTT	CHRISTOPHE	BRANDON		309 BURLINGTON .	GIBSONVILLE	NC	27249	309 BURLINGTON AVE		GIBSONVILLE	NC	27249		W	NL	UNA
29	1	ALAMANCE	9135711	A	ACTIVE	AV	VERIFIED	ABBOTT	COURTNEY	LOVE		309 BURLINGTON .	GIBSONVILLE	NC	27249	309 BURLINGTON AVE		GIBSONVILLE	NC	27249		W	NL	UNA
30	1	ALAMANCE	9028439	A	ACTIVE	AV	VERIFIED	ABBOTT	DWAYNE	ROGER		2839 LADALE LN	MEBANE	NC	27302	2839 LADALE LN		MEBANE	NC	27302	563 3956	W	NL	UNA
31	1	ALAMANCE	9090420	A	ACTIVE	AV	VERIFIED	ABBOTT	FRANK	PATRICK		1202 JAMESTOWN	ELON	NC	27244	1202 JAMESTOWNE DR		ELON	NC	27244	336 227 4088	W	UN	UNA
32	1	ALAMANCE	9079222	A	ACTIVE	AV	VERIFIED	ABBOTT	GLADYS	MARIE MILES		614 TUCKER ST	BURLINGTON	NC	27215	614 TUCKER ST		BURLINGTON	NC	27215	336 570 1418	B	NL	DEM
33	1	ALAMANCE	9129722	A	ACTIVE	AV	VERIFIED	ABBOTT	HAROLD	GRANT		507 EVERETT ST #	BURLINGTON	NC	27215	507 EVERETT ST #320B		BURLINGTON	NC	27215	336 437 3638	W	NL	REP
34	1	ALAMANCE	9094352	A	ACTIVE	AV	VERIFIED	ABBOTT	JESSICA	NADINE		2876 CALLOWAY D	MEBANE	NC	27302	2876 CALLOWAY DR		MEBANE	NC	27302	919 304 4661	W	NL	UNA
35	1	ALAMANCE	9023803	A	ACTIVE	AV	VERIFIED	ABBOTT	JOYCE	HODGES		1934 TUCKER ST #	BURLINGTON	NC	27215	1934 TUCKER ST #A		BURLINGTON	NC	27215	336 227 4079	W	NL	DEM
36	1	ALAMANCE	9084794	R	REMOVED	RS	MOVED FROI	ABBOTT	LATWOIA	BEREA		201 STALEY HALL	ELON	NC	27244	CAMPUS BOX 3039		ELON	NC	27244		B	NL	DEM
37	1	ALAMANCE	9020357	A	ACTIVE	AV	VERIFIED	ABBOTT	LAWRENCE	ELMER	JR	110 OAKVIEW DR	ELON	NC	27244	110 OAKVIEW DR		ELON	NC	27244	336 563 4708	W	NL	UNA
38	1	ALAMANCE	9108338	A	ACTIVE	AV	VERIFIED	ABBOTT	MARIA	LYNETTE		614 TUCKER ST	BURLINGTON	NC	27215	614 TUCKER ST		BURLINGTON	NC	27215	336 570 1418	B	NL	DEM
39	1	ALAMANCE	9077192	A	ACTIVE	AV	VERIFIED	ABBOTT	NANCY	SKIDMORE		110 OAKVIEW DR	ELON	NC	27244	110 OAKVIEW DR		ELON	NC	27244	800 222 7566	W	NL	UNA
40	1	ALAMANCE	9035500	A	ACTIVE	AV	VERIFIED	ABBOTT	PATTI	BELVIN		1202 JAMESTOWN	ELON	NC	27244	1202 JAMESTOWNE DR		ELON	NC	27244	336 228 0571	W	UN	REP
41	1	ALAMANCE	9090949	R	REMOVED	RM	REMOVED AI	ABBOTT	RACHEL	MARA		103 DANIELEY CEN	ELON	NC	27244	CAMPUS BOX 3044		ELON	NC	27244	336 278 4012	W	NL	REP
42	1	ALAMANCE	9135295	A	ACTIVE	AV	VERIFIED	ABBOTT	SUSAN	HANKS		2876 CALLOWAY D	MEBANE	NC	27302	2876 CALLOWAY DR		MEBANE	NC	27302	919 568 8056	W	UN	UNA
43	1	ALAMANCE	9113731	I	INACTIVE	IU	CONFIRMATI	ABBOTT	TAYLOR	RENEE		406 W LEBANON A	ELON	NC	27244	CAMPUS BOX 3077		ELON	NC	27244		W	UN	REP
44	1	ALAMANCE	9120825	I	INACTIVE	IN	CONFIRMATI	ABBOTT	TIFFANY	MURIEL ARLE		144 W CRESCENT S	GRAHAM	NC	27253	144 W CRESCENT SQUARE		GRAHAM	NC	27253	336 233 0429	B	NL	DEM
45	1	ALAMANCE	9013866	I	INACTIVE	IN	CONFIRMATI	ABBOTT	VIRGINIA	SMITH		2820 BLANCHE DR	BURLINGTON	NC	27215	2820 BLANCHE DR		BURLINGTON	NC	27215	584 4663	W	NL	REP
46	1	ALAMANCE	9027717	A	ACTIVE	AV	VERIFIED	ABBOTT-LUN	SHELBY	LYNN		509 FERNWAY DR	BURLINGTON	NC	27217	509 FERNWAY DR		BURLINGTON	NC	27217	336 226 0087	B	NL	DEM
47	1	ALAMANCE	9108552	A	ACTIVE	AV	VERIFIED	ABDALLA	KHALED	ISMAIL		605 ISLEY PL #C	BURLINGTON	NC	27215	605 ISLEY PL #C		BURLINGTON	NC	27215	336 686 0506	W	NL	DEM
48	1	ALAMANCE	9128403	A	ACTIVE	AV	VERIFIED	ABDEL-MAGI	LISA	ANN		1841 DUNBAR PL	BURLINGTON	NC	27215	1841 DUNBAR PL		BURLINGTON	NC	27215	214 437 8955	W	NL	UNA
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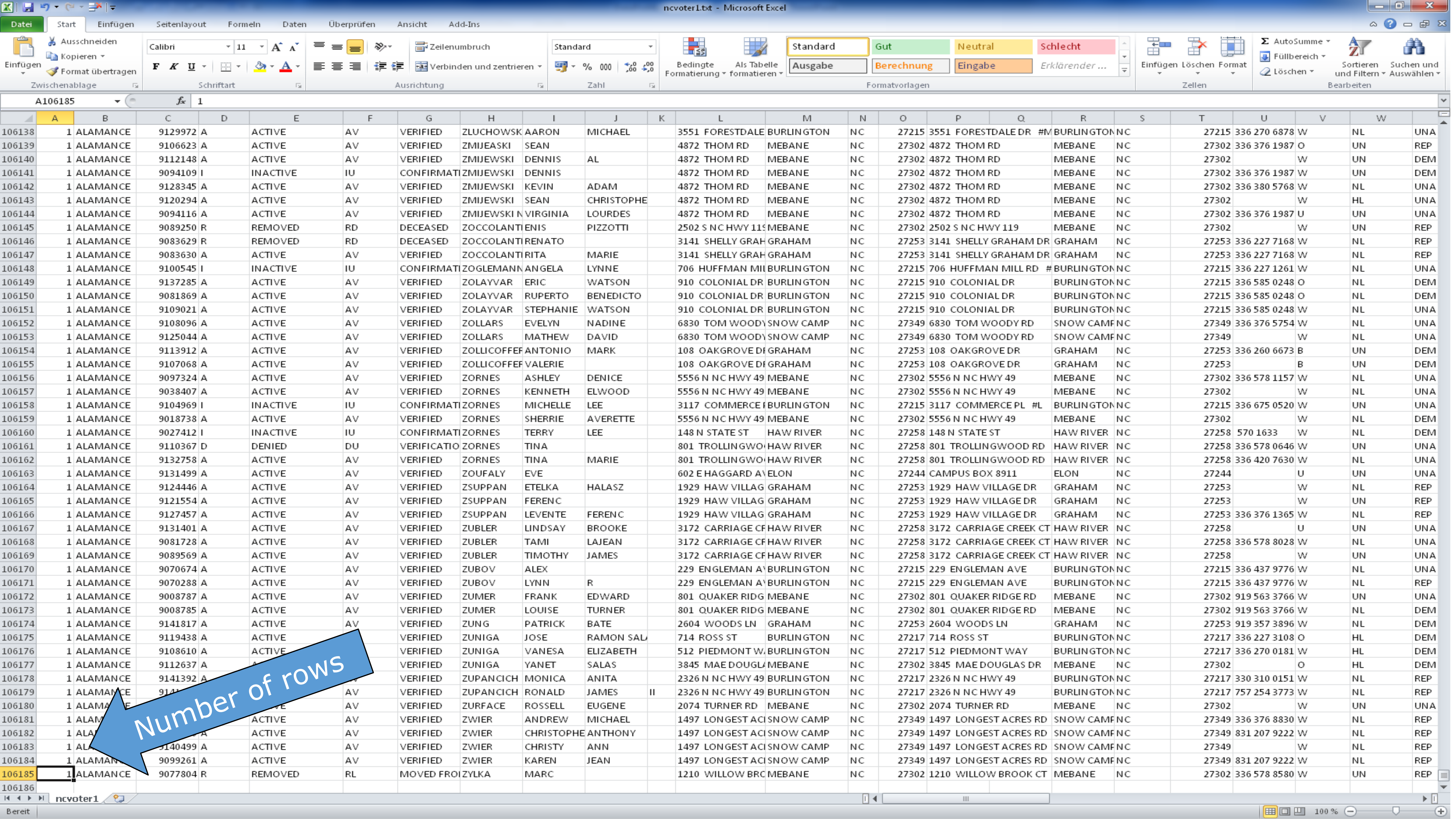
50	1	ALAMANCE	9099437	A	ACTIVE	AV	VERIFIED	ABDELRAHAI	ABUBAKR	MERGANI		2954 ETHAN POIN	BURLINGTON	NC	27215	2954 ETHAN POINTE DR #		BURLINGTON	NC	27215	336 684 0985	O	NL	DEM



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	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	
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106139	1	ALAMANCE	9106623	A	ACTIVE	AV	VERIFIED	ZMIJEASKI	SEAN			4872 THOM RD	MEBANE	NC	27302	4872 THOM RD		MEBANE	NC	27302	336 376 1987	O	UN	REP
106140	1	ALAMANCE	9112148	A	ACTIVE	AV	VERIFIED	ZMIJEWSKI	DENNIS	AL		4872 THOM RD	MEBANE	NC	27302	4872 THOM RD		MEBANE	NC	27302		W	UN	DEM
106141	1	ALAMANCE	9094109	I	INACTIVE	IU	CONFIRMATI	ZMIJEWSKI	DENNIS			4872 THOM RD	MEBANE	NC	27302	4872 THOM RD		MEBANE	NC	27302	336 376 1987	W	UN	DEM
106142	1	ALAMANCE	9128345	A	ACTIVE	AV	VERIFIED	ZMIJEWSKI	KEVIN	ADAM		4872 THOM RD	MEBANE	NC	27302	4872 THOM RD		MEBANE	NC	27302	336 380 5768	W	NL	UNA
106143	1	ALAMANCE	9120294	A	ACTIVE	AV	VERIFIED	ZMIJEWSKI	SEAN	CHRISTOPHE		4872 THOM RD	MEBANE	NC	27302	4872 THOM RD		MEBANE	NC	27302		W	HL	UNA
106144	1	ALAMANCE	9094116	A	ACTIVE	AV	VERIFIED	ZMIJEWSKI N	VIRGINIA	LOURDES		4872 THOM RD	MEBANE	NC	27302	4872 THOM RD		MEBANE	NC	27302	336 376 1987	U	UN	UNA
106145	1	ALAMANCE	9089250	R	REMOVED	RD	DECEASED	ZOCCOLANTI	ENIS	PIZZOTTI		2502 S NC HWY 11	MEBANE	NC	27302	2502 S NC HWY 119		MEBANE	NC	27302		W	UN	REP
106146	1	ALAMANCE	9083629	R	REMOVED	RD	DECEASED	ZOCCOLANTI	RENATO			3141 SHELLY GRAH	GRAHAM	NC	27253	3141 SHELLY GRAHAM DR		GRAHAM	NC	27253	336 227 7168	W	NL	REP
106147	1	ALAMANCE	9083630	A	ACTIVE	AV	VERIFIED	ZOCCOLANTI	RITA	MARIE		3141 SHELLY GRAH	GRAHAM	NC	27253	3141 SHELLY GRAHAM DR		GRAHAM	NC	27253	336 227 7168	W	NL	REP
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106149	1	ALAMANCE	9137285	A	ACTIVE	AV	VERIFIED	ZOLAYVAR	ERIC	WATSON		910 COLONIAL DR	BURLINGTON	NC	27215	910 COLONIAL DR		BURLINGTON	NC	27215	336 585 0248	O	NL	DEM
106150	1	ALAMANCE	9081869	A	ACTIVE	AV	VERIFIED	ZOLAYVAR	RUPERTO	BENEDICTO		910 COLONIAL DR	BURLINGTON	NC	27215	910 COLONIAL DR		BURLINGTON	NC	27215	336 585 0248	O	NL	DEM
106151	1	ALAMANCE	9109021	A	ACTIVE	AV	VERIFIED	ZOLAYVAR	STEPHANIE	WATSON		910 COLONIAL DR	BURLINGTON	NC	27215	910 COLONIAL DR		BURLINGTON	NC	27215	336 585 0248	W	NL	UNA
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106153	1	ALAMANCE	9125044	A	ACTIVE	AV	VERIFIED	ZOLLARS	MATHEW	DAVID		6830 TOM WOODY	SNOW CAMP	NC	27349	6830 TOM WOODY RD		SNOW CAMP	NC	27349		W	NL	UNA
106154	1	ALAMANCE	9113912	A	ACTIVE	AV	VERIFIED	ZOLLICOFFEF	ANTONIO	MARK		108 OAKGROVE DI	GRAHAM	NC	27253	108 OAKGROVE DR		GRAHAM	NC	27253	336 260 6673	B	UN	DEM
106155	1	ALAMANCE	9107068	A	ACTIVE	AV	VERIFIED	ZOLLICOFFEF	VALERIE			108 OAKGROVE DI	GRAHAM	NC	27253	108 OAKGROVE DR		GRAHAM	NC	27253		B	UN	DEM
106156	1	ALAMANCE	9097324	A	ACTIVE	AV	VERIFIED	ZORNES	ASHLEY	DENICE		5556 N NC HWY 49	MEBANE	NC	27302	5556 N NC HWY 49		MEBANE	NC	27302	336 578 1157	W	NL	UNA
106157	1	ALAMANCE	9038407	A	ACTIVE	AV	VERIFIED	ZORNES	KENNETH	ELWOOD		5556 N NC HWY 49	MEBANE	NC	27302	5556 N NC HWY 49		MEBANE	NC	27302		W	NL	UNA
106158	1	ALAMANCE	9104969	I	INACTIVE	IU	CONFIRMATI	ZORNES	MICHELLE	LEE		3117 COMMERCE I	BURLINGTON	NC	27215	3117 COMMERCE PL #L		BURLINGTON	NC	27215	336 675 0520	W	UN	UNA
106159	1	ALAMANCE	9018738	A	ACTIVE	AV	VERIFIED	ZORNES	SHERRIE	AVERETTE		5556 N NC HWY 49	MEBANE	NC	27302	5556 N NC HWY 49		MEBANE	NC	27302		W	NL	DEM
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106162	1	ALAMANCE	9132758	A	ACTIVE	AV	VERIFIED	ZORNES	TINA	MARIE		801 TROLLINGWO	HAW RIVER	NC	27258	801 TROLLINGWOOD RD		HAW RIVER	NC	27258	336 420 7630	W	NL	UNA
106163	1	ALAMANCE	9131499	A	ACTIVE	AV	VERIFIED	ZOUFALY	EVE			602 E HAGGARD A	ELON	NC	27244	CAMPUS BOX 8911		ELON	NC	27244		U	UN	UNA
106164	1	ALAMANCE	9124446	A	ACTIVE	AV	VERIFIED	ZSUPPAN	ETELKA	HALASZ		1929 HAW VILLAG	GRAHAM	NC	27253	1929 HAW VILLAGE DR		GRAHAM	NC	27253		W	NL	REP
106165	1	ALAMANCE	9121554	A	ACTIVE	AV	VERIFIED	ZSUPPAN	FERENC			1929 HAW VILLAG	GRAHAM	NC	27253	1929 HAW VILLAGE DR		GRAHAM	NC	27253		W	UN	REP
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106167	1	ALAMANCE	9131401	A	ACTIVE	AV	VERIFIED	ZUBLER	LINDSAY	BROOKE		3172 CARRIAGE CF	HAW RIVER	NC	27258	3172 CARRIAGE CREEK CT		HAW RIVER	NC	27258		U	UN	UNA
106168	1	ALAMANCE	9081728	A	ACTIVE	AV	VERIFIED	ZUBLER	TAMI	LAJEAN		3172 CARRIAGE CF	HAW RIVER	NC	27258	3172 CARRIAGE CREEK CT		HAW RIVER	NC	27258	336 578 8028	W	NL	UNA
106169	1	ALAMANCE	9089569	A	ACTIVE	AV	VERIFIED	ZUBLER	TIMOTHY	JAMES		3172 CARRIAGE CF	HAW RIVER	NC	27258	3172 CARRIAGE CREEK CT		HAW RIVER	NC	27258		W	UN	UNA
106170	1	ALAMANCE	9070674	A	ACTIVE	AV	VERIFIED	ZUBOV	ALEX			229 ENGLEMAN A	BURLINGTON	NC	27215	229 ENGLEMAN AVE		BURLINGTON	NC	27215	336 437 9776	W	NL	UNA
106171	1	ALAMANCE	9070288	A	ACTIVE	AV	VERIFIED	ZUBOV	LYNN	R		229 ENGLEMAN A	BURLINGTON	NC	27215	229 ENGLEMAN AVE		BURLINGTON	NC	27215	336 437 9776	W	NL	REP
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106174	1	ALAMANCE	9141817	A	ACTIVE	AV	VERIFIED	ZUNG	PATRICK	BATE		2604 WOODS LN	GRAHAM	NC	27253	2604 WOODS LN		GRAHAM	NC	27253	919 357 3896	W	NL	DEM
106175	1	ALAMANCE	9119438	A	ACTIVE	[illegible]	VERIFIED	ZUNIGA	JOSE	RAMON SAL		714 ROSS ST	BURLINGTON	NC	27217	714 ROSS ST		BURLINGTON	NC	27217	336 227 3108	O	HL	DEM
106176	1	ALAMANCE	9108610	A	ACTIVE	[illegible]	VERIFIED	ZUNIGA	VANESA	ELIZABETH		512 PIEDMONT W	BURLINGTON	NC	27217	512 PIEDMONT WAY		BURLINGTON	NC	27217	336 270 0181	W	HL	DEM
106177	1	ALAMANCE	9112637	A	[illegible]	[illegible]	VERIFIED	ZUNIGA	YANET	SALAS		3845 MAE DOUGL	MEBANE	NC	27302	3845 MAE DOUGLAS DR		MEBANE	NC	27302		O	HL	DEM
106178	1	ALAMANCE	9141392	A	[illegible]	[illegible]	VERIFIED	ZUPANCICH	MONICA	ANITA		2326 N NC HWY 49	BURLINGTON	NC	27217	2326 N NC HWY 49		BURLINGTON	NC	27217	330 310 0151	W	NL	REP
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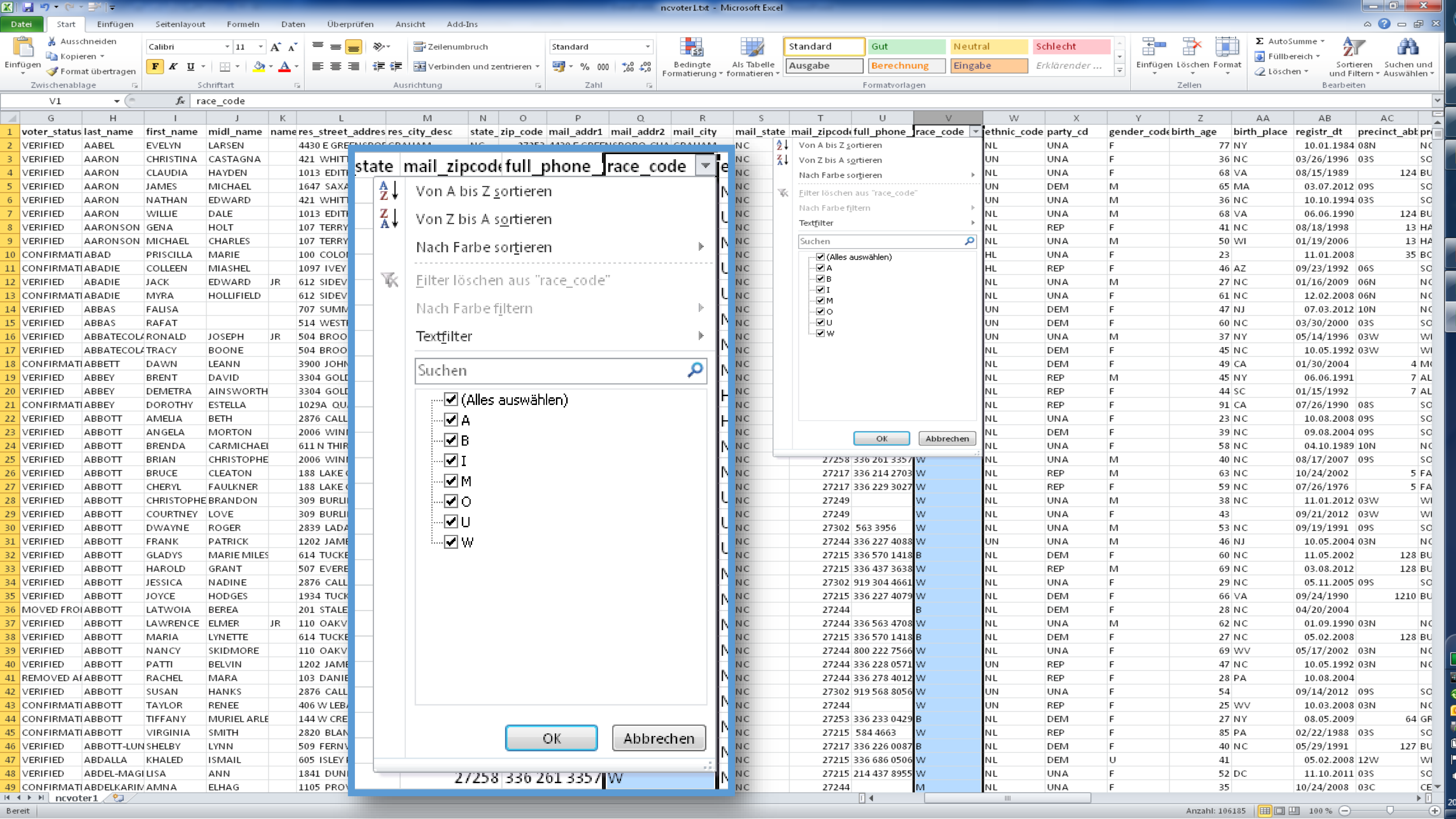
106180	1	ALAMANCE	[illegible]	[illegible]	[illegible]	AV	VERIFIED	ZURFACE	ROSSELL	EUGENE		2074 TURNER RD	MEBANE	NC	27302	2074 TURNER RD		MEBANE	NC	27302		W	UN	UNA
106181	1	[illegible]	[illegible]	[illegible]	ACTIVE	AV	VERIFIED	ZWIER	ANDREW	MICHAEL		1497 LONGEST ACI	SNOW CAMP	NC	27349	1497 LONGEST ACRES RD		SNOW CAMP	NC	27349	336 376 8830	W	NL	REP
106182	1	[illegible]	[illegible]	A	ACTIVE	AV	VERIFIED	ZWIER	CHRISTOPHE	ANTHONY		1497 LONGEST ACI	SNOW CAMP	NC	27349	1497 LONGEST ACRES RD		SNOW CAMP	NC	27349	831 207 9222	W	NL	REP
106183	1	[illegible]	9140499	A	ACTIVE	AV	VERIFIED	ZWIER	CHRISTY	ANN		1497 LONGEST ACI	SNOW CAMP	NC	27349	1497 LONGEST ACRES RD		SNOW CAMP	NC	27349		W	NL	REP
106184	1	ALAMANCE	9099261	A	ACTIVE	AV	VERIFIED	ZWIER	KAREN	JEAN		1497 LONGEST ACI	SNOW CAMP	NC	27349	1497 LONGEST ACRES RD		SNOW CAMP	NC	27349	831 207 9222	W	NL	REP
106185	1	ALAMANCE	9077804	R	REMOVED	RL	MOVED FROI	ZYLKA	MARC			1210 WILLOW BRC	MEBANE	NC	27302	1210 WILLOW BROOK CT		MEBANE	NC	27302	336 578 8580	W	UN	REP
106186																								

Number of rows



☑ (Alles auswählen)
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☑ W

	G	H	I	J	K	L	S	T	U	V	W	X	Y	Z	AA	AB	AC	
1	voter_status	last_name	first_name	midl_name	name	res_street_addres	mail_state	mail_zipcod	full_phone_	race_code	ethnic_code	party_cd	gender_cod	birth_age	birth_place	registr_dt	precinct_abb	pr
2	VERIFIED	AABEL	EVELYN	LARSEN		4430 E GRE	NC				NL	UNA	F	77	NY	10.01.1984	08N	NC
3	VERIFIED	AARON	CHRISTINA	CASTAGNA		421 WHITT	NC				UN	UNA	F	36	NC	03/26/1996	03S	SO
4	VERIFIED	AARON	CLAUDIA	HAYDEN		1013 EDITH	NC				NL	UNA	F	68	VA	08/15/1989	124	BU
5	VERIFIED	AARON	JAMES	MICHAEL		1647 SAXA	NC				UN	DEM	M	65	MA	03.07.2012	09S	SO
6	VERIFIED	AARON	NATHAN	EDWARD		421 WHITT	NC				UN	UNA	M	36	NC	10.10.1994	03S	SO
7	VERIFIED	AARON	WILLIE	DALE		1013 EDITH	NC				NL	UNA	M	68	VA	06.06.1990	124	BU
8	VERIFIED	AARONSON	GENA	HOLT		107 TERRY	NC				NL	REP	F	41	NC	08/18/1998	13	HA
9	VERIFIED	AARONSON	MICHAEL	CHARLES		107 TERRY	NC				NL	UNA	M	50	WI	01/19/2006	13	HA
10	CONFIRMATI	ABAD	PRISCILLA	MARIE		100 COLOI	NC				HL	UNA	F	23		11.01.2008	35	BC
11	CONFIRMATI	ABADIE	COLLEEN	MIASHEL		1097 IVEY	NC				HL	REP	F	46	AZ	09/23/1992	06S	SO
12	VERIFIED	ABADIE	JACK	EDWARD	JR	612 SIDEV	NC				NL	UNA	M	27	NC	01/16/2009	06N	NC
13	CONFIRMATI	ABADIE	MYRA	HOLLIFIELD		612 SIDEV	NC				NL	UNA	F	61	NC	12.02.2008	06N	NC
14	VERIFIED	ABBAS	FALISA			707 SUMM	NC				UN	DEM	F	47	NJ	07.03.2012	10N	NC
15	VERIFIED	ABBAS	RAFAT			514 WESTI	NC				UN	DEM	F	60	NC	03/30/2000	03S	SO
16	VERIFIED	ABBATECOLA	RONALD	JOSEPH	JR	504 BROO	NC				UN	UNA	M	37	NY	05/14/1996	03W	WI
17	VERIFIED	ABBATECOLA	TRACY	BOONE		504 BROO	NC				NL	DEM	F	45	NC	10.05.1992	03W	WI
18	CONFIRMATI	ABBETT	DAWN	LEANN		3900 JOHN	NC				NL	DEM	F	49	CA	01/30/2004	4	MC
19	VERIFIED	ABBEY	BRENT	DAVID		3304 GOLD	NC				NL	REP	M	45	NY	06.06.1991	7	AL
20	VERIFIED	ABBEY	DEMETRA	AINSWORTH		3304 GOLD	NC				NL	REP	F	44	SC	01/15/1992	7	AL
21	CONFIRMATI	ABBEY	DOROTHY	ESTELLA		1029A QUA	NC				NL	REP	F	91	CA	07/26/1990	08S	SO
22	VERIFIED	ABBOTT	AMELIA	BETH		2876 CALL	NC				NL	UNA	F	23	NC	10.08.2008	09S	SO
23	VERIFIED	ABBOTT	ANGELA	MORTON		2006 WINI	NC				NL	DEM	F	39	NC	09.08.2004	09S	SO
24	VERIFIED	ABBOTT	BRENDA	CARMICHAEL		611 N THIR	NC				NL	UNA	F	58	NC	04.10.1989	10N	NC
25	VERIFIED	ABBOTT	BRIAN	CHRISTOPHE		2006 WINI	NC	27258	336 261 3357	W	NL	UNA	M	40	NC	08/17/2007	09S	SO
26	VERIFIED	ABBOTT	BRUCE	CLEATON		188 LAKE	NC	27217	336 214 2703	W	NL	REP	M	63	NC	10/24/2002	5	FA
27	VERIFIED	ABBOTT	CHERYL	FAULKNER		188 LAKE	NC	27217	336 229 3027	W	NL	REP	F	59	NC	07/26/1976	5	FA
28	VERIFIED	ABBOTT	CHRISTOPHE	BRANDON		309 BURLI	NC	27249		W	NL	UNA	M	38	NC	11.01.2012	03W	WI
29	VERIFIED	ABBOTT	COURTNEY	LOVE		309 BURLI	NC	27249		W	NL	UNA	F	43		09/21/2012	03W	WI
30	VERIFIED	ABBOTT	DWAYNE	ROGER		2839 LADA	NC	27302	563 3956	W	NL	UNA	M	53	NC	09/19/1991	09S	SO
31	VERIFIED	ABBOTT	FRANK	PATRICK		1202 JAME	NC	27244	336 227 4088	W	UN	UNA	M	46	NJ	10.05.2004	03N	NC
32	VERIFIED	ABBOTT	GLADYS	MARIE MILES		614 TUCKE	NC	27215	336 570 1418	B	NL	DEM	F	60	NC	11.05.2002	128	BU
33	VERIFIED	ABBOTT	HAROLD	GRANT		507 EVERE	NC	27215	336 437 3638	W	NL	REP	M	69	NC	03.08.2012	128	BU
34	VERIFIED	ABBOTT	JESSICA	NADINE		2876 CALL	NC	27302	919 304 4661	W	NL	UNA	F	29	NC	05.11.2005	09S	SO
35	VERIFIED	ABBOTT	JOYCE	HODGES		1934 TUCK	NC	27215	336 227 4079	W	NL	DEM	F	66	VA	09/24/1990	1210	BU
36	MOVED FROI	ABBOTT	LATWOIA	BEREA		201 STALE	NC	27244		B	NL	DEM	F	28	NC	04/20/2004		
37	VERIFIED	ABBOTT	LAWRENCE	ELMER	JR	110 OAKV	NC	27244	336 563 4708	W	NL	UNA	M	62	NC	01.09.1990	03N	NC
38	VERIFIED	ABBOTT	MARIA	LYNETTE		614 TUCKE	NC	27215	336 570 1418	B	NL	DEM	F	27	NC	05.02.2008	128	BU
39	VERIFIED	ABBOTT	NANCY	SKIDMORE		110 OAKV	NC	27244	800 222 7566	W	NL	UNA	F	69	WV	05/17/2002	03N	NC
40	VERIFIED	ABBOTT	PATTI	BELVIN		1202 JAME	NC	27244	336 228 0571	W	UN	REP	F	47	NC	10.05.1992	03N	NC
41	REMOVED AF	ABBOTT	RACHEL	MARA		103 DANIE	NC	27244	336 278 4012	W	NL	REP	F	28	PA	10.08.2004		
42	VERIFIED	ABBOTT	SUSAN	HANKS		2876 CALL	NC	27302	919 568 8056	W	UN	UNA	F	54		09/14/2012	09S	SO
43	CONFIRMATI	ABBOTT	TAYLOR	RENEE		406 W LEBA	NC	27244		W	UN	REP	F	25	WV	10.03.2008	03N	NC
44	CONFIRMATI	ABBOTT	TIFFANY	MURIEL ARLE		144 W CRE	NC	27253	336 233 0429	B	NL	DEM	F	27	NY	08.05.2009	64	GR
45	CONFIRMATI	ABBOTT	VIRGINIA	SMITH		2820 BLAN	NC	27215	584 4663	W	NL	REP	F	85	PA	02/22/1988	03S	SO
46	VERIFIED	ABBOTT-LUN	SHELBY	LYNN		509 FERNV	NC	27217	336 226 0087	B	NL	DEM	F	40	NC	05/29/1991	127	BU
47	VERIFIED	ABDALLA	KHALED	ISMAIL		605 ISLEY	NC	27215	336 686 0506	W	NL	DEM	U	41		05.02.2008	12W	WI
48	VERIFIED	ABDEL-MAGI	LISA	ANN		1841 DUNI	NC	27215	214 437 8955	W	NL	UNA	F	52	DC	11.10.2011	03S	SO
49	CONFIRMATI	ABDELKARIM	AMNA	ELHAG		1105 PROV	NC	27244		M	NL	UNA	F	35		10/24/2008	03C	CE

[illegible]	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
1	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
1	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
1	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
1	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
1	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
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1	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
1	ALAMANCE	[illegible]	I	INACTIVE	IN	[illegible]
1	ALAMANCE	[illegible]	I	INACTIVE	IN	[illegible]
1	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
1	ALAMANCE	[illegible]	I	INACTIVE	IN	[illegible]
1	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
1	ALAMANCE	[illegible]	A	ACTIVE	AV	[illegible]
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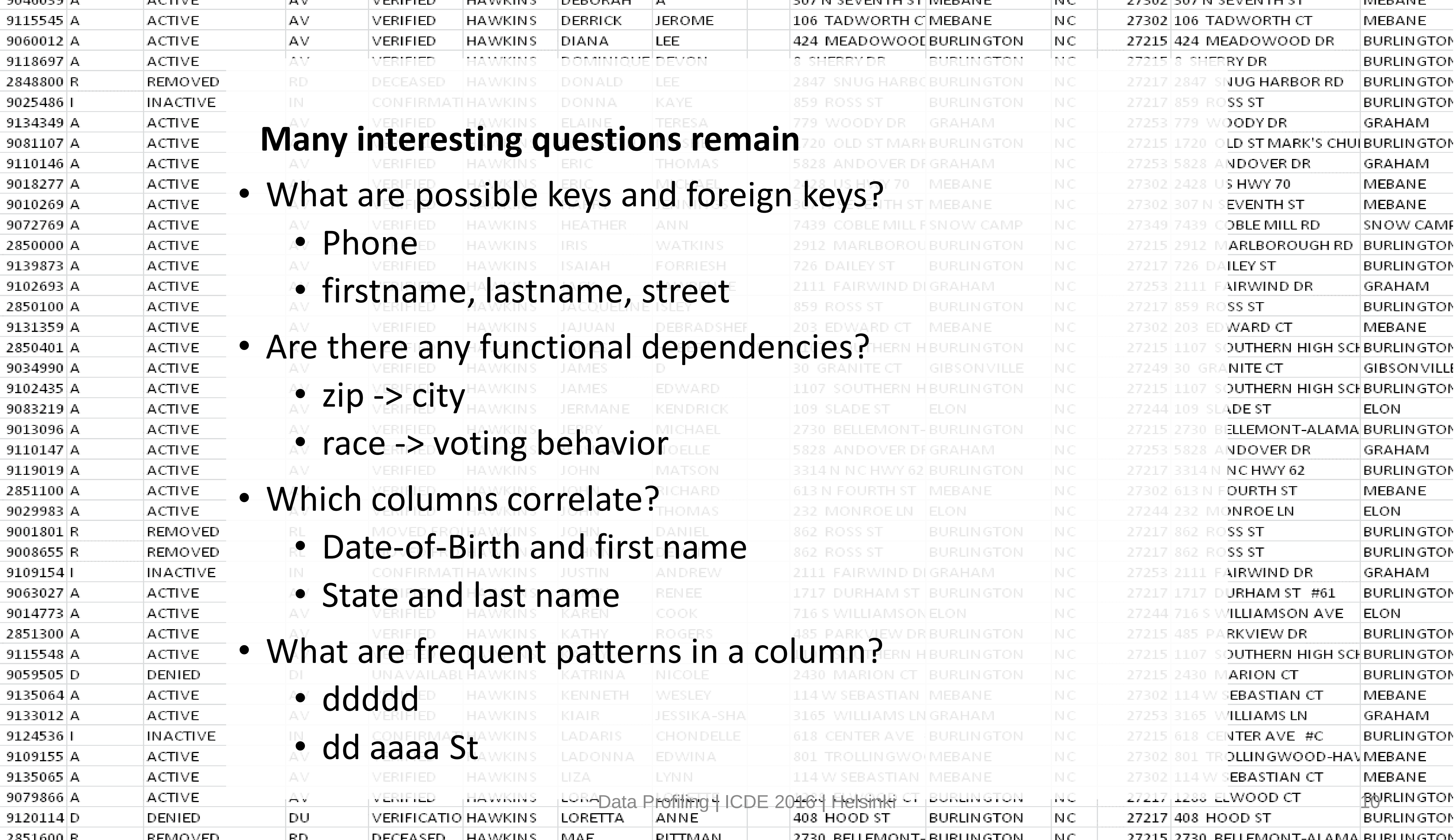


Many interesting questions remain

- What are possible keys and foreign keys?
  - Phone
  - firstname, lastname, street
- Are there any functional dependencies?
  - zip -> city
  - race -> voting behavior
- Which columns correlate?
  - Date-of-Birth and first name
  - State and last name
- What are frequent patterns in a column?
  - ddddd
  - dd aaaa St

Definition Data Profiling

- Data profiling is the process of examining the data available in an existing data source [...] and collecting statistics and information about that data.

[Wikipedia 04/2016]

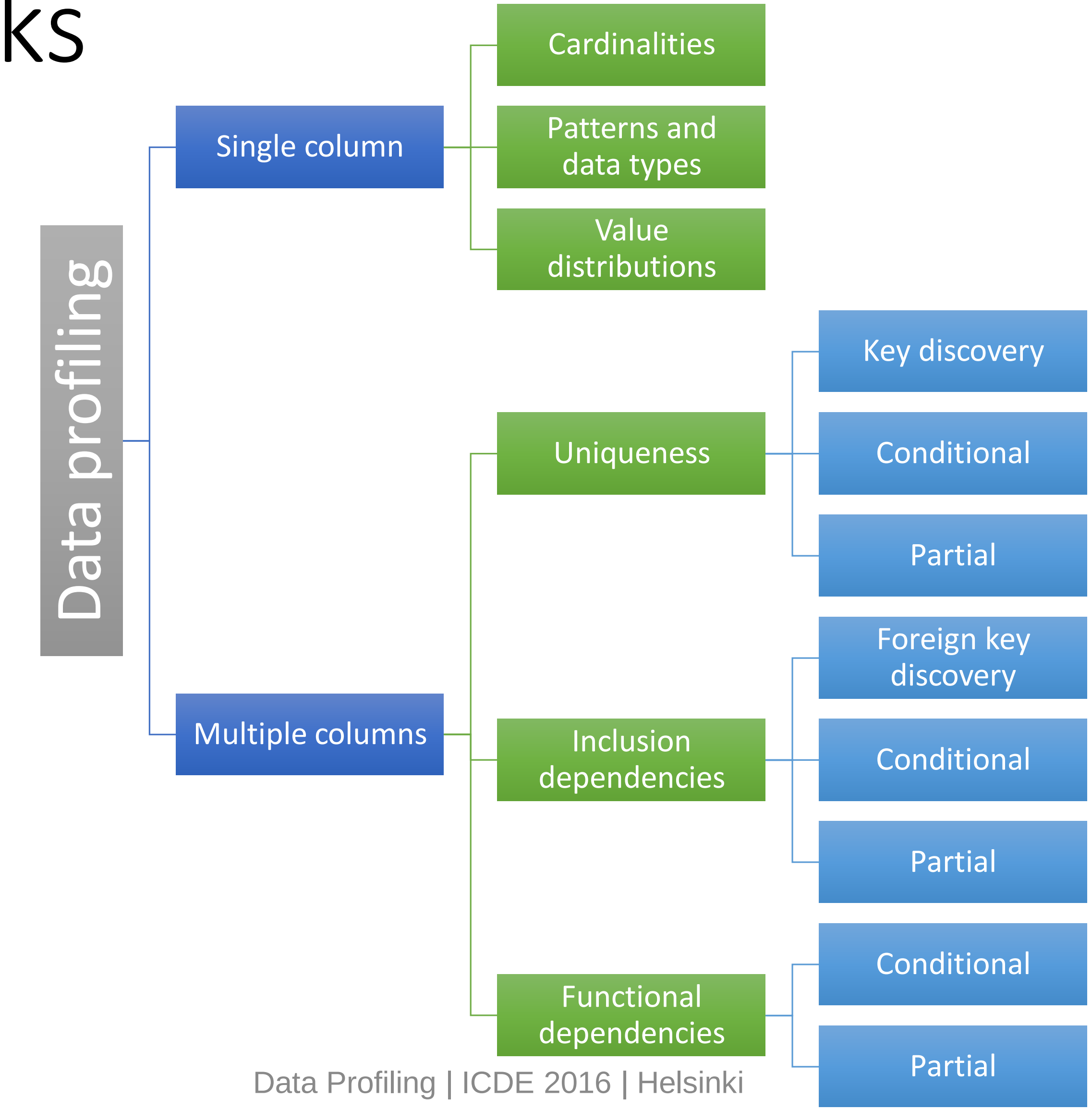
- Data profiling refers to the activity of creating small but informative summaries of a database.

[Ted Johnson, Data Profiling, Encyclopedia of Database Systems, 2009]

- Data profiling is the set of activities and processes to determine the metadata about a given dataset.

- A fixed set of data profiling tasks / results

Classification of Traditional Profiling Tasks



Data Profiling vs. Data Mining

- Data profiling gathers technical metadata to support data management
- Data mining and data analytics discovers non-obvious results to support business management

- Data profiling results: information about columns and column sets
- Data mining results: information about rows or row sets
  - clustering, summarization, association rules, …

- Rahm and Do on data cleaning
  - Profiling: Individual attributes
  - Mining: Multiple attributes

[Rahm and Do, Data Cleaning: Problems and Current Approaches, IEEE DE Bulletin, 2000]

Challenges of (Big) Data Profiling

- Large search space
  - Number of rows AND number of columns (and column combinations)
  - "Small" table with 100 columns:
    $2^{100} - 1$ = 1,267,650,600,228,229,401,496,703,205,375
    = 1.3 nonillion column combinations
- Large solution space: Exponential number of dependencies

- New data types and new data models
- New requirements: User-oriented, interactive, streaming

- Solutions: Scale up, scale out, scale in
- Better: Intelligent enumeration and aggressive pruning

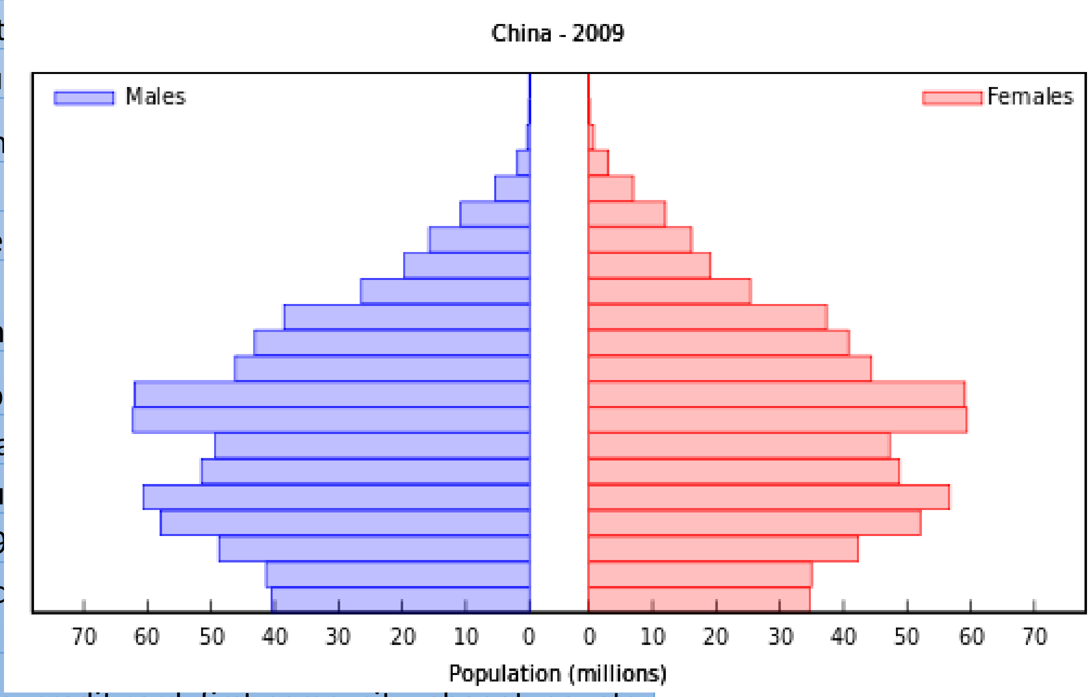
Use Cases for Profiling

- Query optimization
  - Counts and histograms
- Data cleansing
  - Patterns and violations
- Data integration
  - Cross-DB inclusion dependencies
- Scientific data management
  - Handle new datasets
- Data analytics
  - Profiling as preparation and for initial insights
  - Borderline to data mining
- Database reverse engineering

Basic Statistics

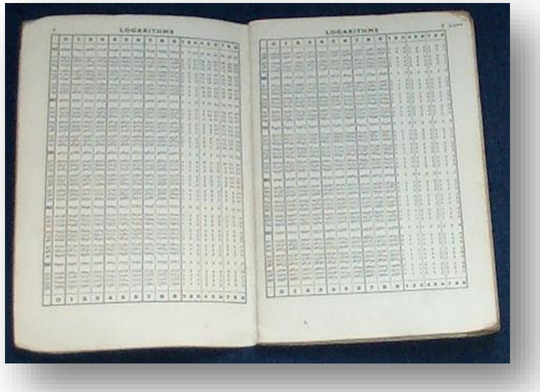
Cardinalities, Distributions, and Patterns

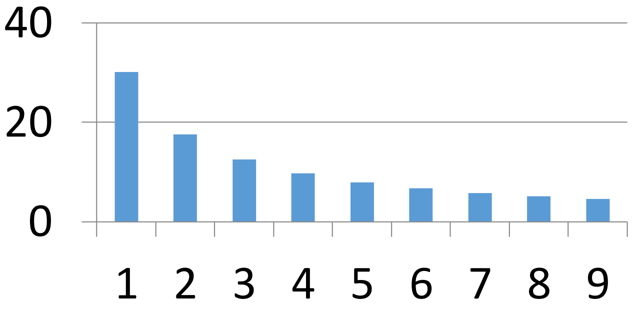
Category	Task	Description
Cardinalities	num-rows	Number of rows
	value length	Measurements of value lengths (min, max, median, and average)
	null values	Number or percentage of null values
	distinct	Number of distinct values; aka “cardinality”
	uniqueness	Number of distinct values divided by number of rows
Value distributions	histogram	Frequency histograms (equi-widt
	constancy	Frequency of most frequent valu
	quartiles	Three points that divide the (nun
	soundex	Distribution of soundex codes
	first digit	Distribution of first digit in nume
Patterns, data types, and domains	basic type	Generic data type: numeric, alph
	data type	Concrete DBMS-specific data typ
	decimals	Maximum number of decimal pla
	precision	Maximum number of digits in nu
	patterns	Histogram of value patterns (Aa9
	data class	Semantic, generic data type: coc identifier, etc.
	domain	Classification of semantic domain: credit card, first name, city, phenotype, etc.



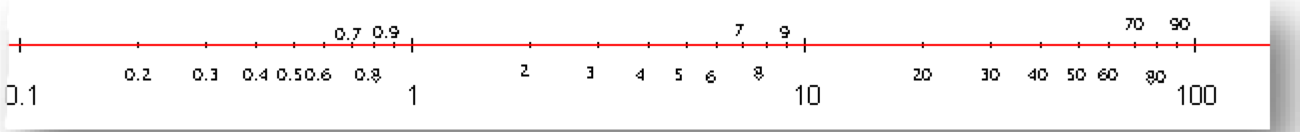
An Aside: Benford Law Frequency (“first digit law”)

- Statement about the distribution of first digits d in (many) naturally occurring numbers:
  - $P(d) = log_{10}(d+1) - log_{10}(d) = log_{10}(1 + {}^{1}/_{d})$





  - Holds if log(x) is uniformly distributed

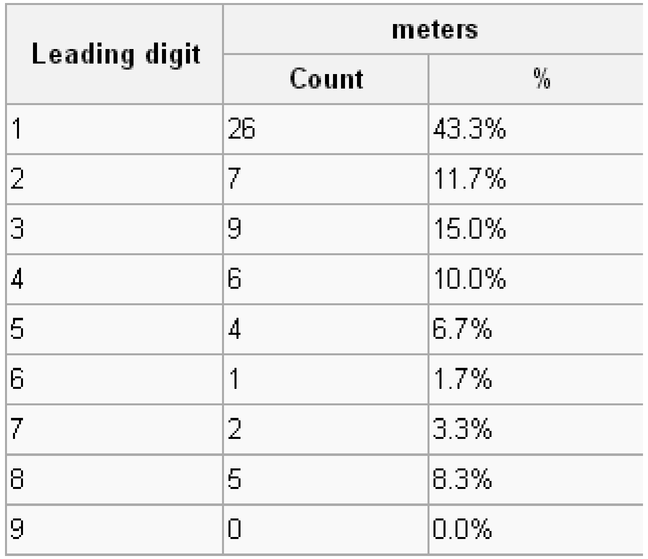


[Benford: The law of anomalous numbers". Proc. Am. Philos. Soc. 78 (4): 551–572, 1938]

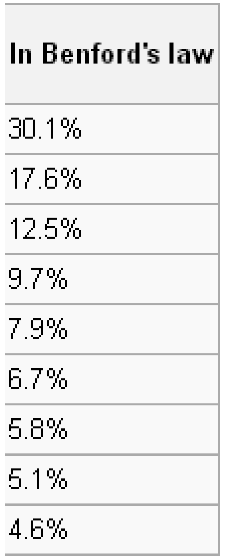
Examples for Benford‘s Law

- Surface areas of 335 rivers
- Sizes of 3259 US populations
- 104 physical constants
- 1800 molecular weights
- 308 numbers contained in an issue of Reader's Digest
- Street addresses of the first 342 persons listed in American Men of Science

Heights of the 60 tallest structures



Leading digit	meters	
	Count	%
1	26	43.3%
2	7	11.7%
3	9	15.0%
4	6	10.0%
5	4	6.7%
6	1	1.7%
7	2	3.3%
8	5	8.3%
9	0	0.0%



In Benford's law
30.1%
17.6%
12.5%
9.7%
7.9%
6.7%
5.8%
5.1%
4.6%

Fraud detection

http://en.wikipedia.org/wiki/List_of_tallest_buildings_and_structures_in_the_world#Tallest_structure_by_category

Uses for Basic Statistics

- Traditional uses
  - Query optimization
  - Outlier/error detection
  - Visualize distribution

- Semantic uses
  - Categorization of attributes: Data types
  - Relevance of attributes: Completeness and quality
  - Semantics of attributes: Matching and cleansing

Unique Column Combinations

Unique Column Combinations

- Unique column
  - Only unique values
- Unique column combination
  - Only unique value combinations
  - Minimality: No subset is unique
- (Primary) key candidate
  - No null values
  - Uniqueness and non-null in one instance does not imply key: Only human can specify keys (and foreign keys)
- Meaning of NULL values?

Uses for UCCs

- Learn characteristics of a new data set
- Database management
  - Find a primary key
  - Find unique constraints
- Query optimization
  - Cardinality estimations for joins
- Find duplicates / data quality issues
  - If expected unique column combinations are not unique
  - Or with partial uniques

Inclusion Dependencies

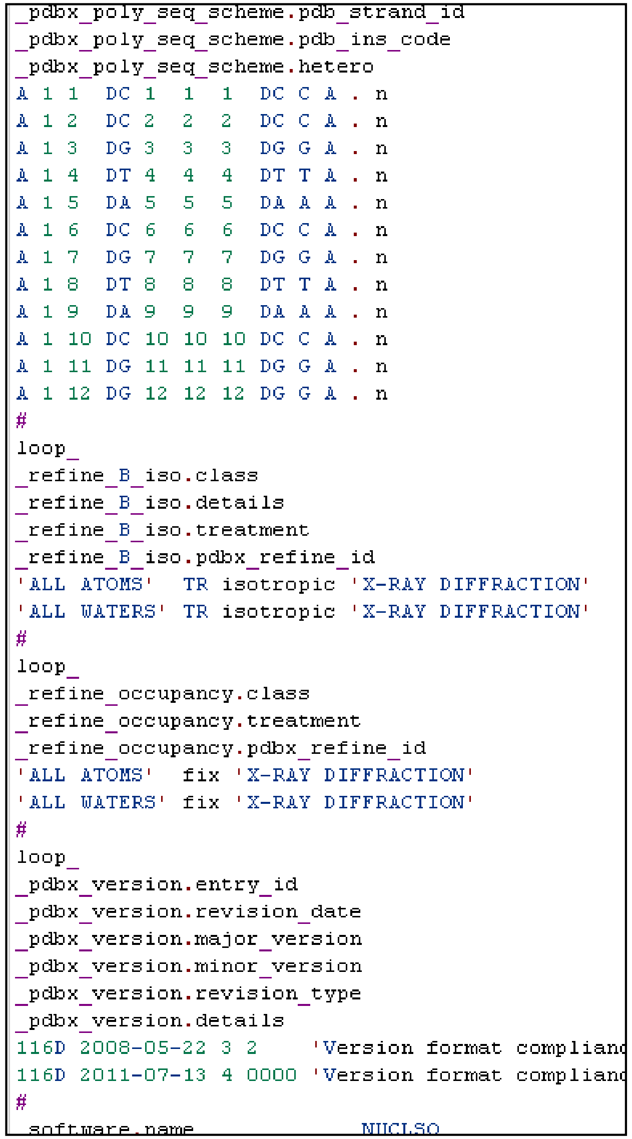
Inclusion Dependencies

- $A \subseteq B$: All values in A are also present in B
- $A_1,\ldots,A_i \subseteq B_1,\ldots,B_i$:
  All value combinations in $A_1,\ldots,A_i$ are also present in $B_1,\ldots,B_i$

- Prerequisite for foreign key
  - Used across relations
  - Use across databases
  - But again: Discovery on a given instance, only user can specify for schema

Motivation for IND Discovery

- General insight into data
- Detect unknown foreign keys
- Example: PDB – Protein Data Bank
  - OpenMMS provides relational schema
  - 175 tables, 2705 attributes
  - Not a single foreign key constraint!
- Example: Ensembl – genome database
  - Shipped as MySQL dump files
  - More than 200 tables
  - Not a single foreign key constraint!
- Web tables: No schema, no constraints, but many connections



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_pdbx_poly_seq_scheme.pdb_ins_code
_pdbx_poly_seq_scheme.hetero
A 1 1  DC 1  1  1  DC C A . n
A 1 2  DC 2  2  2  DC C A . n
A 1 3  DG 3  3  3  DG G A . n
A 1 4  DT 4  4  4  DT T A . n
A 1 5  DA 5  5  5  DA A A . n
A 1 6  DC 6  6  6  DC C A . n
A 1 7  DG 7  7  7  DG G A . n
A 1 8  DT 8  8  8  DT T A . n
A 1 9  DA 9  9  9  DA A A . n
A 1 10 DC 10 10 10 DC C A . n
A 1 11 DG 11 11 11 DG G A . n
A 1 12 DG 12 12 12 DG G A . n
#
loop_
_refine_B_iso.class
_refine_B_iso.details
_refine_B_iso.treatment
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'ALL WATERS' TR isotropic 'X-RAY DIFFRACTION'
#
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_refine_occupancy.treatment
_refine_occupancy.pdbx_refine_id
'ALL ATOMS'  fix 'X-RAY DIFFRACTION'
'ALL WATERS' fix 'X-RAY DIFFRACTION'
#
loop_
_pdbx_version.entry_id
_pdbx_version.revision_date
_pdbx_version.major_version
_pdbx_version.minor_version
_pdbx_version.revision_type
_pdbx_version.details
116D 2008-05-22 3 2    'Version format complianc
116D 2011-07-13 4 0000 'Version format complianc
#
_software.name             NUCLSQ
```

Functional and other dependencies

Functional and Other Dependencies

- Functional dependency
  - „X → A“: whenever two records have the same X values, they also have the same A values.
- Multi-valued dependencies
  - Join dependencies
- Order dependencies

  -
    ```
    SELECT emp_name
    FROM employees
    ORDER BY rank, salary
    ```
    Remove rank

  -
    ```
    SELECT emp_name
    FROM employees
    ORDER BY rank
    ```
    Replace with salary (if index only on salary)

salary orders **rank**

emp_name	rank	salary
Smith	1	40k
Johnson	1	40k
Williams	1	45k
Brown	2	60k
Davis	2	60k
Miller	3	70k
Wilson	4	100k

Uses for FDs

- Schema design
  - Normalization
  - Keys
- Data cleansing
- Schema design and normalization
- Key discovery

- Data cleansing (especially partial/conditional FDs)
- Anomaly detection
  - Data integrity constraints
  - Data curation rules
- Query optimization: Independence of column attributes
- Index selection

… and genealogy research!

Functional Dependencies

Functional Dependencies

Person	Lineage	Hair	Religion
	House Baratheon		New gods
	House Baratheon		New Gods
	House Stark "Winter is Coming"		Old gods
	House Lannister		New gods
	House Baratheon		Old gods

Some Functional Dependencies:

1. Person → Lineage
2. Person → Hair
3. Person → Religion
4. Lineage → Hair
5. Religion, Hair → Lineage
6. …

Ned Stark: „#4 looks like a reasonable quality constraint“

Ned Stark: „I believe Joffrey violates my database constraint.“

Properties of Dependencies

Partial Dependencies

- Aka. “approximate dependencies”
- INDs and FDs that do not perfectly hold
  - For all but 10 of the tuples
  - Only for 80% of the tuples
  - Only for 1% of the tuples

- Also for patterns, types, uniques, and other constraints

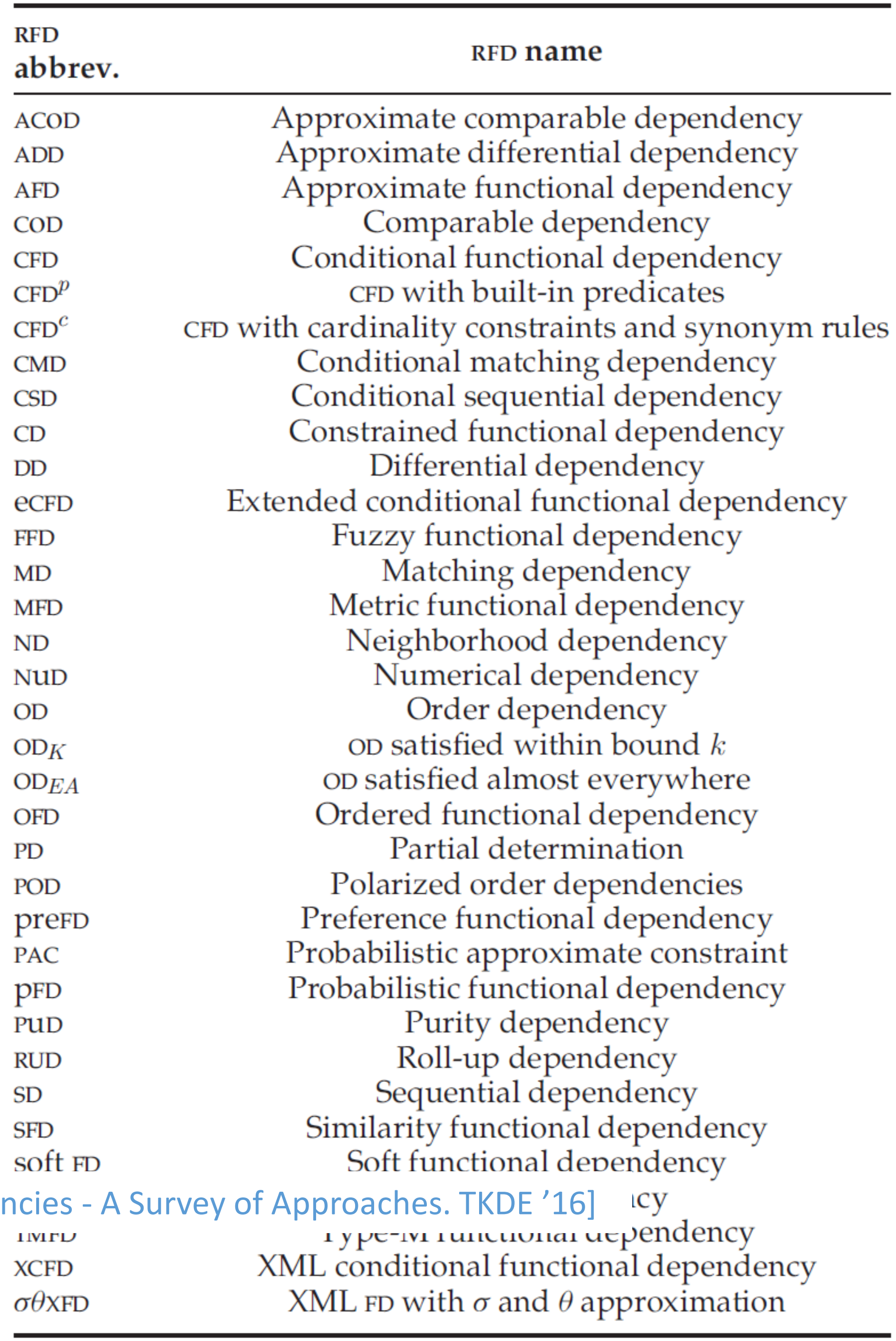
- Useful for: Data cleansing

Conditional Dependencies

- Given a partial IND or FD: For **which** part do the hold?
- Expressed as a condition over the attributes of the relation
- Problems:
  - Infinite possibilities of conditions
  - Interestingness:
    - Many distinct values: less interesting
    - Few distinct values: surprising condition – high coverage
- Useful for Integration
  - Cross-database cINDs

Other (Relaxed) Dependencies

- Partial dependencies
- Approximate dependencies
- Conditional dependencies
- Matching dependencies
- Metric dependencies

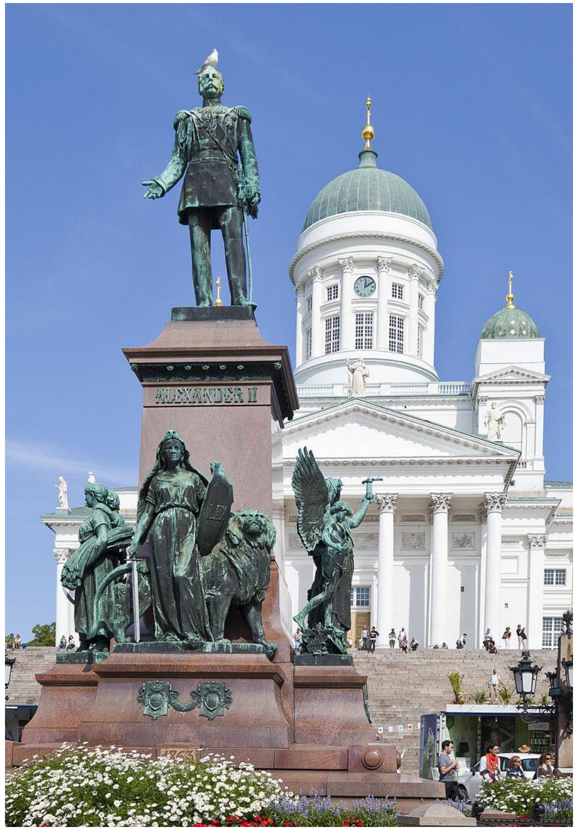


RFD abbrev.	RFD name
ACOD	Approximate comparable dependency
ADD	Approximate differential dependency
AFD	Approximate functional dependency
COD	Comparable dependency
CFD	Conditional functional dependency
CFD^p	CFD with built-in predicates
CFD^c	CFD with cardinality constraints and synonym rules
CMD	Conditional matching dependency
CSD	Conditional sequential dependency
CD	Constrained functional dependency
DD	Differential dependency
eCFD	Extended conditional functional dependency
FFD	Fuzzy functional dependency
MD	Matching dependency
MFD	Metric functional dependency
ND	Neighborhood dependency
NuD	Numerical dependency
OD	Order dependency
OD_K	OD satisfied within bound k
OD_{EA}	OD satisfied almost everywhere
OFD	Ordered functional dependency
PD	Partial determination
POD	Polarized order dependencies
preFD	Preference functional dependency
PAC	Probabilistic approximate constraint
pFD	Probabilistic functional dependency
PuD	Purity dependency
RUD	Roll-up dependency
SD	Sequential dependency
SFD	Similarity functional dependency
soft FD	Soft functional dependency
[illegible]	[illegible]cy
TMFD	Type-M functional dependency
XCFD	XML conditional functional dependency
$\sigma\theta$XFD	XML FD with σ and θ approximation

[Caruccio, Deufemia, Polese: Relaxed Functional Dependencies - A Survey of Approaches. TKDE '16]

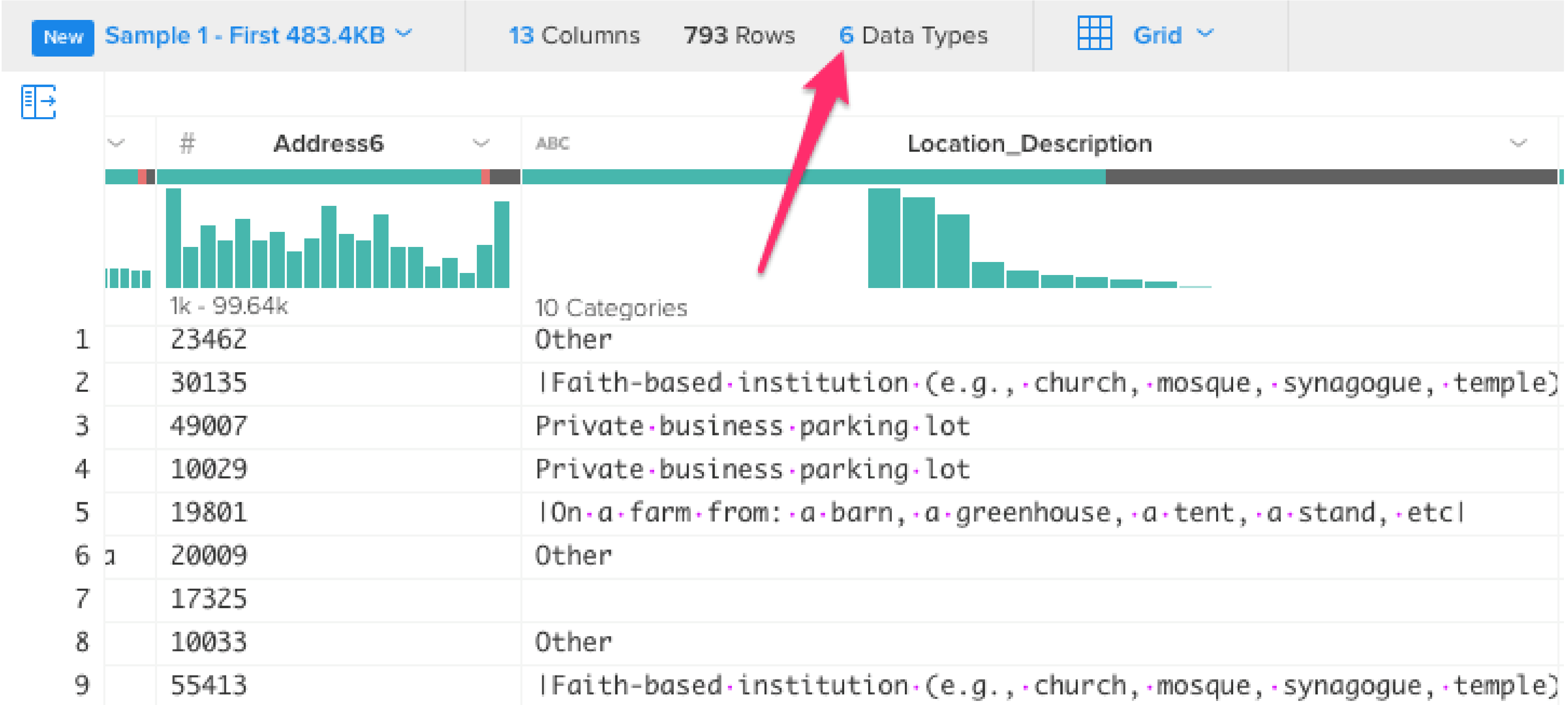
Tutorial Overview

- Motivation
  - Task classification
  - Use cases
- **Tools**
  - **Research and industry**
  - **Shortcomings**
- Single and Multiple Column Analysis
  - Cardinalities and datatypes
  - Co-occurrences and summaries
- Dependencies
  - UCCs, INDs, FDs
  - and their discover algorithms
- Outlook
  - Functionality
  - Semantics



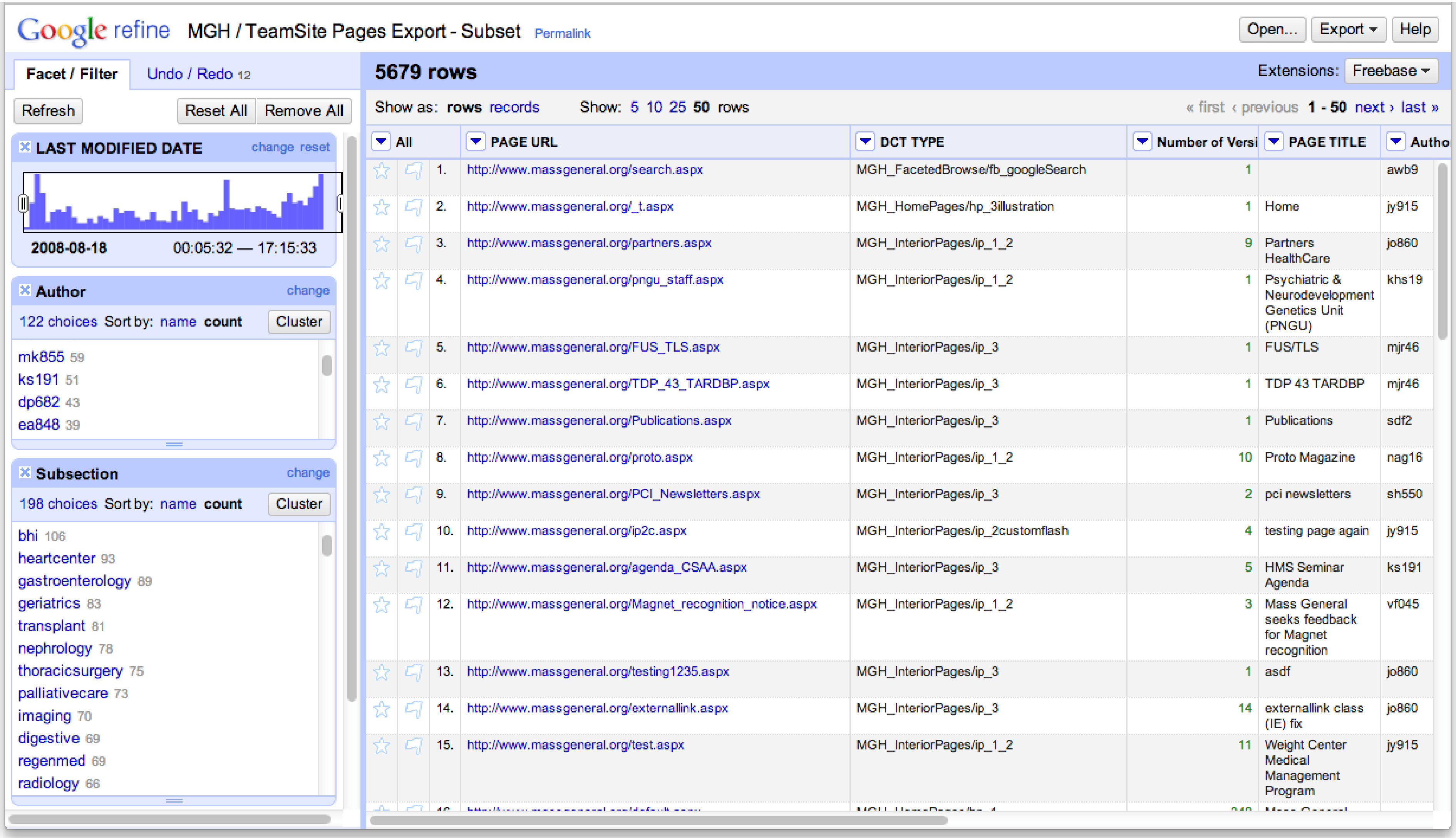
Tools in Industry

Trifacta



		Address6	Location_Description
1		23462	Other
2		30135	|Faith-based·institution·(e.g.,·church,·mosque,·synagogue,·temple)
3		49007	Private·business·parking·lot
4		10029	Private·business·parking·lot
5		19801	|On·a·farm·from:·a·barn,·a·greenhouse,·a·tent,·a·stand,·etc|
6	a	20009	Other
7		17325	
8		10033	Other
9		55413	|Faith-based·institution·(e.g.,·church,·mosque,·synagogue,·temple)

Open Refine



Google refine MGH / TeamSite Pages Export - Subset Permalink

Open... Export ▾ Help

Facet / Filter | Undo / Redo 12

Refresh | Reset All | Remove All

LAST MODIFIED DATE change reset

2008-08-18 00:05:32 — 17:15:33

Author change

122 choices Sort by: name count Cluster

mk855	59
ks191	51
dp682	43
ea848	39

Subsection change

198 choices Sort by: name count Cluster

bhi	106
heartcenter	93
gastroenterology	89
geriatrics	83
transplant	81
nephrology	78
thoracicsurgery	75
palliativecare	73
imaging	70
digestive	69
regenmed	69
radiology	66

5679 rows

Extensions: Freebase ▾

Show as: rows records Show: 5 10 25 50 rows

« first ‹ previous 1 - 50 next › last »

All	PAGE URL	DCT TYPE	Number of Versi	PAGE TITLE	Autho
1.	http://www.massgeneral.org/search.aspx	MGH_FacetedBrowse/fb_googleSearch	1		awb9
2.	http://www.massgeneral.org/_t.aspx	MGH_HomePages/hp_3illustration	1	Home	jy915
3.	http://www.massgeneral.org/partners.aspx	MGH_InteriorPages/ip_1_2	9	Partners HealthCare	jo860
4.	http://www.massgeneral.org/pngu_staff.aspx	MGH_InteriorPages/ip_1_2	1	Psychiatric & Neurodevelopment Genetics Unit (PNGU)	khs19
5.	http://www.massgeneral.org/FUS_TLS.aspx	MGH_InteriorPages/ip_3	1	FUS/TLS	mjr46
6.	http://www.massgeneral.org/TDP_43_TARDBP.aspx	MGH_InteriorPages/ip_3	1	TDP 43 TARDBP	mjr46
7.	http://www.massgeneral.org/Publications.aspx	MGH_InteriorPages/ip_3	1	Publications	sdf2
8.	http://www.massgeneral.org/proto.aspx	MGH_InteriorPages/ip_1_2	10	Proto Magazine	nag16
9.	http://www.massgeneral.org/PCI_Newsletters.aspx	MGH_InteriorPages/ip_3	2	pci newsletters	sh550
10.	http://www.massgeneral.org/ip2c.aspx	MGH_InteriorPages/ip_2customflash	4	testing page again	jy915
11.	http://www.massgeneral.org/agenda_CSAA.aspx	MGH_InteriorPages/ip_3	5	HMS Seminar Agenda	ks191
12.	http://www.massgeneral.org/Magnet_recognition_notice.aspx	MGH_InteriorPages/ip_1_2	3	Mass General seeks feedback for Magnet recognition	vf045
13.	http://www.massgeneral.org/testing1235.aspx	MGH_InteriorPages/ip_3	1	asdf	jo860
14.	http://www.massgeneral.org/externallink.aspx	MGH_InteriorPages/ip_3	14	externallink class (IE) fix	jo860
15.	http://www.massgeneral.org/test.aspx	MGH_InteriorPages/ip_1_2	11	Weight Center Medical Management Program	jy915

Uses Cases Covered By Industrial Tools

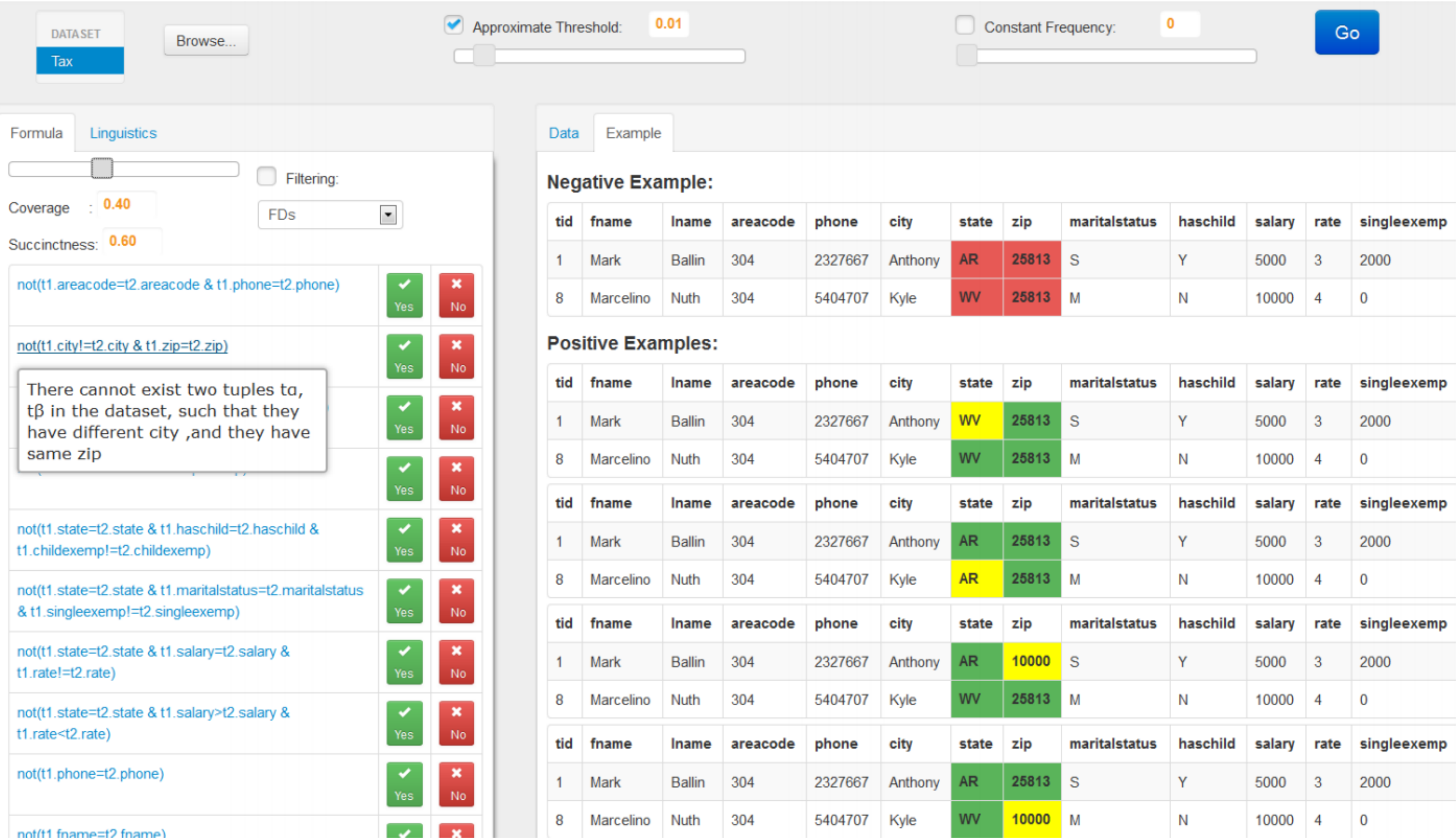
Restricted data types

Restricted number of columns

Tool	Statistics	Patterns	Data types	Uniques	C n c de r	D c de r
Attacama, DQ Analyzer	✓	✓		✓		
IBM, InfoSphere Information Analyzer	✓	✓		✓	✓	
Microsoft SQL Server Data Profiling Task	✓	✓			✓	
Oracle Enterprise Data Quality	✓	✓				
Paxata Adaptive Preparation	✓					
SAP Information Steward	✓	✓	✓		✓	
Splunk Enterprise/Hunk		✓				✓
Talend Data Profiler	✓	✓			✓	
Trifacta	✓	✓	✓			
Tamr	✓			✓		
OpenRefine	✓	✓	✓			

Tools in Research

RuleMiner



☑ Approximate Threshold: 0.01

□ Constant Frequency: 0

Coverage : 0.40

Succinctness: 0.60

□ Filtering: FDs

- not(t1.areacode=t2.areacode & t1.phone=t2.phone) ✓ Yes ✖ No
- not(t1.city!=t2.city & t1.zip=t2.zip) ✓ Yes ✖ No
- ✓ Yes ✖ No
- ✓ Yes ✖ No
- not(t1.state=t2.state & t1.haschild=t2.haschild & t1.childexemp!=t2.childexemp) ✓ Yes ✖ No
- not(t1.state=t2.state & t1.maritalstatus=t2.maritalstatus & t1.singleexemp!=t2.singleexemp) ✓ Yes ✖ No
- not(t1.state=t2.state & t1.salary=t2.salary & t1.rate!=t2.rate) ✓ Yes ✖ No
- not(t1.state=t2.state & t1.salary>t2.salary & t1.rate<t2.rate) ✓ Yes ✖ No
- not(t1.phone=t2.phone) ✓ Yes ✖ No
- not(t1.fname=t2.fname) ✓ ✖

There cannot exist two tuples tα, tβ in the dataset, such that they have different city ,and they have same zip

Negative Example:

tid	fname	lname	areacode	phone	city	state	zip	maritalstatus	haschild	salary	rate	singleexemp
1	Mark	Ballin	304	2327667	Anthony	AR	25813	S	Y	5000	3	2000
8	Marcelino	Nuth	304	5404707	Kyle	WV	25813	M	N	10000	4	0

Positive Examples:

tid	fname	lname	areacode	phone	city	state	zip	maritalstatus	haschild	salary	rate	singleexemp
1	Mark	Ballin	304	2327667	Anthony	WV	25813	S	Y	5000	3	2000
8	Marcelino	Nuth	304	5404707	Kyle	WV	25813	M	N	10000	4	0

tid	fname	lname	areacode	phone	city	state	zip	maritalstatus	haschild	salary	rate	singleexemp
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tid	fname	lname	areacode	phone	city	state	zip	maritalstatus	haschild	salary	rate	singleexemp
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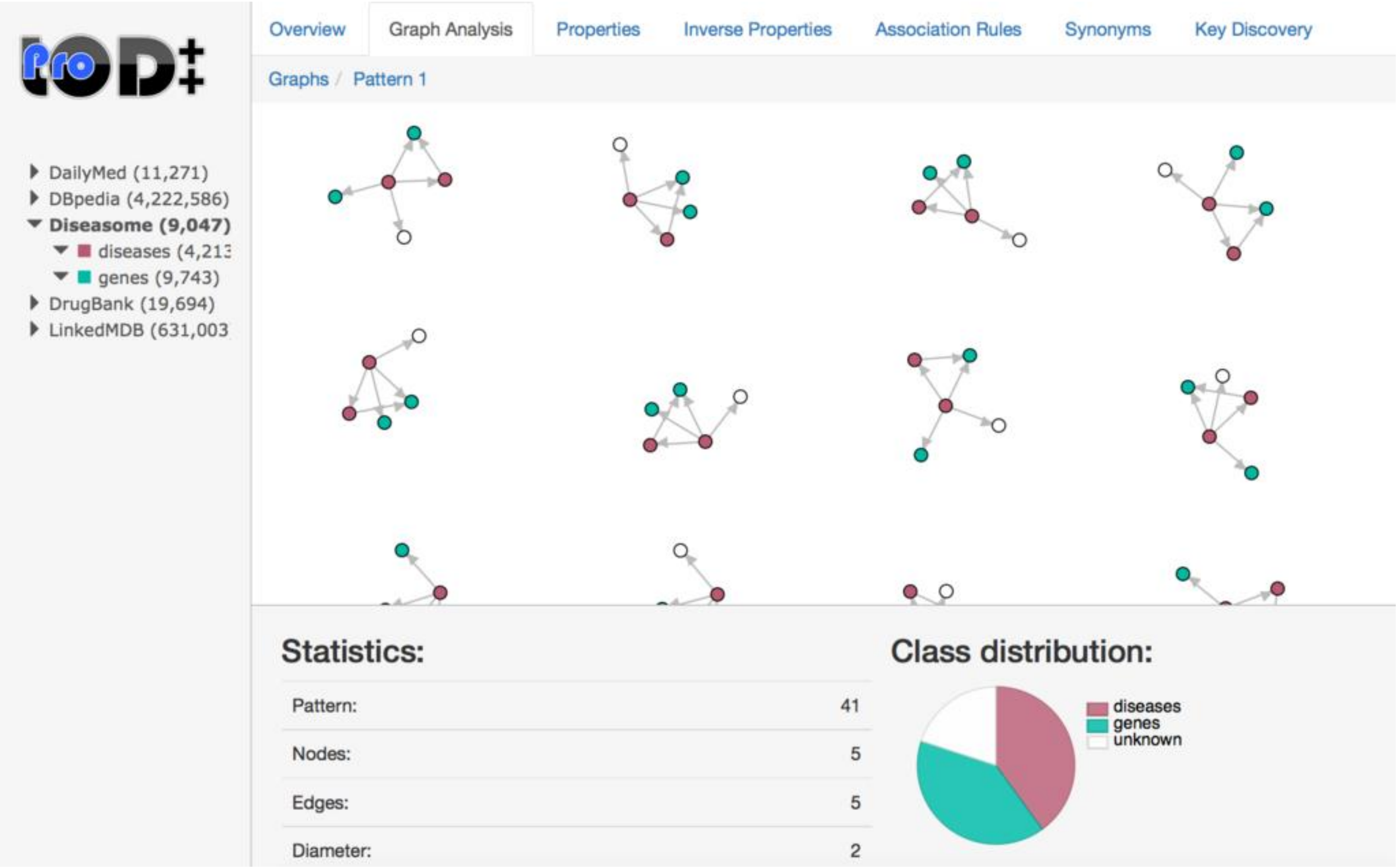
tid	fname	lname	areacode	phone	city	state	zip	maritalstatus	haschild	salary	rate	singleexemp
1	Mark	Ballin	304	2327667	Anthony	AR	25813	S	Y	5000	3	2000
8	Marcelino	Nuth	304	5404707	Kyle	WV	10000	M	N	10000	4	0

ProLOD++



Statistics:

Pattern:	41
Nodes:	5
Edges:	5
Diameter:	2

Tools in Research

Tool	Main purpose	Statistics	Patterns	Data types	Uniques	Dependencies	Data Mining
Bellmann	Data quality browser	✓			✓		
Potter’s Wheel	ETL tool	✓	✓				
Data Auditor	Rule discovery						
RuleMiner	Dependency discovery					✓	
MADLib	Machine learning	✓				✓	
Metanome	Data profiling	✓			✓		
ProLOD++	Profiling and Mining	✓	✓		✓	✓	✓

Shortcomings

- No “real” profiling tool
- Tools focus on “easy” problems:
  - Statistics
  - Single column or “few” column dependencies
  - Many industry tools use SQL instead of optimized algorithms
- No tool covers all types of meta-data
- Management of large meta-data results
  - Summarizing meta-data
  - Ranking meta-data based on relevance

Tutorial Overview

- Motivation
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  - **Co-occurrences and summaries**
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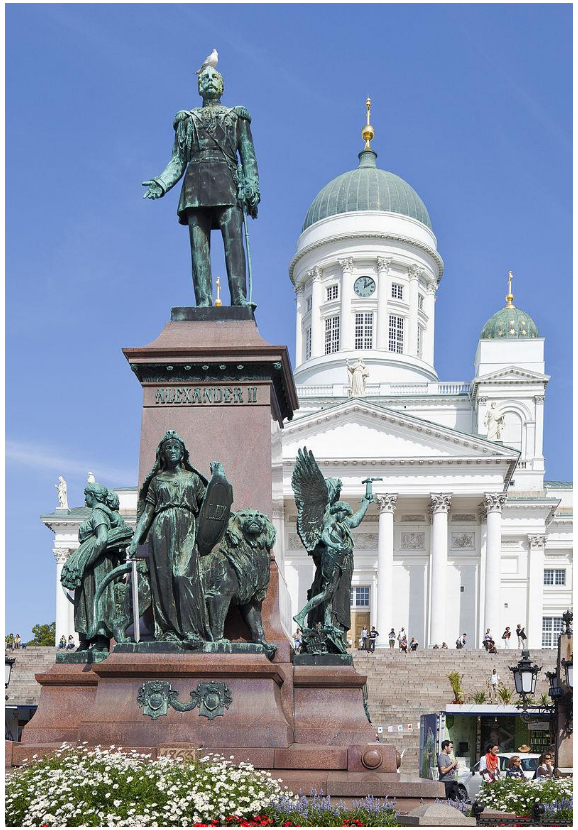


Single Column Analysis

Cardinalities and distributions

- Number of values
- Number of distinct values
- Number of NULLs

Count(*)
count(distinct X),
count (X) where X=null

- MIN and MAX value

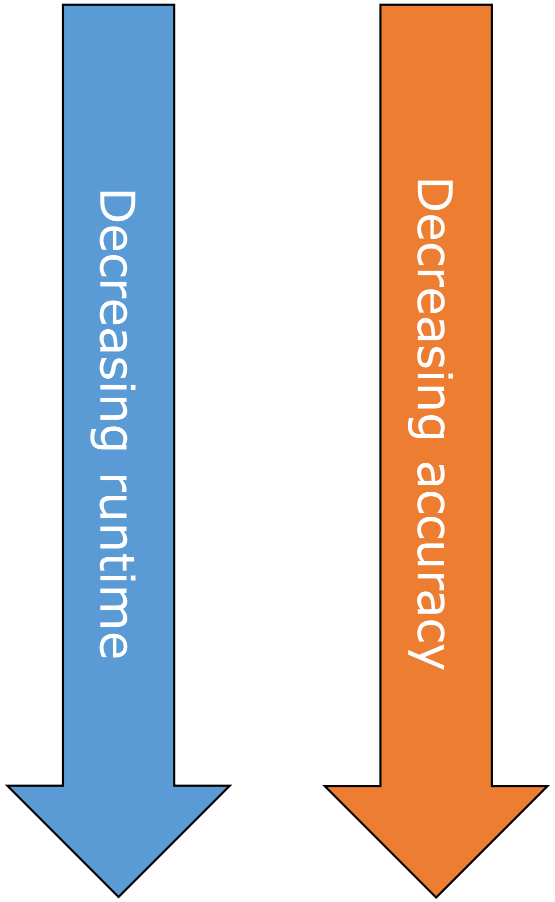
```
For (value in column)
If (value>max)
max=value
```

- Histograms
- Probability distribution for numeric values
- Detect whether data follows some well-known distribution

Bottleneck is sorting the data

Count distinct in sublinear time and space?

- Linear Counting
  - [Whang, Vander-Zanden, Taylor: A linear-time probabilistic counting algorithm for database applications. TODS, 1990]
- Stochastic Averaging
  - [Flajolet, Martin: Probabilistic counting algorithms for data base applications. JCSS, 1985]
- Loglog Algorithm
  - [Durand, Flajolet: Loglog counting of large cardinalities. Algorithms-ESA, 2003]
- SuperLogLog Algorithm
  - [Durand, Flajolet: Loglog counting of large cardinalities. Algorithms-ESA, 2003]
- HyperLogLog Algorithm
  - [Flajolet, Fusy, Gandouet, Meunier: Hyperloglog: the analysis of a near-optimal cardinality estimation algorithm. DMTCS, 2008]

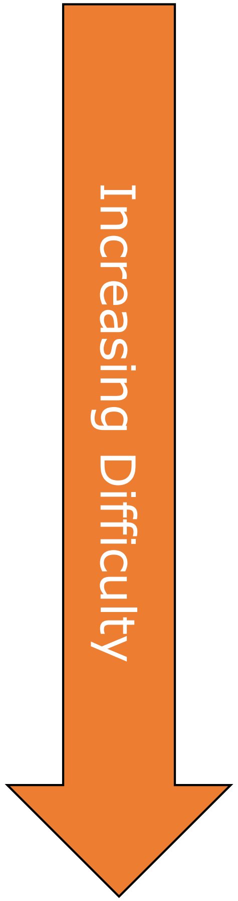


Decreasing runtime

Decreasing accuracy

Data types and value patterns

- String vs. number
- String vs. number vs. date
- Categorical vs. continuous
  - Days of the week vs. measurements
- SQL data types
  - CHAR, INT, DECIMAL, TIMESTAMP, BIT, CLOB, …
- Domains
  - VARCHAR(12) vs. VARCHAR (13)
- XML data types
  - More fine grained
- Regular expressions (\d{3})-(\d{3})-(\d{4})-(\d+)
- Semantic domains
  - Adress, phone, email, first name



Increasing Difficulty

Multi Column Analysis

Frequencies, Rules, Correlations

- Frequencies:
  - Which values co-occur with each other?

- Rules:
  - Which values depend on a specific value?

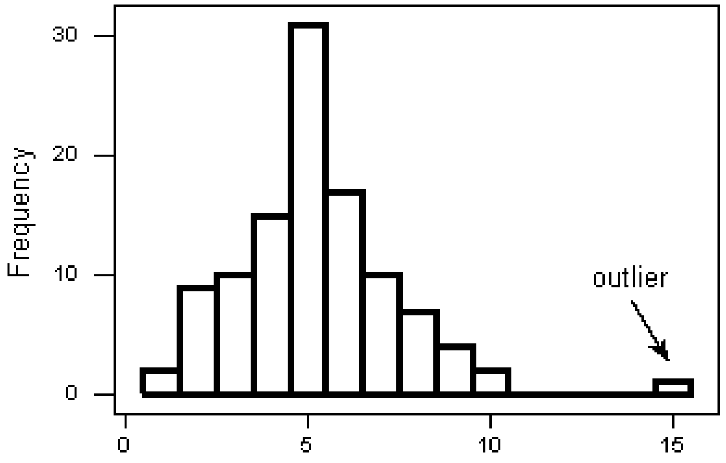
- Correlations:
  - Which values correlate?
  - Which values substitute each other?

Core step: Frequent Itemset Mining

- Origin: Transactional Analysis
  - Which products have been bought together?
- Main step:
  - Find frequencies for all item combinations
- Optimization:
  - Find frequencies for all relevant item combinations, i.e., item combinations with minimum support
- Algorithms:
  - Apriori [Aggrawal, Srikant: fast Algorithms for Mining Association rules, VLDB’94]
  - FP-Growth [Han, Pei, Yin: Mining frequent patterns without candidate generation, SIGMOD’00]
  - ..
  - Survey: [Hipp, Guentzer, Nakhaeizadeh: Algorithms for Association Mining – A General Survey and Comparison, KDD’00]

Outlier detection

- Low-frequent values
- Structural outliers
  - Wrong value representations, e.g.:
    - CA instead of California
- Numerical outliers
  - E.g., according to Gaussian distribution
- Outlier combinations
  - Co-occurrence analysis



- Survey: [Hodge, Austin: A survey of outlier detection methodologies, AI'04]

Sketches and Summaries

- Use cases:
  - Assess column similarity
  - Dimension reduction
  - Data stream samples
- Techniques:
  - Sampling
  - Hashing:
    - Minhash [Broder: Compression and Complexity of Sequences, 1997]
    - LSH [Gionis, Indyk, Motwani: Similarity search in high Dimensions via hashing, VLDB’99]
  - Sketches [Cormode, Garofalakis, Haas, Jermaine: Synopses for Massive Data:Samples, Histograms, Wavelets, Sketches, FTD’12]

Column Similarity: Jaccard(C1,C2) = intersect(C1,C2)/Union(C1,C2)

- N^2 pairwise comparisons
- Reduce dimension through Minhash:
  - Find a hash function ***h(·)*** such that:
    - If ***sim(C$_1$,C$_2$)*** is high, then with high prob. ***h(C$_1$) = h(C$_2$)***
    - If ***sim(C$_1$,C$_2$)*** is low, then with high prob. ***h(C$_1$) ≠ h(C$_2$)***
    - Estimate similarity by applying ***k*** different ***h$_i$(·)***
  - Transform table into a Boolean matrix

Residence (A)	Country (B)	Birthplace (C)
Helsinki	Finland	Oslo
Oslo	Germany	Copenhagen
Berlin	Denmark	Helsinki

Values	A	B	C
Helsinki	1	0	1
Oslo	1	0	1
Berlin	1	0	0
Finland	0	1	0
Germany	0	1	0
Denmark	0	1	0
Copenhagen	0	0	1

Minhash Example

- Simulate hash through permutation of row numbers
- Pick smallest row number where matrix value equals 1

Values	**A**	**B**	**C**
Helsinki	1	0	1
Oslo	1	0	1
Berlin	1	0	0
Finland	0	1	0
Germany	0	1	0
Denmark	0	1	0
Copenhagen	0	0	1

h1	h2	h3
1	7	5
2	4	6
3	1	7
4	5	2
5	3	3
6	6	4
7	2	1

Hash	**A**	**B**	**C**
h1	1	4	1
h2	1	3	2
h3	5	2	1

sim(A,B)= 0

sim(A,C)= 0.33

sim(B,C)= 0

Single & Multi-Column Analysis

- Cardinalities
- Data types
- Patterns
- Co-occurrences
- Sketches, summaries
- ….
- Strong overlap with data mining
- Most of them:
  - Not very complex but approximations needed on big data

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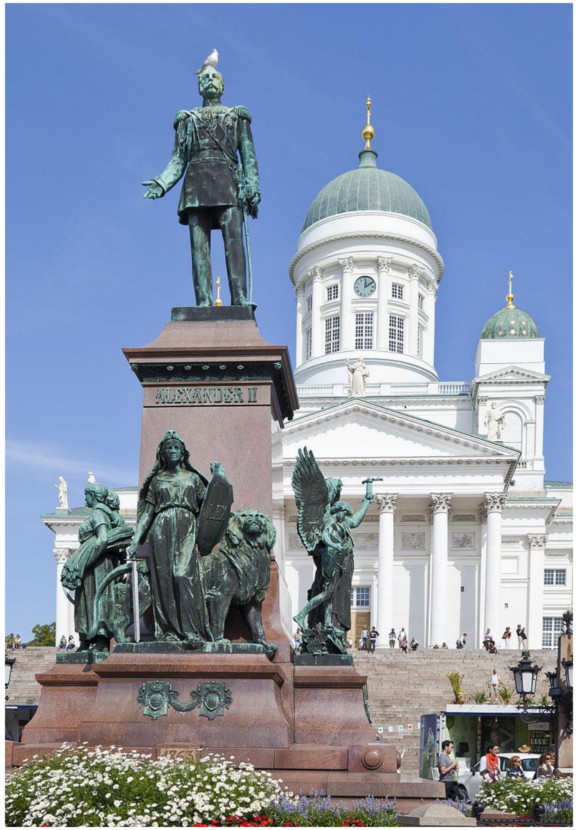

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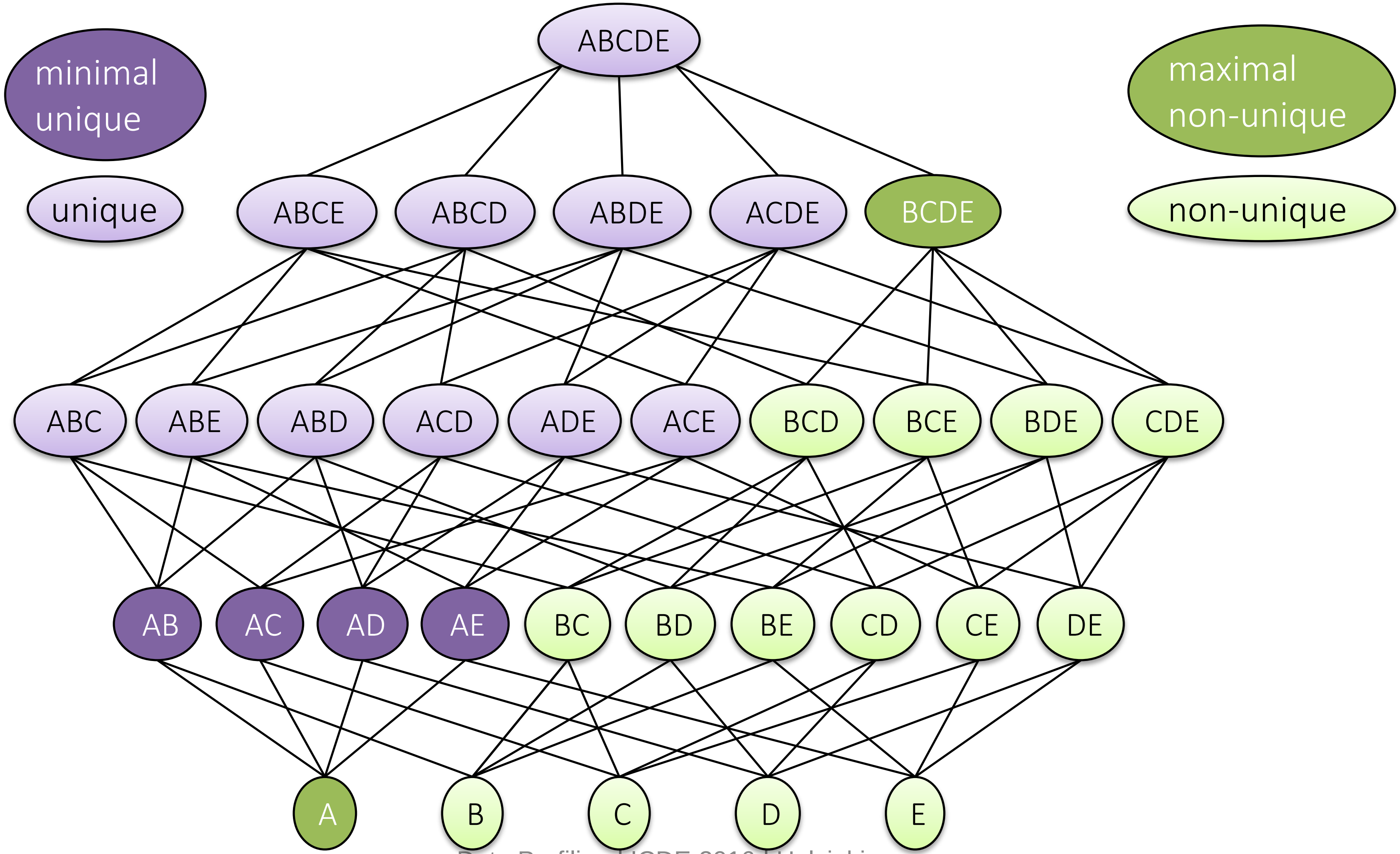
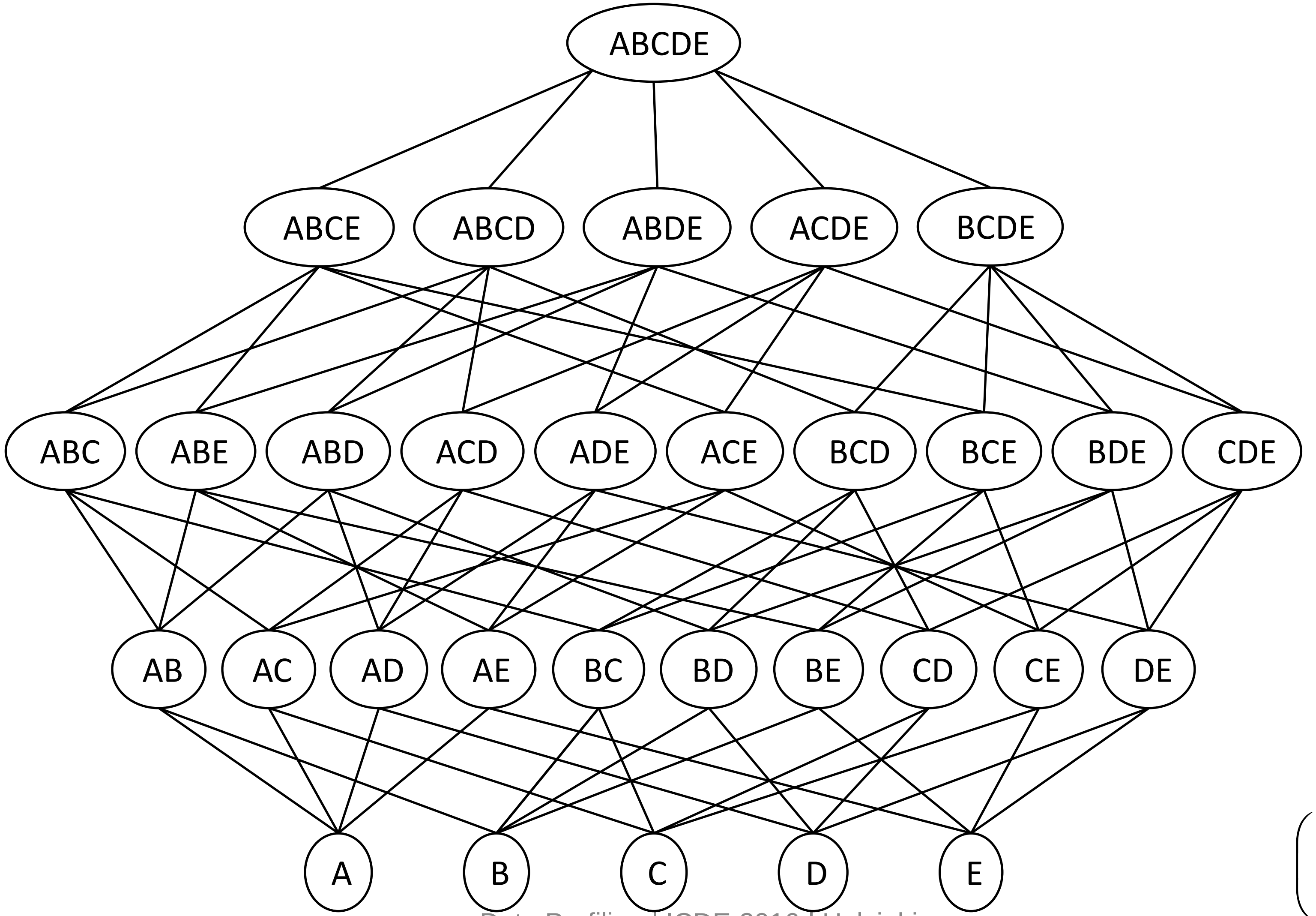
UNIQUE

JUST BECAUSE YOU ARE UNIQUE DOES NOT MEAN YOU ARE USEFUL

Result of algorithm



Challenge: Exponential search space



$$\binom{5}{5} = 1$$

$$\binom{5}{4} = 5$$

$$\binom{5}{3} = \frac{5 \cdot 4}{2}$$

$$\binom{5}{2} = \frac{5 \cdot 4 \cdot 3}{2 \cdot 3}$$

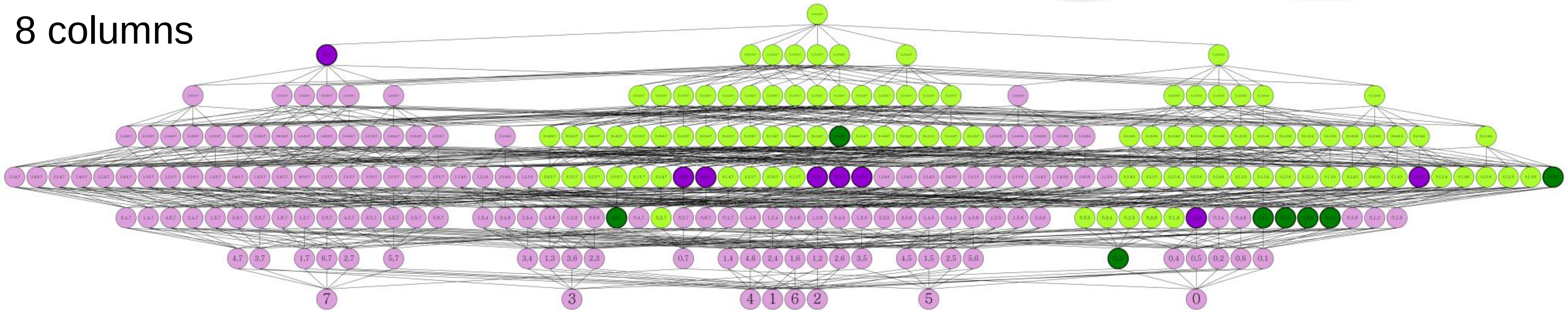
$$\binom{5}{1} = \frac{5 \cdot 4 \cdot 3 \cdot 2}{2 \cdot 3 \cdot 4}$$

TPCH line item

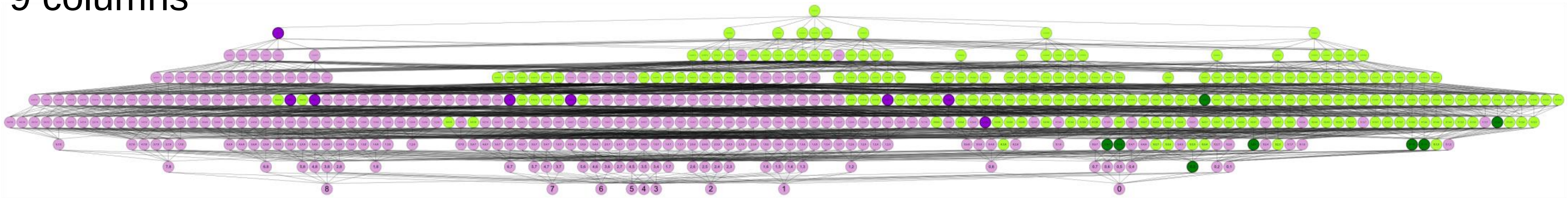
unique

non-unique

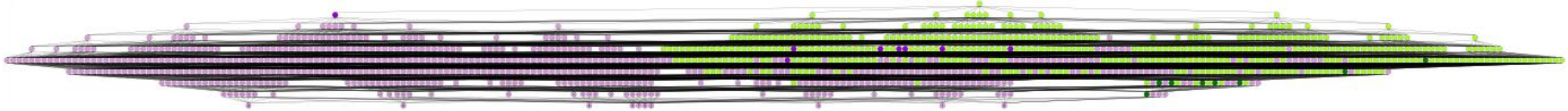
8 columns



9 columns



10 columns



Computational feasibility

- For a lattice over n columns
  - $\binom{n}{k}$ combinations of size k
  - All combinations: 2^n-1 (let's ignore -1 for the remaining slides)
  - Largest solution set: $\binom{n}{n/2}$ minimal uniques are of size $\frac{n}{2}$

$$\binom{n}{k} \in \Theta(n^k) \Rightarrow \binom{n}{n/2} \in \Theta(n^n)$$

    - Verifying minimality, requires to check also all combinations of size $\frac{n}{2} - 1$

  - Adding a column doubles search space (and vice versa)

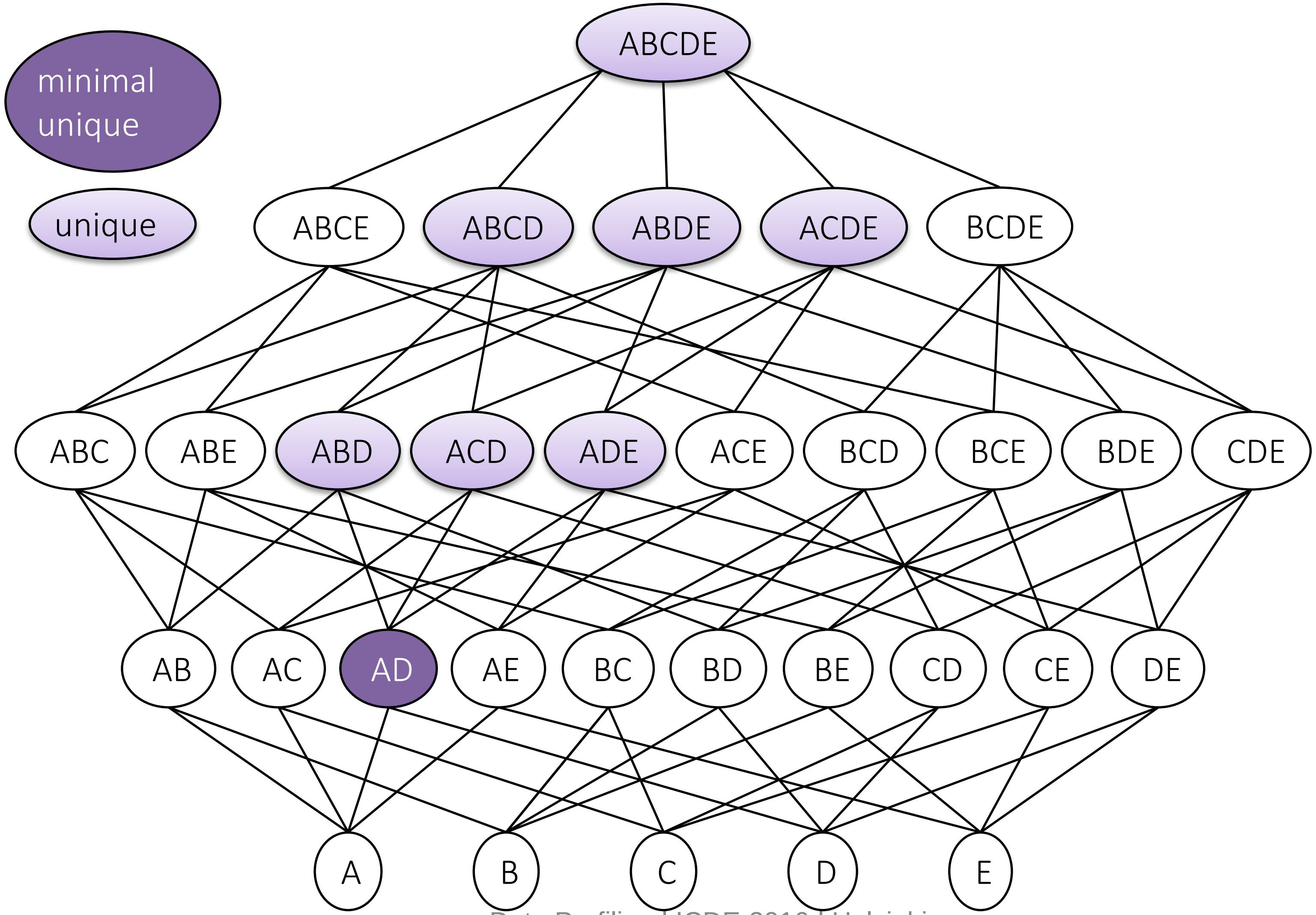
Pruning with uniques #2

- Pruning: inferring the type of a combination without actual verification

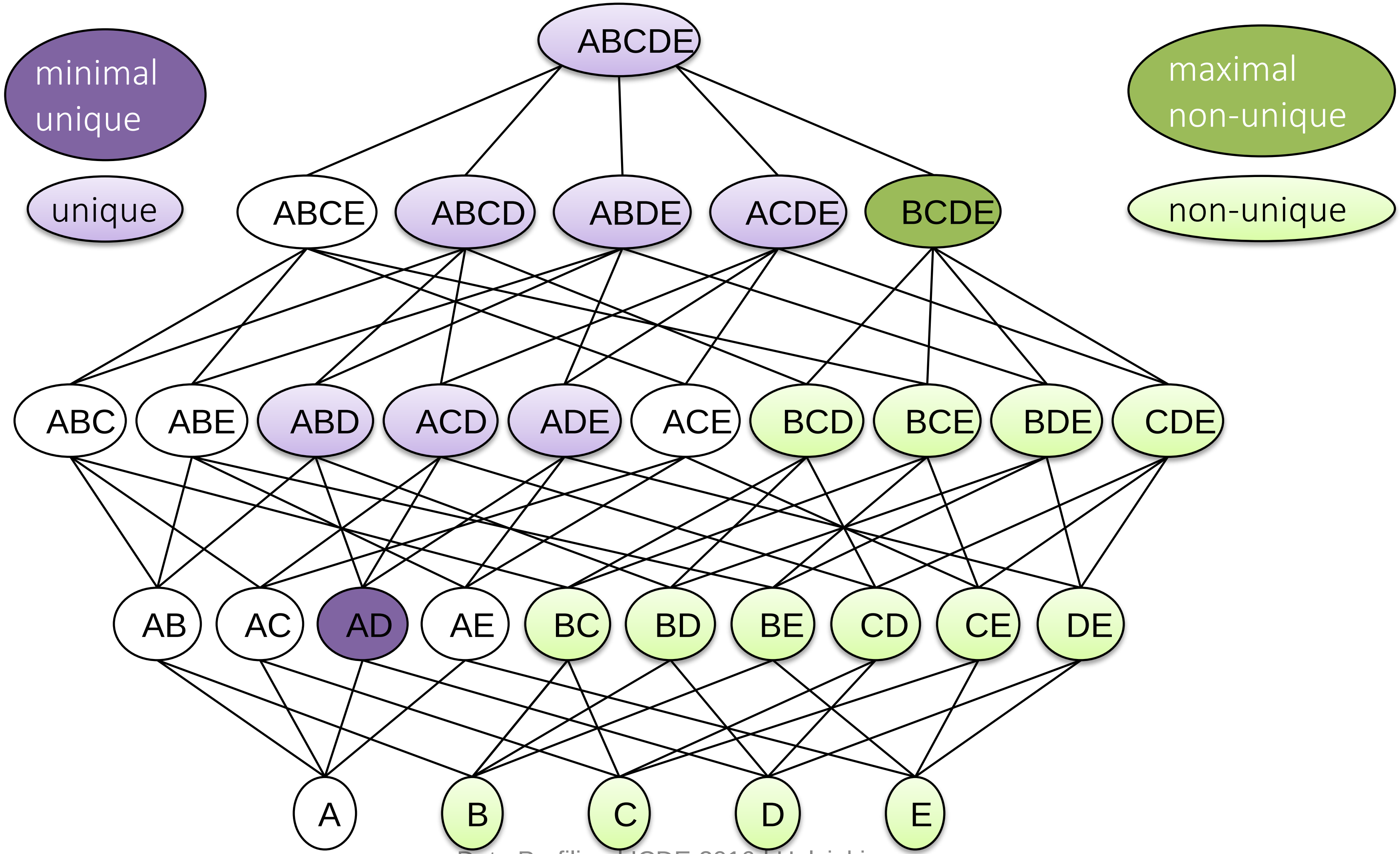
- If A is unique, supersets must be unique
- Finding a unique column prunes half of the lattice
    - Remove column from initial data set and restart
- Finding a unique column pair removes a quarter of the lattice
    - In general, the lattice over the combination is removed

- The pruning power of a combination is reduced by prior findings
    - AB prunes a quarter
    - BC additionally prunes only one eighth
    - ABC was already pruned by AB and constitutes already one eighth

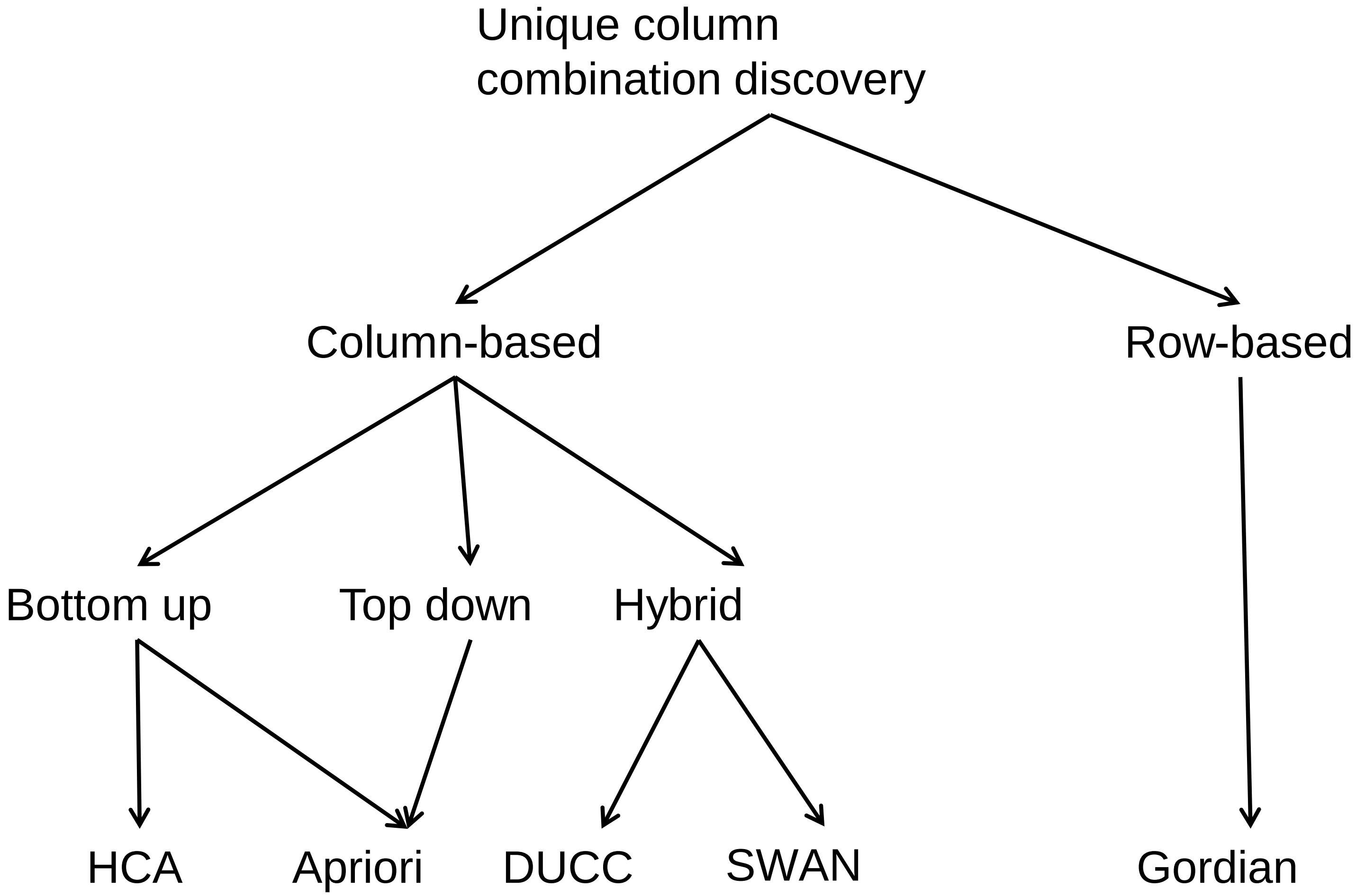
Pruning effect of a pair



Pruning both ways



Discovery Algorithms


Unique column combination discovery

Column-based

Row-based

Bottom up

Top down

Hybrid

HCA

Apriori

DUCC

SWAN

Gordian

Column-based algorithms

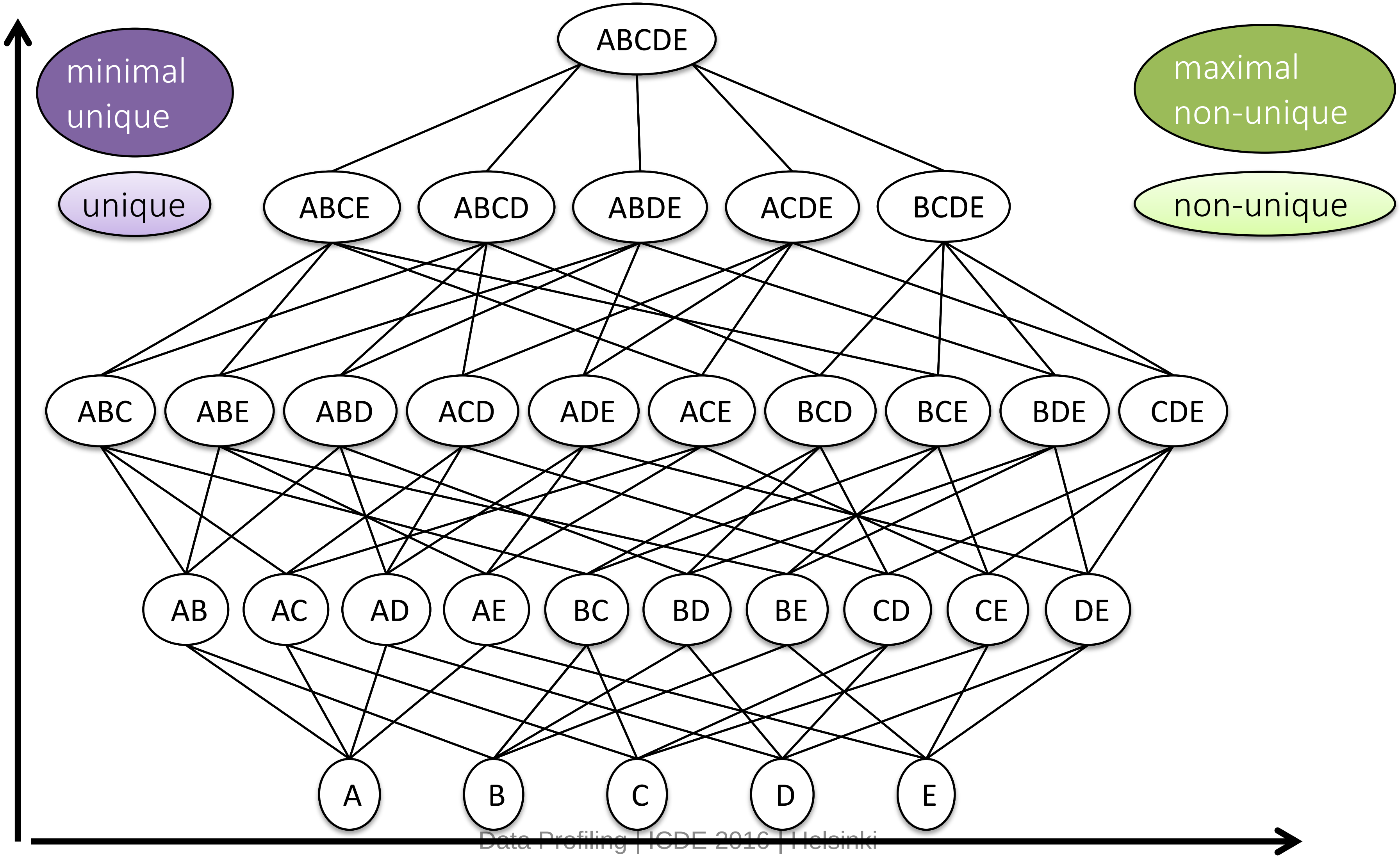
- Traverse through lattice
- Check for uniqueness
  - Different approaches possible
  - Use database backend and distinctness query
    - SELECT COUNT(DISTINCT A, B, C) FROM R
    - Compare with row-count
  - Position list indexes (explained later)
  - For now, check is blackbox
- Prune lattice accordingly

Apriori-based

[Giannella, Wyss: Finding minimal keys in a relation instance. (1999)]

- Basic idea:
  - Using the state of combinations of size k
  - We need to visit only unpruned combinations of size k+1
  - Add non-unique columns to combination of size k
- Start with individual columns
- Check pairs of non-unique columns
- Check triples of non-unique pairs …
- Terminate if no new combinations can be enumerated

Apriori visualized



Characteristics of Apriori

- Works well for small uniques
  - Bottom-up checks columns first
- Best case: all columns are unique
  - n checks
- Worst case: no uniques = one duplicate row
  - 2^n checks
- Apriori is exponential in n

Extensions

- Top-down
  - Start from top and go down
  - Performs better if solution set is high up
  - Candidate pruning becomes more tricky
- Hybrid[Giannella, Wyss: Finding minimal keys in a relation instance. (1999)]
  - Combine bottom-up and top-down
  - Interleave checks
  - Works well if solution set has many small and large combinations
  - Worst case: solution set in the middle
- Statistics-based extensions [Abedjan, Naumann: Advancing the discovery of unique column combinations, *CIKM*'11]
  - More sophisticated candidate generation
  - Uses histograms for pruning
  - Finds and uses functional dependencies on-the-fly

DUCC

[Heise, Quiané-Ruiz, Abedjan, Jentzsch, Naumann: Scalable Discovery of Unique Column Combinations, PVLDB'14]

- Scalability is major design goal of DUCC
    - Random walk well suited for parallelization
        - Few coordination overhead
    - Threads/worker share findings through event bus
        - Uniques/non-uniques
        - Holes in graph
    - Lock-free to avoid bottlenecks
        - Only memory barrier in local event bus
- Basic idea: random walk through lattice
    - Pick random superset if current combination is non-unique
    - Pick random subset otherwise

ACD and BCD are minimal uniques

Visited nodes: 10 out of 26

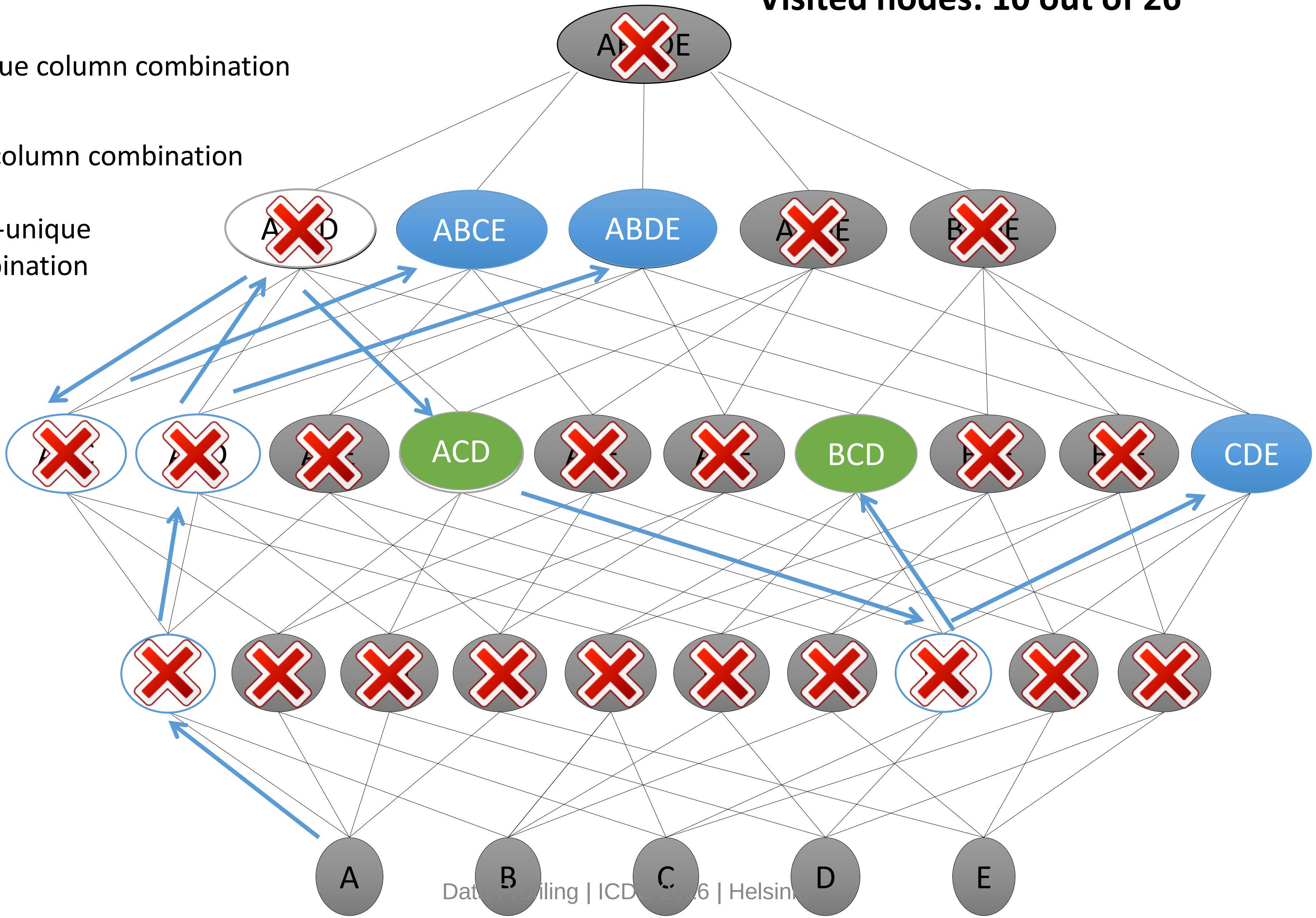
○ Unique column combination

● Minimal unique column combination

○ Non-unique column combination

● Maximal non-unique column combination

✗ Pruned



Position List Index

- Aka “partitions”
- Incorporates row-based pruning
- Intuition: number of duplicates decrease when going up the lattice
  - Many unnecessary rows are checked again and again

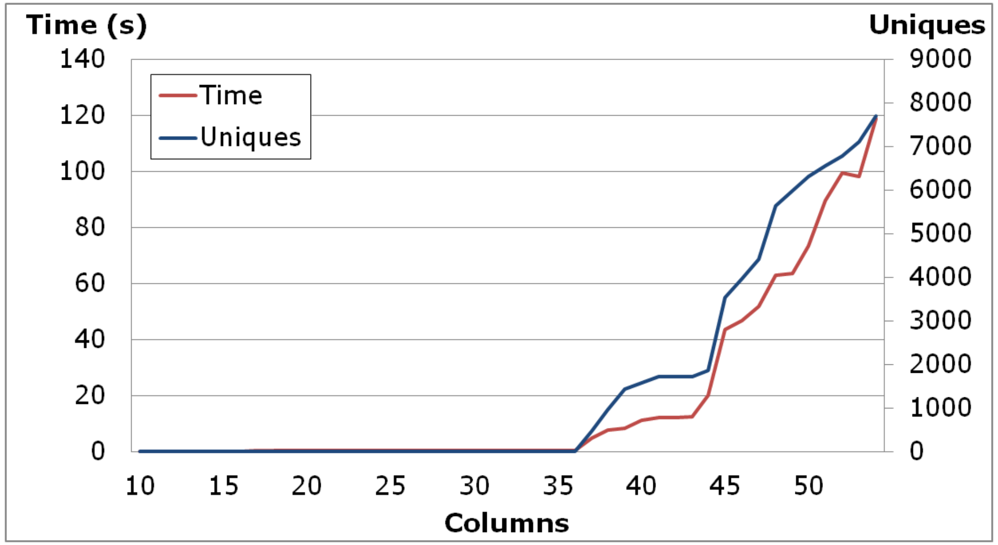
- Keep track of duplicates with inverted index
  - X: a->{r_1, r_2, r_3}, b->{r_4, r_5}
  - Y: 1->{r_1, r_3}, 2->{r_2, r_5}, 3->{r_4}

- Stripped partitions:
  - Remove clusters of size 1:
  - X: {{r_1, r_2, r_3}, {r_4, r_5}}
  - Y: {{r_1, r_3}, {r_2, r_5}}

X	Y
a	1
a	2
a	1
b	3
b	2

Analysis of DUCC

- Runtime mainly depends on size of solution set



- Worst case: Solution set is in the middle: $\binom{n}{n/2}$
- Aggressive pruning may lead to loss of minimal uniques!
  - Gordian’s final step can be used to plug these holes

Gordian

[Sismanis, Brown, Haas, Reinwald: GORDIAN: efficient and scalable discovery of composite keys, *VLDB'06*]

- Row-based algorithm
- Builds prefix tree while reading data
    - Discover maximal non-uniques on prefix tree
- Compute minimal uniques from maximal non-uniques
    - Complementation

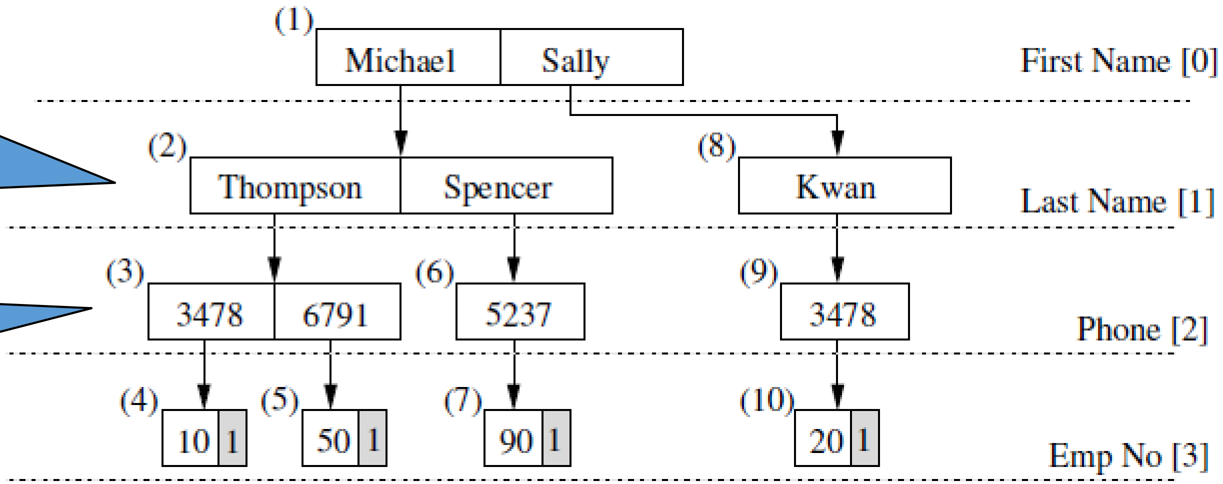
Prefix tree

FirstName	*LastName*	*Phone*	*EmpNo*	*COUNT*
Michael	Thompson	3478	10	1
Sally	Kwan	3478	20	1
Michael	Spencer	5237	90	1
Michael	Thompson	6791	50	1

One tree per attribute order

3 nodes, thus max. non-unique

4 nodes, thus unique



Analysis Gordian

- According to paper, polynomial in the number of tuples for data with a Zipfian distribution of values
  - Can abort scan as soon as duplicate has been found

- Worst case
  - Exponential in the number of columns
  - All data needs to be stored in memory

- Computing minimal uniques from maximal non-uniques
  - O(non-uniques^3 x columns)
  - Can be sped up with presorted list

Uniques on Dynamic Data: SWAN

[Abedjan, Quanie-Ruiz, Naumann: Detecting Unique Column Combinations on Dynamic Data, ICDE'14]

- **Inserts** may create new duplicate combinations
  - Minimal uniques might become non-unique
  - Maximal non-uniques might lose maximality
- **Deletes** remove duplicate value combinations
  - Non-uniques might get unique
  - Minimal uniques might lose minimality
- SWAN
  - Leverage the knowledge of previously discovered minimal uniques and maximal non-uniques
  - Create appropriate indices

Functional Dependencies

Trivial and minimal FDs

- „X → A“ is a statement about a relation R: When two tuples have same value in attribute set X, the must have same values in attribute A.
- Non-trivial: At least one attribute on RHS does not appear on LHS
  - Street, City → Zip, City
- Completely non-trivial: Attributes on LHS and RHS are disjoint.
  - Street, City → Zip
- Minimal FD: RHS does not depend on any subset of LHS
- Typical goal: Given a relation R, find all minimal completely non-trivial functional dependencies.

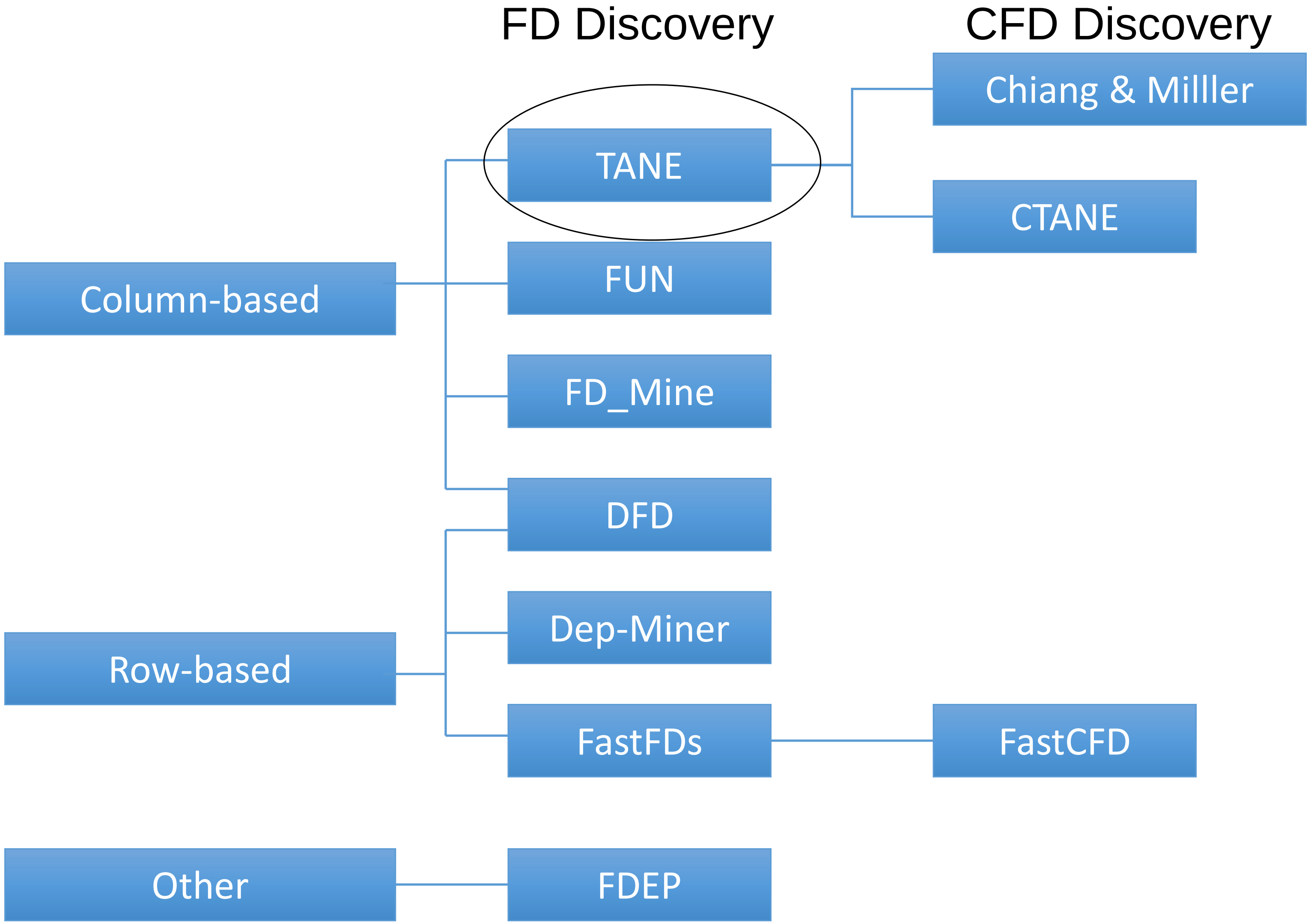
Naive Discovery Approach

- Task: Given relation R, detect all minimal, non-trivial FDs X → A.

- For each A $\in$ R
  - For each column combination X\A
    - For each pair of tuples (t_1,t_2)
      - If t_1[X] = t_2[X] and t_1[A] $\neq$ t_2[A]: Break
    - Return X → A

- Complexity
  - For each of the |R| possibilities for RHS
    - check $2^{(|R|-1)}$ combinations for LHS
    - And scan each record pair ($n^2/2$) for each check

Current FD Discovery approaches



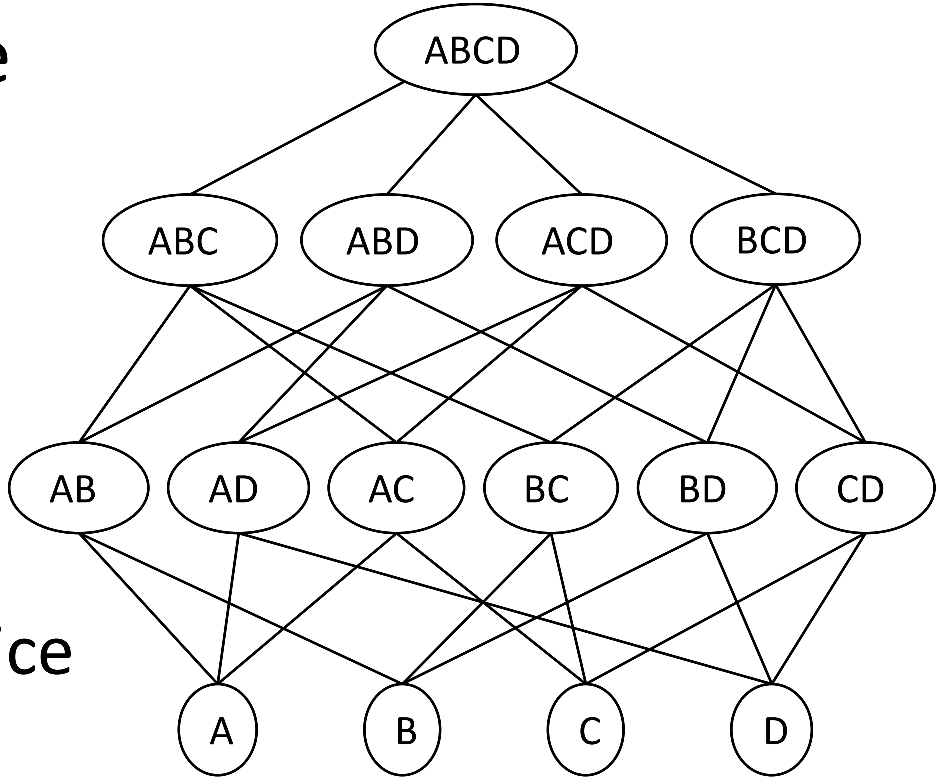
Tane – General Idea

[Huhtala, Kärkkäinen, Porkka, Toivonen:TANE: An Efficient Algorithm for Discovering Functional and Approximate Dependencies, Computer Journal’99]

- Two key ideas
  1. Reduce column combinations through pruning
     - Reasoning over FDs
  2. Reduce tuple sets through partitioning
     - Partition data according to attribute values
     - Level-wise increase of size of attribute set
       - Consider sets of tuples whose values agree on that set

TANE: Discovery strategy

- Bottom up traversal through lattice
  - ⇒ only minimal dependencies
  - Pruning
  - Re-use results from previous level
- For a set X, test all X\A → A, A∈X
  - ⇒ only non-trivial dependencies
  - Interpretation: Test each edge in lattice
  - Test on efficient data structure

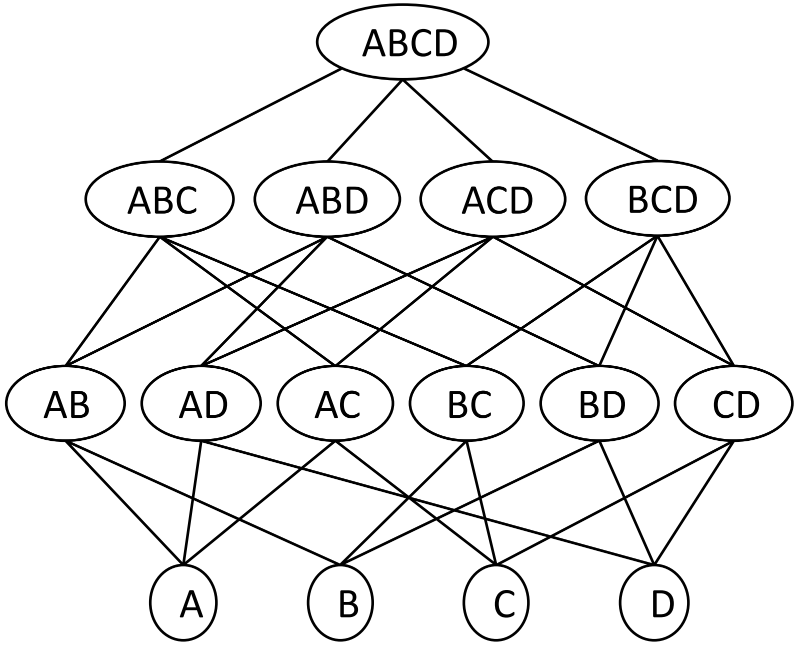


Candidate Sets

- RHS candidate set C(X)
- Stores only those attributes that might depend on **all** other attributes in X.
  - I.e., those that still need to be checked
  - If A∈C(X) then A does not depend on any proper subset of X.
- C(X) = R \ {A∈X | X\A → A holds}
- Examples: R= {ABCD}, and A → C and CD → B hold
  - C(A) = {ABCD}\{} = C(B) = C(C) = C(D)
  - C(AB) = {ABCD}\{}
  - C(AC) = {ABCD}\{C} = {ABD}
  - C(CD) = {ABCD}\{}
  - C(BCD) = {ABCD}\{B} = {ACD}

RHS Candidate Pruning

- RHS candidates: $C^+(X) = \{A \in R \mid \forall B \in X: X \setminus \{A,B\} \rightarrow B \text{ does not hold}\}$
  - Special case: A = B corresponds to C(X)
    - Reminder: $C(X) = R \setminus \{A \in X \mid X \setminus A \rightarrow A \text{ holds}\}$
- This definition removes three types of candidates:
  - Minimality
  - Pseudotransitivity
  - Superkey
- Examples: R= {ABCD}, and A → C and CD → B hold
  - C(ABC) = {A}
  - C(BCD) = {ACD}

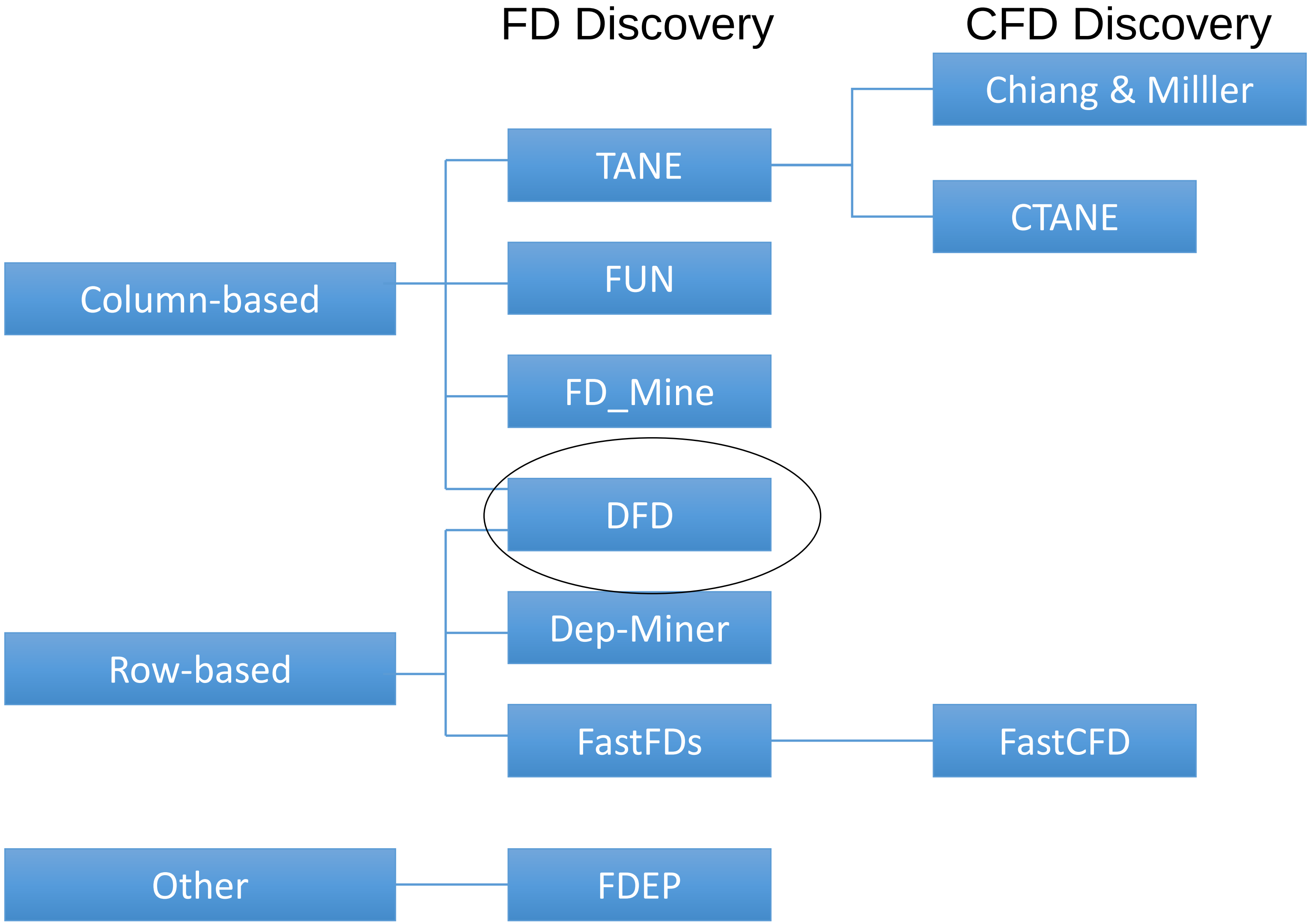


Partial FDs with TANE

- Definition based on minimum number of tuples to be removed from R for X→A to hold in R.
- Discovery problem:
  - Given relation R and threshold ε, find all minimal non-trivial FDs X→A such that $e(X \to A) \leq \varepsilon$.
  - Called “approximate” FDs in paper

1. Define error: Fraction of tuples causing FD violation
   - Error $e(X \to A) = \min\{|S| \mid S \subseteq R,\ R \setminus S \models X \to A\} / |R|$
2. Specify error threshold $\boldsymbol{\varepsilon}$
3. Modify dependency checking algorithm
   - Efficient algorithm to compute error
   - Bounds to avoid error calculation

Current FD Discovery approaches


FD Discovery

CFD Discovery

Column-based

Row-based

Other

TANE

FUN

FD_Mine

DFD

Dep-Miner

FastFDs

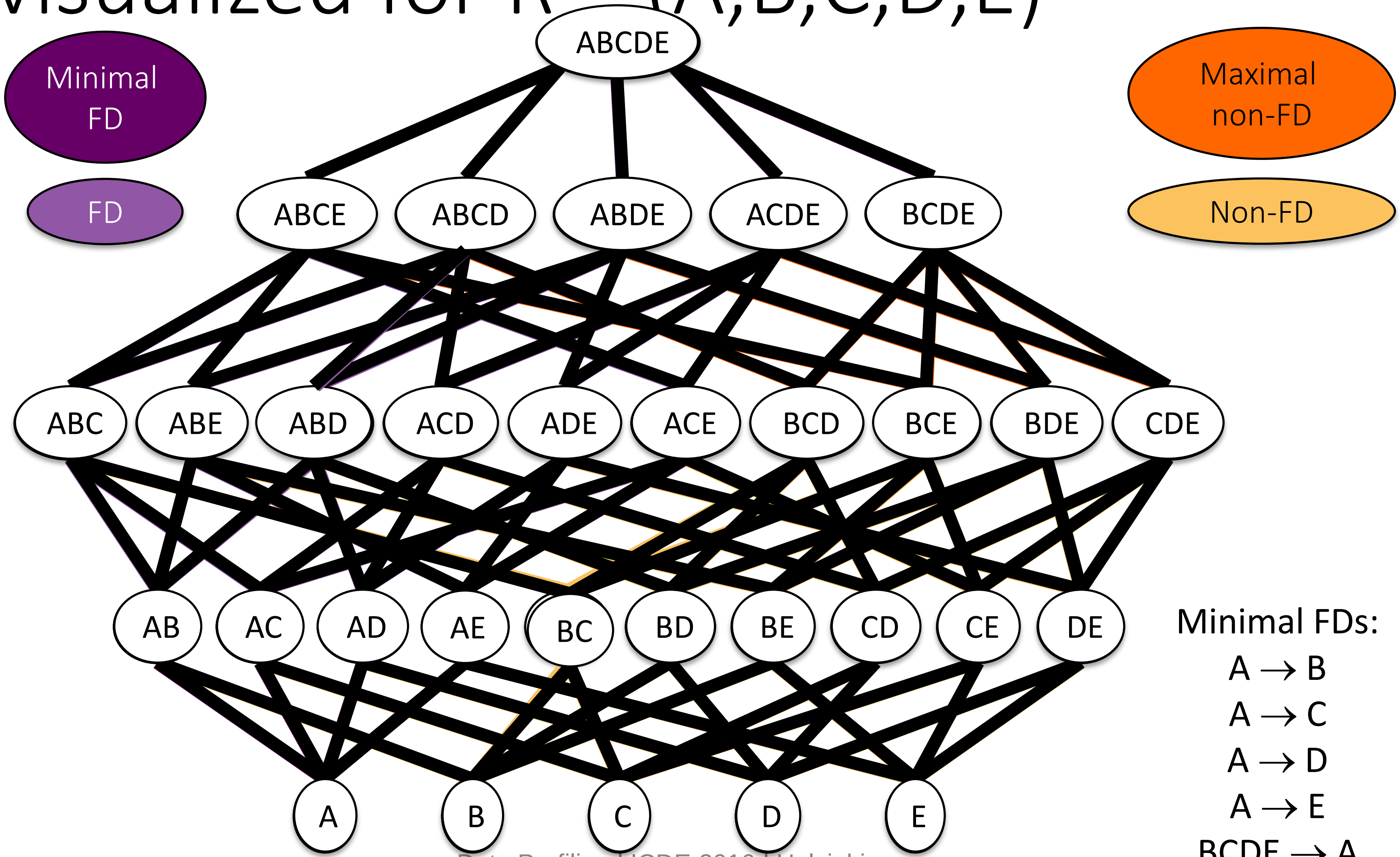
FDEP

Chiang & Millller

CTANE

FastCFD

DFD Explanation:
Tane visualized for R = (A,B,C,D,E)



Minimal FDs:

A → B

A → C

A → D

A → E

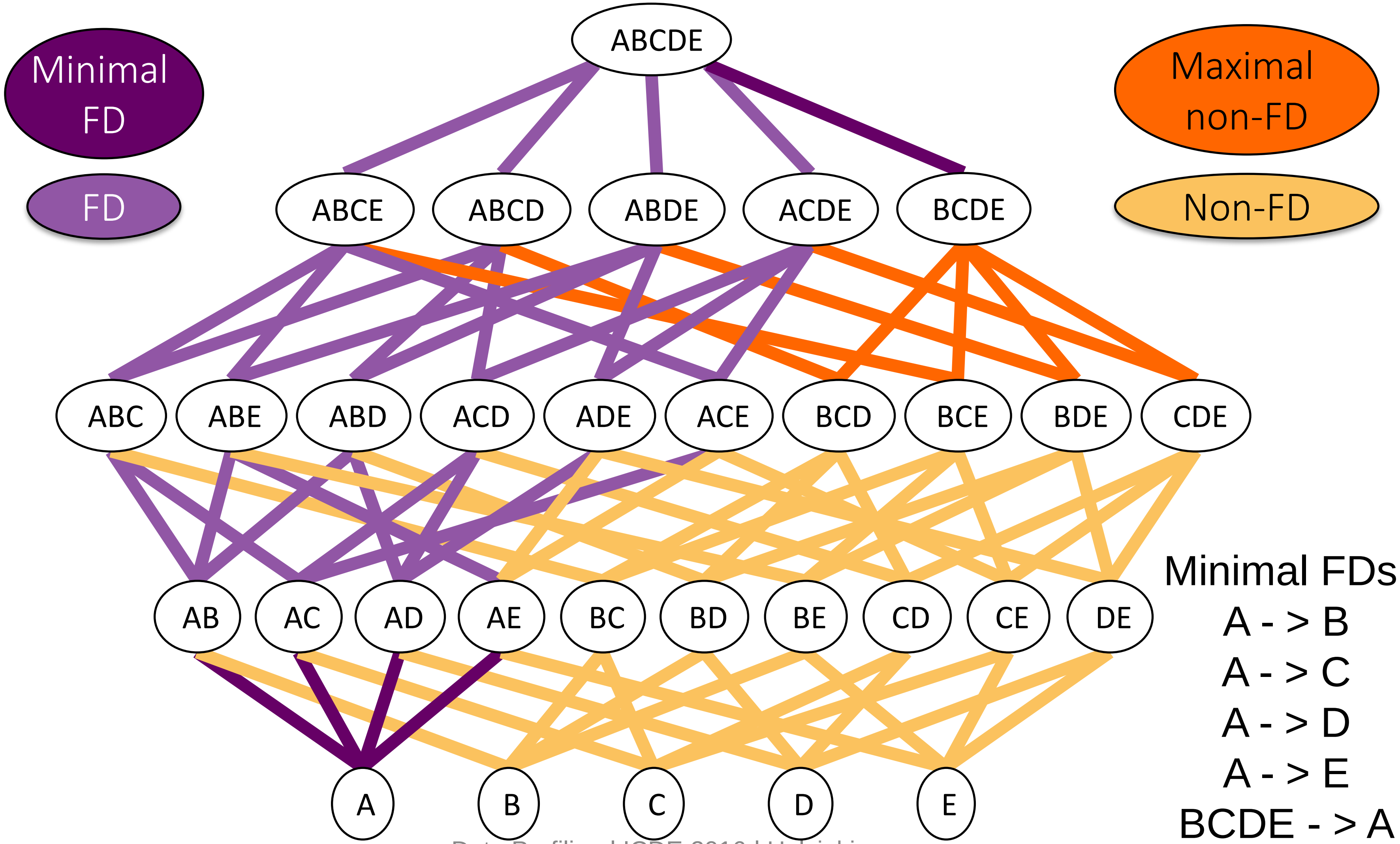
BCDE → A

DFD: Depth-first approach for functional dependency discovery

[Abedjan,Schulze,Naumann: DFD:Efficient Functional Dependency Discovery, CIKM’14]

- Traverse depth-first and prune upwards and downwards
- Applied for key/unique discovery: DUCC
  - Key discovery is a subproblem of FD discovery
  - Adapt the concept of minimality in keys to LHS of FDs:
    - An FD X→C is minimal if $"X' \subset X : X' \xrightarrow{NOT} C$
    - A non-dependency $X \xrightarrow{NOT} C$ is maximal if $"X' \supset X : X' \rightarrow C$

Decompose Relation for each RHS



Minimal FDs:

A - > B

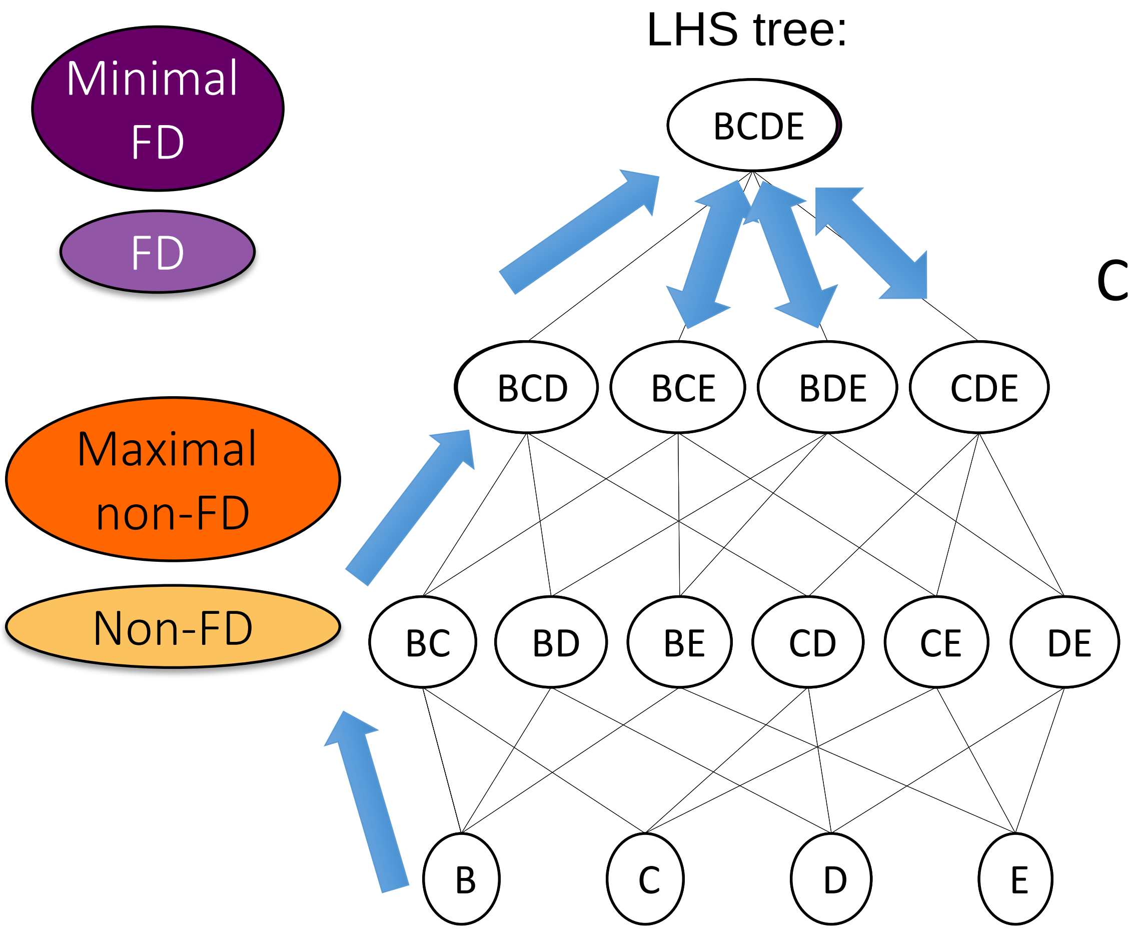
A - > C

A - > D

A - > E

BCDE - > A

Decomposition for RHS=A



Checked combinations

Tane: 15

DFD: 7

Minimal FDs:

BCDE → A

Traversal Holes

- Aggressive traversal and pruning
  - As for DUCC: Some nodes might never be reached.
- GORDIAN [VLDB’06]:
  - Complement the set of **maximal non-keys**
- **=** set of **minimal keys**
- Key observation from DUCC: the **difference** of one set and the complement of its counterpart delivers the **unvisited nodes**!
- Hole discovery works for FDs too:
  - Consider **minimal FD LHS** and **maximal non-FD LHS**

Execution time - uniprot

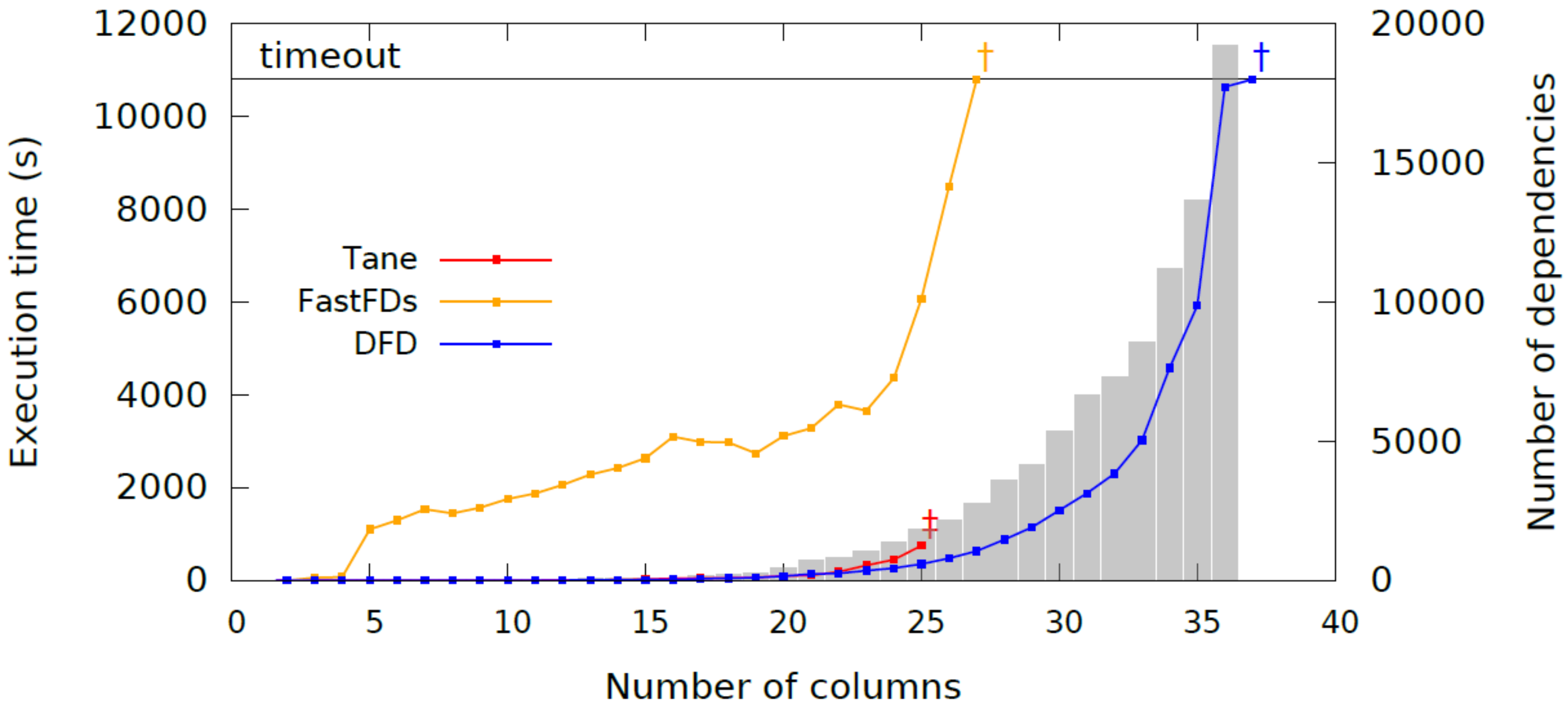
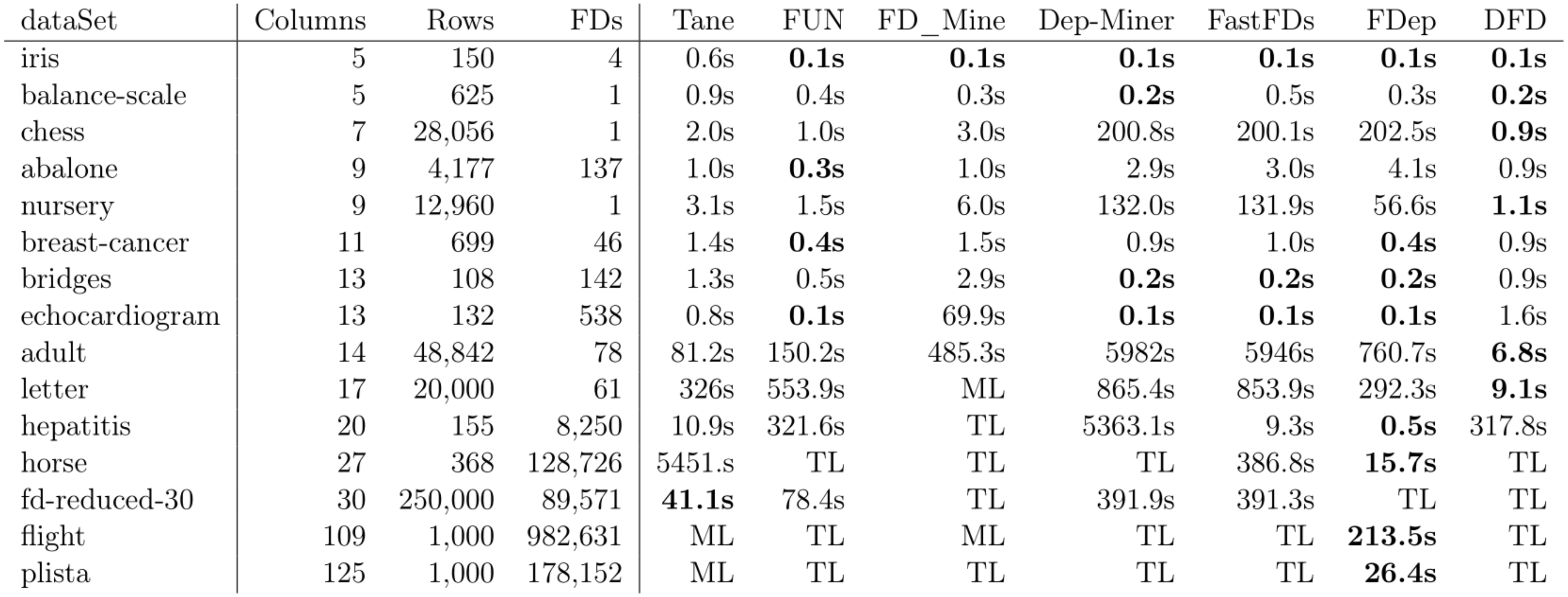


Figure 4.2: Execution time for Tane, FastFDs, and DFD on the first 100,000 rows of the uniprot dataset. († - Time Limit ‡ - Memory Limit)

Functional Dependency Evaluation



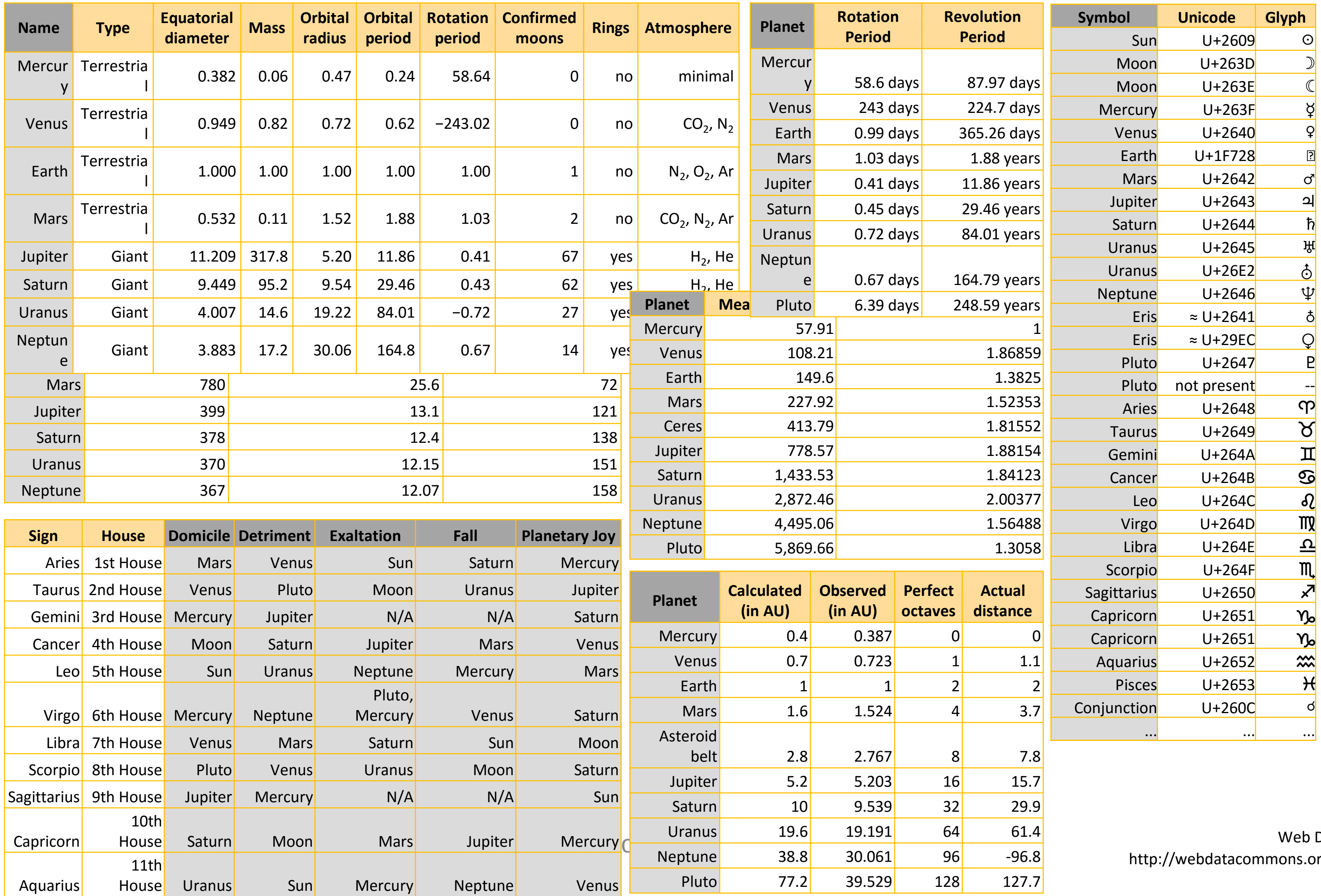
dataSet	Columns	Rows	FDs	Tane	FUN	FD_Mine	Dep-Miner	FastFDs	FDep	DFD
iris	5	150	4	0.6s	**0.1s**	**0.1s**	**0.1s**	**0.1s**	**0.1s**	**0.1s**
balance-scale	5	625	1	0.9s	0.4s	0.3s	**0.2s**	0.5s	0.3s	**0.2s**
chess	7	28,056	1	2.0s	1.0s	3.0s	200.8s	200.1s	202.5s	**0.9s**
abalone	9	4,177	137	1.0s	**0.3s**	1.0s	2.9s	3.0s	4.1s	0.9s
nursery	9	12,960	1	3.1s	1.5s	6.0s	132.0s	131.9s	56.6s	**1.1s**
breast-cancer	11	699	46	1.4s	**0.4s**	1.5s	0.9s	1.0s	**0.4s**	0.9s
bridges	13	108	142	1.3s	0.5s	2.9s	**0.2s**	**0.2s**	**0.2s**	0.9s
echocardiogram	13	132	538	0.8s	**0.1s**	69.9s	**0.1s**	**0.1s**	**0.1s**	1.6s
adult	14	48,842	78	81.2s	150.2s	485.3s	5982s	5946s	760.7s	**6.8s**
letter	17	20,000	61	326s	553.9s	ML	865.4s	853.9s	292.3s	**9.1s**
hepatitis	20	155	8,250	10.9s	321.6s	TL	5363.1s	9.3s	**0.5s**	317.8s
horse	27	368	128,726	5451.s	TL	TL	TL	386.8s	**15.7s**	TL
fd-reduced-30	30	250,000	89,571	**41.1s**	78.4s	TL	391.9s	391.3s	TL	TL
flight	109	1,000	982,631	ML	TL	ML	TL	TL	**213.5s**	TL
plista	125	1,000	178,152	ML	TL	TL	TL	TL	**26.4s**	TL

IND Discovery

1. **DeMarchi‘s Algorithm**
2. **Spider**
3. **BINDER & MIND**
   - High performance IND detection
   - Work by Thorsten Papenbrock

BINDER – divide & conquer based IND detection

Linking web tables – an example



Name	Type	Equatorial diameter	Mass	Orbital radius	Orbital period	Rotation period	Confirmed moons	Rings	Atmosphere
Mercury	Terrestrial	0.382	0.06	0.47	0.24	58.64	0	no	minimal
Venus	Terrestrial	0.949	0.82	0.72	0.62	−243.02	0	no	CO_2, N_2
Earth	Terrestrial	1.000	1.00	1.00	1.00	1.00	1	no	N_2, O_2, Ar
Mars	Terrestrial	0.532	0.11	1.52	1.88	1.03	2	no	CO_2, N_2, Ar
Jupiter	Giant	11.209	317.8	5.20	11.86	0.41	67	yes	H_2, He
Saturn	Giant	9.449	95.2	9.54	29.46	0.43	62	yes	H_2, He
Uranus	Giant	4.007	14.6	19.22	84.01	−0.72	27	yes	
Neptune	Giant	3.883	17.2	30.06	164.8	0.67	14	yes	

Mars	780	25.6	72
Jupiter	399	13.1	121
Saturn	378	12.4	138
Uranus	370	12.15	151
Neptune	367	12.07	158

Planet	Rotation Period	Revolution Period
Mercury	58.6 days	87.97 days
Venus	243 days	224.7 days
Earth	0.99 days	365.26 days
Mars	1.03 days	1.88 years
Jupiter	0.41 days	11.86 years
Saturn	0.45 days	29.46 years
Uranus	0.72 days	84.01 years
Neptune	0.67 days	164.79 years
Pluto	6.39 days	248.59 years

Planet	Mea	
Mercury	57.91	1
Venus	108.21	1.86859
Earth	149.6	1.3825
Mars	227.92	1.52353
Ceres	413.79	1.81552
Jupiter	778.57	1.88154
Saturn	1,433.53	1.84123
Uranus	2,872.46	2.00377
Neptune	4,495.06	1.56488
Pluto	5,869.66	1.3058

Symbol	Unicode	Glyph
Sun	U+2609	☉
Moon	U+263D	☽
Moon	U+263E	☾
Mercury	U+263F	☿
Venus	U+2640	♀
Earth	U+1F728	⍰
Mars	U+2642	♂
Jupiter	U+2643	♃
Saturn	U+2644	♄
Uranus	U+2645	♅
Uranus	U+26E2	⛢
Neptune	U+2646	♆
Eris	≈ U+2641	♁
Eris	≈ U+29EC	⧬
Pluto	U+2647	♇
Pluto	not present	--
Aries	U+2648	♈
Taurus	U+2649	♉
Gemini	U+264A	♊
Cancer	U+264B	♋
Leo	U+264C	♌
Virgo	U+264D	♍
Libra	U+264E	♎
Scorpio	U+264F	♏
Sagittarius	U+2650	♐
Capricorn	U+2651	♑
Capricorn	U+2651	♑
Aquarius	U+2652	♒
Pisces	U+2653	♓
Conjunction	U+260C	☌
…	…	…

Sign	House	Domicile	Detriment	Exaltation	Fall	Planetary Joy
Aries	1st House	Mars	Venus	Sun	Saturn	Mercury
Taurus	2nd House	Venus	Pluto	Moon	Uranus	Jupiter
Gemini	3rd House	Mercury	Jupiter	N/A	N/A	Saturn
Cancer	4th House	Moon	Saturn	Jupiter	Mars	Venus
Leo	5th House	Sun	Uranus	Neptune	Mercury	Mars
Virgo	6th House	Mercury	Neptune	Pluto, Mercury	Venus	Saturn
Libra	7th House	Venus	Mars	Saturn	Sun	Moon
Scorpio	8th House	Pluto	Venus	Uranus	Moon	Saturn
Sagittarius	9th House	Jupiter	Mercury	N/A	N/A	Sun
Capricorn	10th House	Saturn	Moon	Mars	Jupiter	Mercury
Aquarius	11th House	Uranus	Sun	Mercury	Neptune	Venus

Planet	Calculated (in AU)	Observed (in AU)	Perfect octaves	Actual distance
Mercury	0.4	0.387	0	0
Venus	0.7	0.723	1	1.1
Earth	1	1	2	2
Mars	1.6	1.524	4	3.7
Asteroid belt	2.8	2.767	8	7.8
Jupiter	5.2	5.203	16	15.7
Saturn	10	9.539	32	29.9
Uranus	19.6	19.191	64	61.4
Neptune	38.8	30.061	96	-96.8
Pluto	77.2	39.529	128	127.7

Web Data Commons Project
http://webdatacommons.org/webtables/index.html

Unary IND detection complexity

Name	Type	Equatorial diameter	Mass	Orbital radius	Orbital period	Rotation period	Confirmed moons	Rings	Atmosphere
Mercury	Terrestrial	0.382	0.06	0.47	0.24	58.64	0	no	minimal
Venus	Terrestrial	0.949	0.82	0.72	0.62	−243.02	0	no	CO_2, N_2
Earth	Terrestrial	1.000	1.00	1.00	1.00	1.00	1	no	N_2, O_2, Ar
Mars	Terrestrial	0.532	0.11	1.52	1.88	1.03	2	no	CO_2, N_2, Ar
Jupiter	Giant	11.209	317.8	5.20	11.86	0.41	67	yes	H_2, He
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Uranus	Giant	4.007	14.6	19.22	84.01	−0.72	27	yes	H_2, He
Neptune	Giant	3.883	17.2	30.06	164.8	0.67	14	yes	H_2, He

Complexity: **$O(n^2-n)$** for n attributes

Example:
10 attr ~ 90 checks
1,000 attr ~ 999,000 checks

- Name ⊆ Type ?
- Name ⊆ Equatorial_diameter ?
- Name ⊆ Mass ?
- Name ⊆ Orbital_radius ?
- Name ⊆ Orbital_period ?
- Name ⊆ Rotation_period ?
- Name ⊆ Confirmed_moons ?
- Name ⊆ Rings ?
- Name ⊆ Atmosphere ?

- Type ⊆ Name ?
- Type ⊆ Equatorial_diameter ?
- Type ⊆ Mass ?
- Type ⊆ Orbital_radius ?
- Type ⊆ Orbital_period ?
- Type ⊆ Rotation_period ?
- Type ⊆ Confirmed_moons ?
- Type ⊆ Rings ?
- Type ⊆ Atmosphere ?

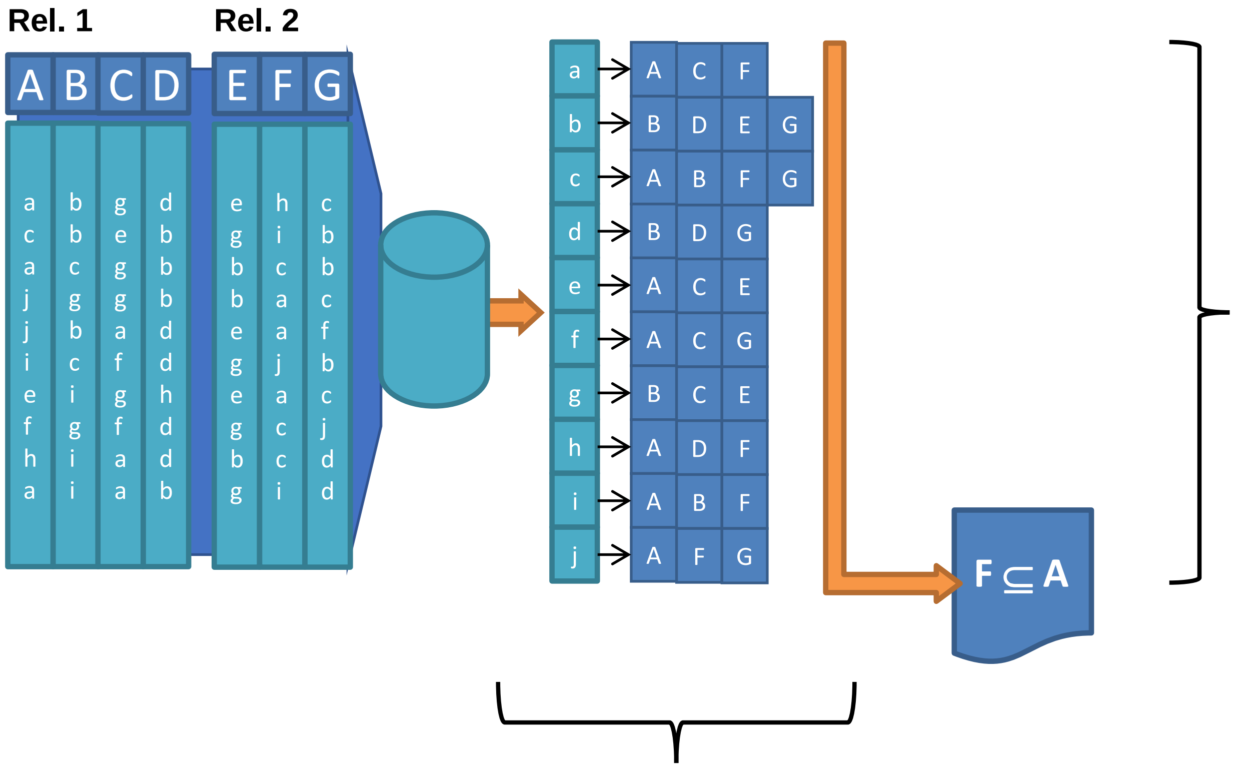
- Mass ⊆ Name ?
- Mass ⊆ Type ?
- Mass ⊆ Equatorial_diameter ?
- …

MIND

[Marchi, Lopes, Petit: Unary and n-ary inclusion dependency discovery in relational databases,JIIS’09]

🟦 attributes 🟦 values

➡ dataflow ☒ ignored



A	B	C	D	E	F	G
a	b	g	d	e	h	c
c	b	e	b	g	i	b
a	c	g	b	b	c	b
j	g	g	b	b	a	c
j	b	a	d	e	a	f
i	c	f	d	g	j	b
e	i	g	h	e	a	c
f	g	f	d	g	c	j
h	i	a	d	b	c	d
a	i	a	b	g	i	d

a	A	C	F	
b	B	D	E	G
c	A	B	F	G
d	B	D	G	
e	A	C	E	
f	A	C	G	
g	B	C	E	
h	A	D	F	
i	A	B	F	
j	A	F	G	

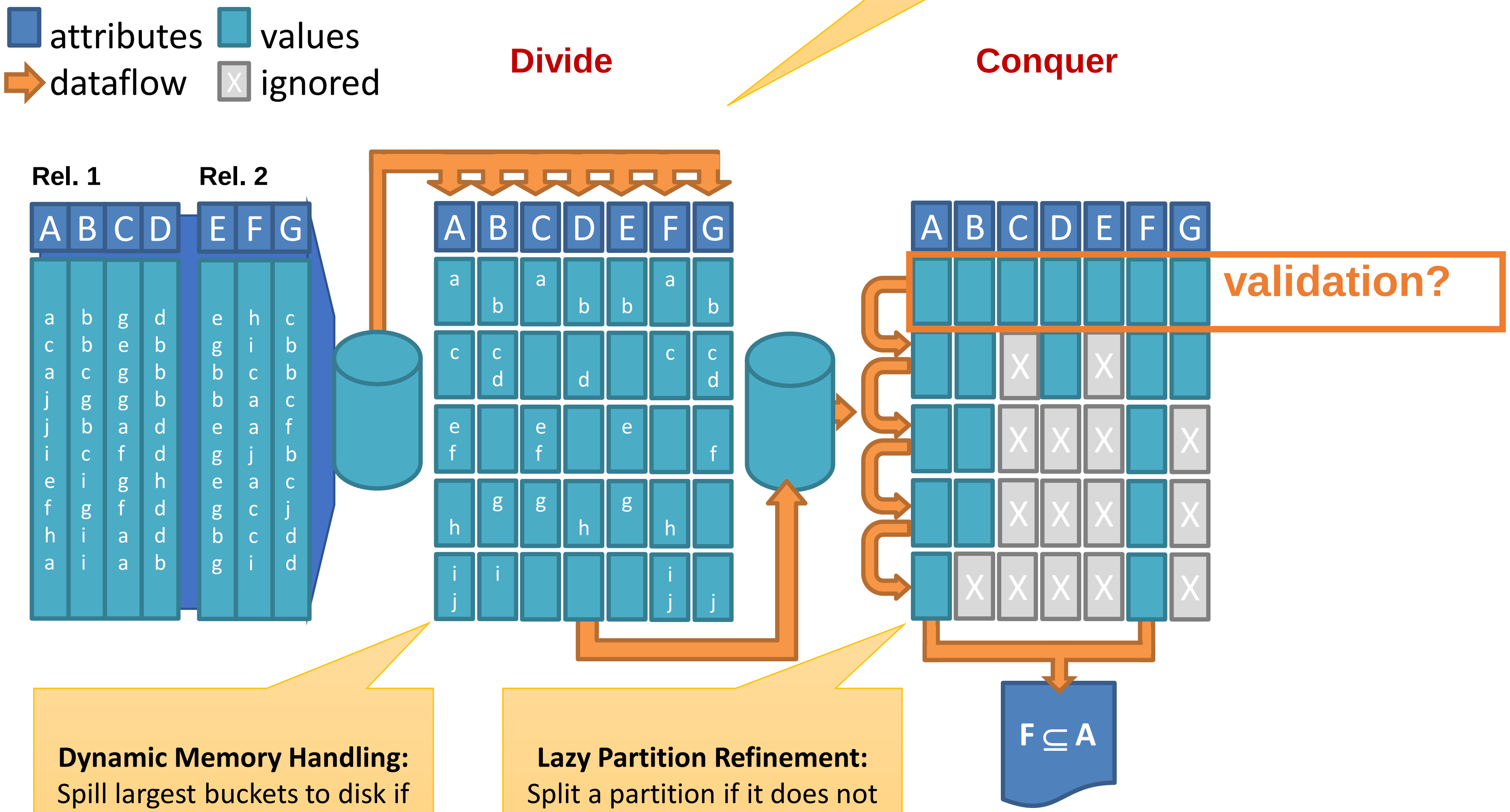
All intersections are executed, but not all are necessary!

Needs to fit into main memory!

BINDER algorithm – workflow

[Papenbrock, Quiane, Naumann: Divide & Conquer-based Inclusion Dependency Discovery, PVL

No sortation needed, just hashing



Rel. 1

A	B	C	D
a	b	g	d
c	b	e	b
a	c	g	b
j	g	g	b
j	b	a	d
i	c	f	d
e	i	g	h
f	g	f	d
h	i	a	d
a	i	a	b

Rel. 2

E	F	G
e	h	c
g	i	b
b	c	b
b	a	c
e	a	f
g	j	b
e	a	c
g	c	j
b	c	d
g	i	d

Divide

A	B	C	D	E	F	G
a	b	a	b	b	a	b
c	c d		d		c	c d
e f		e f		e		f
h	g	g	h	g	h	
i j	i				i j	j

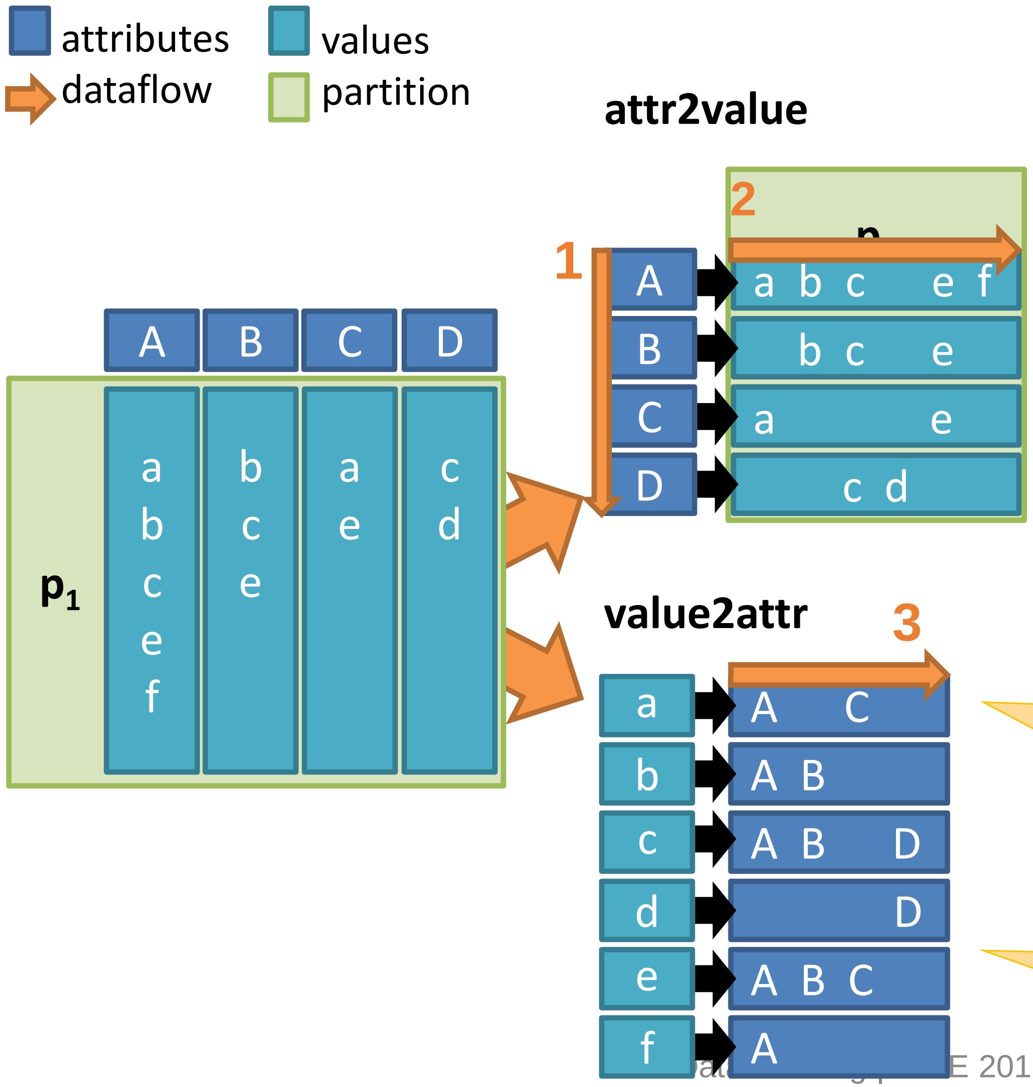
Conquer

A	B	C	D	E	F	G
		X		X		
		X	X	X		X
		X	X	X		X
	X	X	X	X		X

Dynamic Memory Handling: Spill largest buckets to disk if memory is exhausted.

Lazy Partition Refinement: Split a partition if it does not fit into main memory.

BINDER algorithm – validation

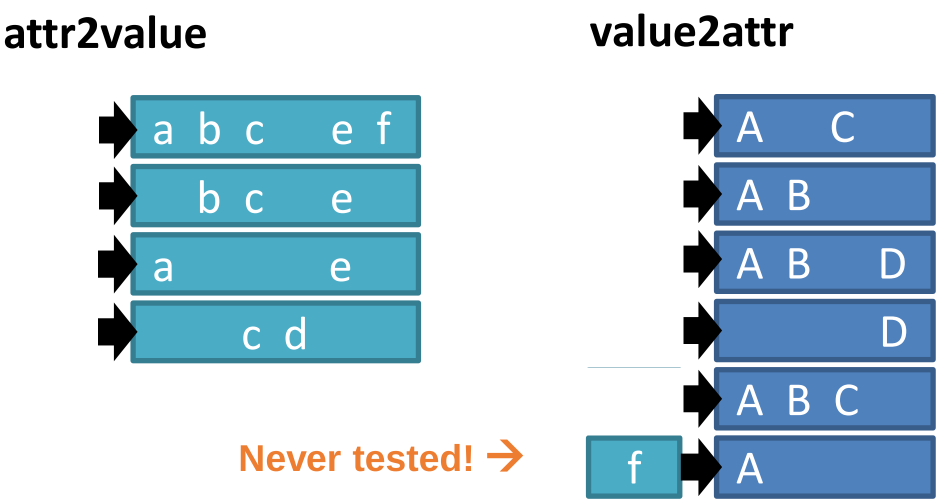


1. Iterate attributes
2. Iterate values
3. If value2attr entry exists
   - Intersect candidates with this list
   - Remove value2attr entry
   - If attribute removed from all candidates
     - Remove entry from attr2value

Both indexes fit into main memory due to the partitioning!

see DeMarchi's algorithm

BINDER algorithm – validation example

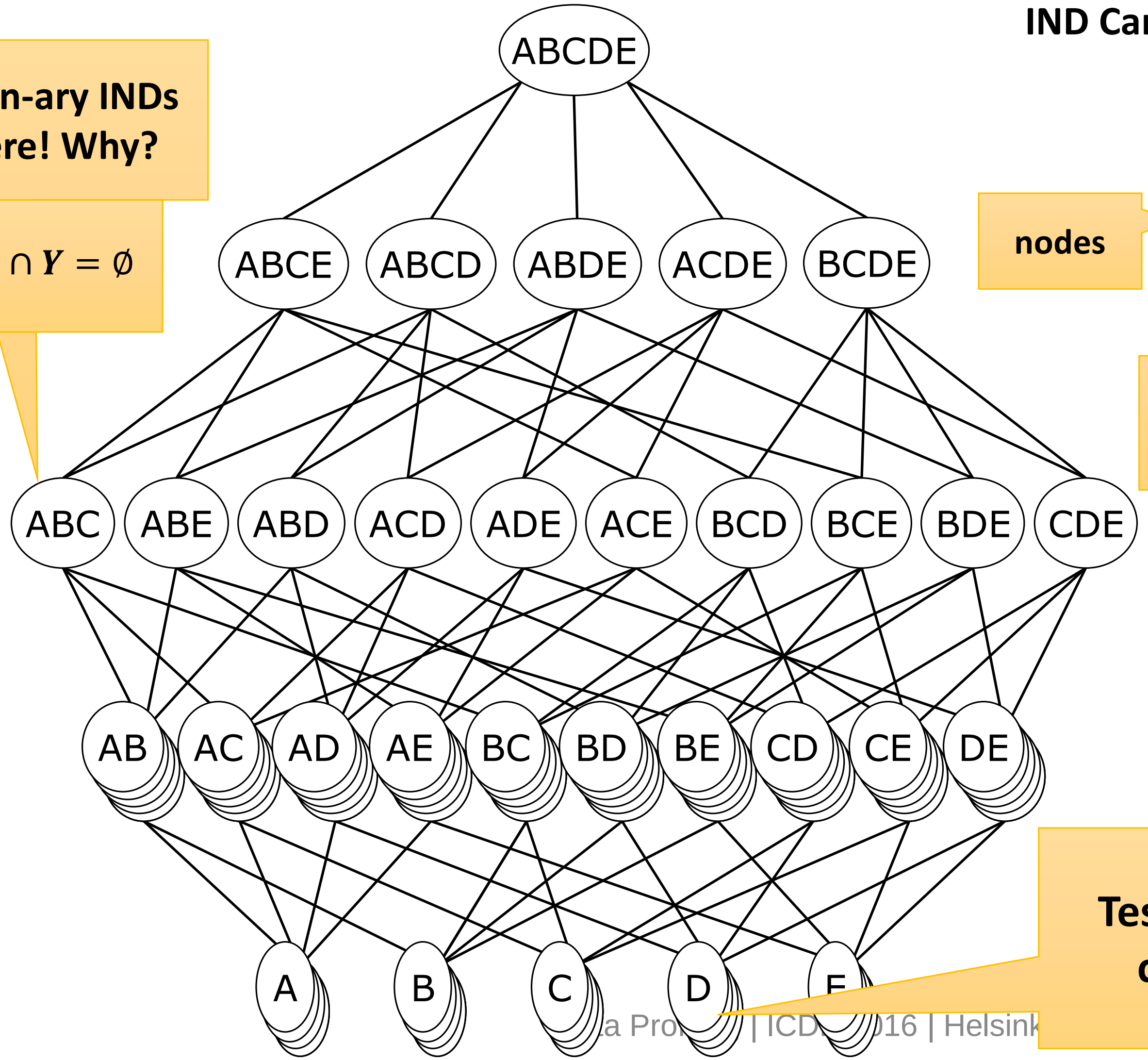


	A	B	C	D
look up	**B,C,D**	**A,C,D**	**A,B,D**	**A,B,C**

1. Iterate attributes
2. Iterate values
3. If value2attr entry exists
   - Intersect candidates with this list
   - Remove value2attr entry
   - If attribute removed from all candidates
     - Remove entry from attr2value

B ⊆ A
C ⊆ A

N-ary IND detection complexity



No n-ary INDs here! Why?

$\boldsymbol{X} \cap \boldsymbol{Y} = \emptyset$

IND Candidates in level k:

$$\overset{X}{\binom{n}{k}} * \overset{Y}{\binom{n-k}{k} * k!}$$

nodes

All permutations

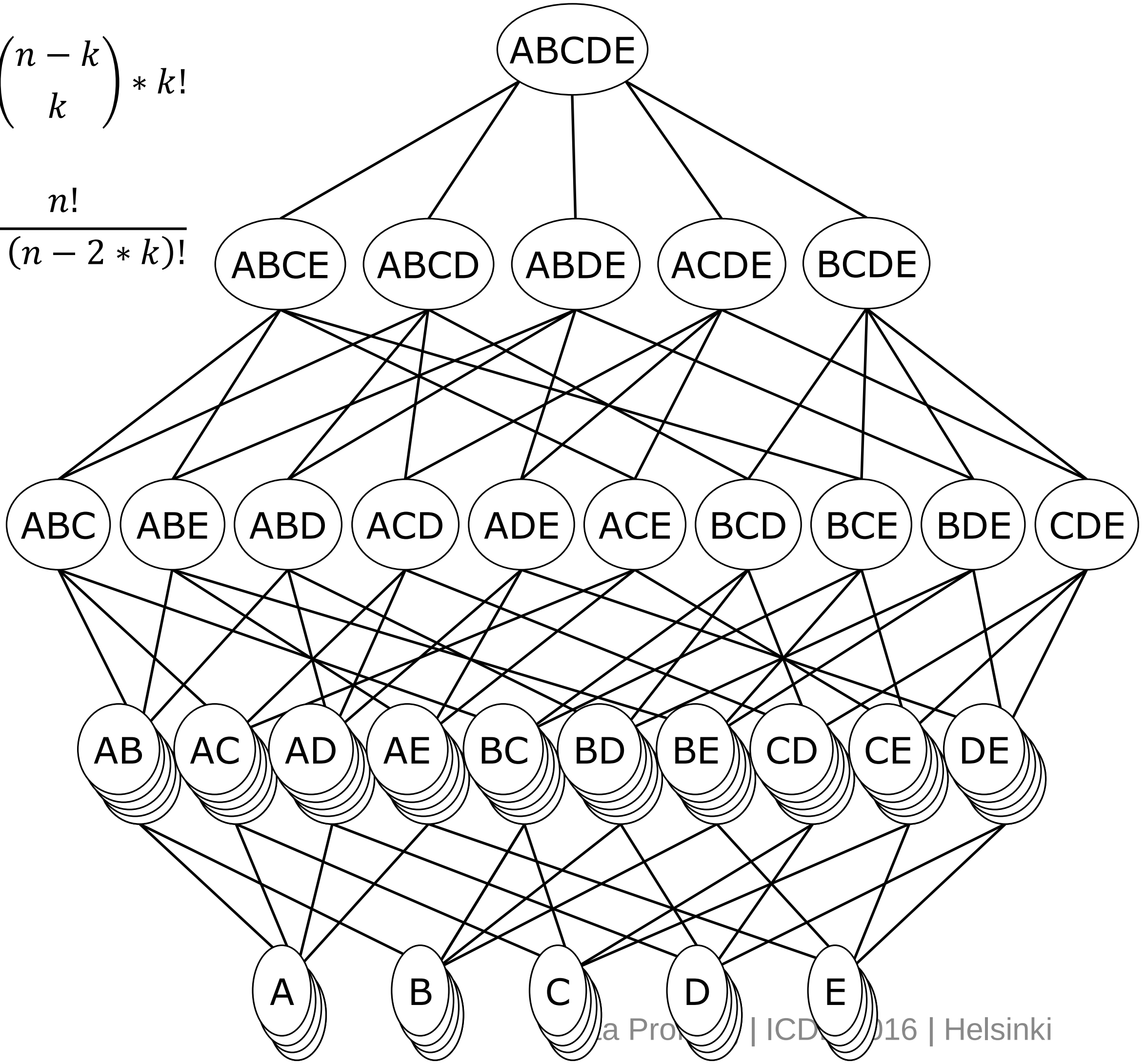
Other, non-overlapping nodes

Test combination with all other combinations of same size!

N-ary IND detection complexity

$$\binom{n}{k} * \binom{n-k}{k} * k!$$

$$= \frac{n!}{k! * (n - 2 * k)!}$$



ABCDE

ABCE ABCD ABDE ACDE BCDE

ABC ABE ABD ACD ADE ACE BCD BCE BDE CDE

AB AC AD AE BC BD BE CD CE DE

A B C D E

$$\binom{5}{5} * \binom{5-5}{5} * 5! \sim 0$$

$$\binom{5}{4} * \binom{5-4}{4} * 4! \sim 0$$

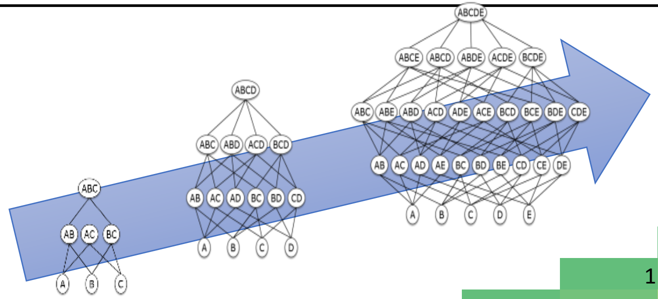
$$\binom{5}{3} * \binom{5-3}{3} * 3! \sim 0$$

$$\binom{5}{2} * \binom{5-2}{2} * 2! = 60$$

$$\binom{5}{1} * \binom{5-1}{1} * 1! = 20 = n^2 - n$$

N-ary IND detection complexity

Unique Column Combinations

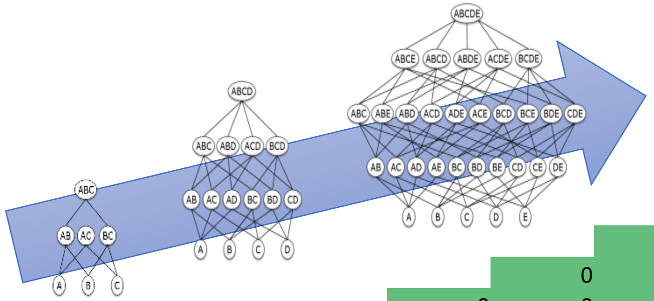


Number of levels: k

total	1	3	7	15	31	63	127	255	511	1023	2047	4095	8191	16383	32767
15															1
14														1	15
13													1	14	105
12												1	13	91	455
11											1	12	78	364	1365
10										1	11	66	286	1001	3003
9									1	10	55	220	715	2002	5005
8								1	9	45	165	495	1287	3003	6435
7							1	8	36	120	330	792	1716	3432	6435
6						1	7	28	84	210	462	924	1716	3003	5005
5					1	6	21	56	126	252	462	792	1287	2002	3003
4				1	5	15	35	70	126	210	330	495	715	1001	1365
3			1	4	10	20	35	56	84	120	165	220	286	364	455
2		1	3	6	10	15	21	28	36	45	55	66	78	91	105
1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Number of attributes: n

Inclusion Dependencies



Number of levels: k

total	0	2	6	24	80	330	1302	5936	26784	133650	669350	3609672	19674096	113525594	664400310
15															0
14														0	0
13													0	0	0
12												0	0	0	0
11											0	0	0	0	0
10										0	0	0	0	0	0
9									0	0	0	0	0	0	0
8								0	0	0	0	0	0	0	0
7							0	0	0	0	0	0	0	17297280	259459200
6						0	0	0	0	0	0	665280	8648640	60540480	302702400
5					0	0	0	0	0	30240	332640	1995840	8648640	30270240	90810720
4				0	0	0	0	1680	15120	75600	277200	831600	2162160	5045040	10810800
3			0	0	0	120	840	3360	10080	25200	55440	110880	205920	360360	600600
2		0	0	12	60	180	420	840	1512	2520	3960	5940	8580	12012	16380
1	0	2	6	12	20	30	42	56	72	90	110	132	156	182	210
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Number of attributes: n

MIND & BINDER – candidate generation

- **Apriori algorithm:**
  - Bottom-up lattice traversal strategy
  - Input: all valid attribute combinations of size n
  - Output: all candidate attribute combinations of size n+1

- **Adaption for n-ary IND detection:**
  - Let R_i be the i-th relation in the relational schemata R. For each valid IND $R_j[X] \subseteq R_k[Y]$ with $|X|=|Y|=n$ generate all IND candidates $R_j[XA] \subseteq R_k[YB]$ so that:

1. $R_j[X] \subseteq \subseteq R_k[Y]$ and $R_j[A] \subseteq \subseteq R_k[B]$ (both are valid INDs)
2. $\forall X_i \in X: X_i < A$ (INDs are permutable; do not generate them twice)
3. $A \notin X,\ B \notin Y$ (do not generate trivial candidates)

Intrinsic limitations of IND algorithms

- Observations: all IND algorithms follow a common pattern

Algorithm	Phase 1 Data Reorganization	Phase 2 Comparison
De Marchi	Create Inverted Index	Intersect Attribute Groups
SPIDER	Sort Columns	Value-based Iteration
BINDER	Partition Columns	In-Memory Partition Comparison

- e.g., IND A⊆B
  - to prove, need to read A completely
  - to disprove, need to read B completely
- Data reorganization is the most expensive phase
  - I/O-heavy workload, but other phase brings considerable I/O as well

Visualisation

```
[1011066.Name] =] [1011057.Name]
[129284.Reference] =] [1223862.null] [586920.Ref.] [1030730.RCDB page] [108435.No.] [1248790.Source] [983315.References] [207338.Home railway
    (external link)] [975850.Ref] [1375996.Source] [1129539.References] [1168707.References] [744488.Ref] [1169311.Ref] [1068498.Ref]
    [163214.Reference] [604676.References] [1002900.Ref] [749972.Reference] [951640.References] [939700.Page] [900853.Ref] [788203.Ref]
    [788409.References] [978758.Ref] [652885.Link] [652377.Ref] [1320358.Reference] [1287392.Ref] [1012269.Report] [1180077.References]
    [1274408.Ref] [856227.NFL Recap] [1286480.Ref] [1354142.null] [525501.References] [630016.Notes] [762537.Refs] [902406.Report]
    [1005369.Link] [1255682.Source] [1157534.Source] [1065320.Ref] [956840.Ref] [775466.References] [988811.Ref] [1005838.Link] [1005593.Link]
    [576411.References] [1134428.Ref] [1170953.Reference(s)] [699144.Note] [268733.References] [931606.Notes] [1284557.Ref.] [1357973.Source]
    [1238931.Report] [867400.Reference] [794774.Ref] [716064.Refs] [377521.References] [995370.Ref] [1282132.References] [1358158.Ref.]
    [1120007.Ref] [1342522.Ref] [1319381.null] [889114.Ref] [1004839.Link] [697527.Website] [980509.Ref(s)] [1078901.Ref]
[1390416.Rank] =] [1169921.Rank] [1183098.Rank] [1011765.Rank] [1225076.Rank] [454782.Rank] [1186535.Rank] [1209635.Rank] [1161665.Rank]
    [708465.Rank] [708648.Rank]
[637307.Date] =] [1311505.Date] [1337020.Date]
[1083420.Event] =] [976659.Event] [976901.Event] [975917.Event] [1060037.Event] [1068182.Event] [1067251.Event] [1067097.Event] [1000067.Event]
    [972968.Event] [1058267.Event] [988323.Event] [1003312.Event] [1063506.Event] [1027145.Event] [1078507.Event] [1062268.Event]
[302006.Role:] =] [391330.Role:] [703281.Role:] [387497.Role:] [735612.Role:] [151885.Role:] [150598.Role:]
[1083410.Event] =] [983546.Event] [975773.Event] [1071989.Event] [1068219.Event] [1002900.Event] [1074984.Event] [967160.Event] [1052352.Event]
    [1066949.Event] [1082562.Event] [1151162.Event] [1042660.Event] [1056643.Event] [950860.Event] [958921.Event] [1063309.Event]
    [973967.Event] [1027145.Event] [1062263.Event]
[73362.State] =] [1185141.State]
[1083402.Event] =] [1083339.Event] [1068498.Event] [1060027.Event] [1002823.Event] [1046135.Event] [1249836.Event] [1000145.Event]
    [994576.Event] [990543.Event]
[854590.Venue] =] [883202.Venue] [890993.Venue] [1104659.Venue]
[648260.TEAM] =] [1286540.Club] [1308745.Club]
[627822.Division Record] =] [466958.Sets W - L]
[1236345.Match] =] [1231569.Match]
...
```

Visualisation

INDs = {

$R_1.A \subseteq R_2.B$,

$R_3.A \subseteq R_1.D$,

$R_3.C \subseteq R_2.A$,

$R_3.B \subseteq R_4.A$

}

G= (

V = {

R_1, R_2, R_3, R_4

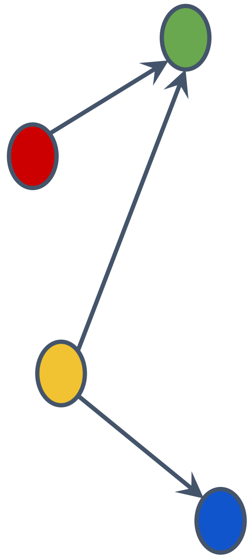
},

E = { (R_1, R_2), (R_3, R_1),

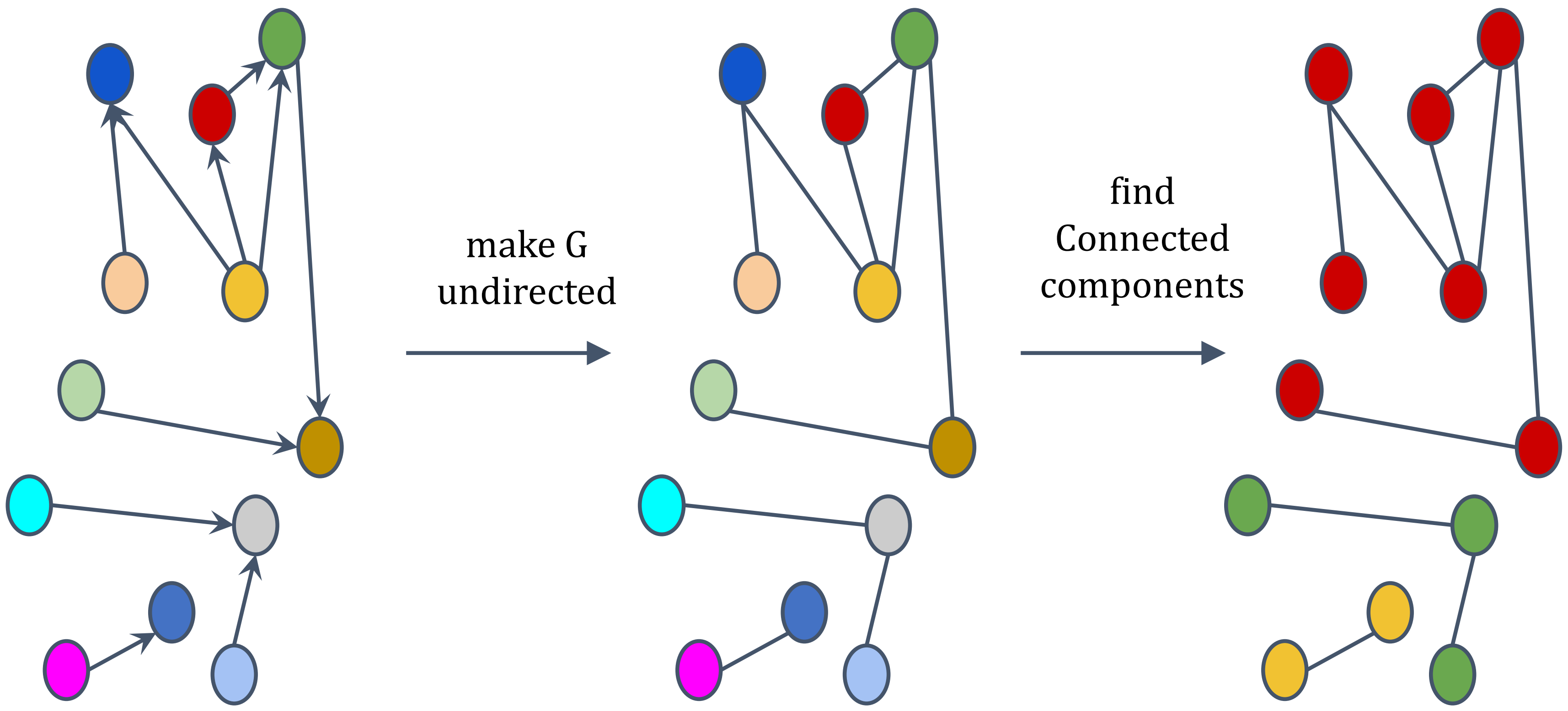
(R_3, R_2), (R_3, R_4)

}

)



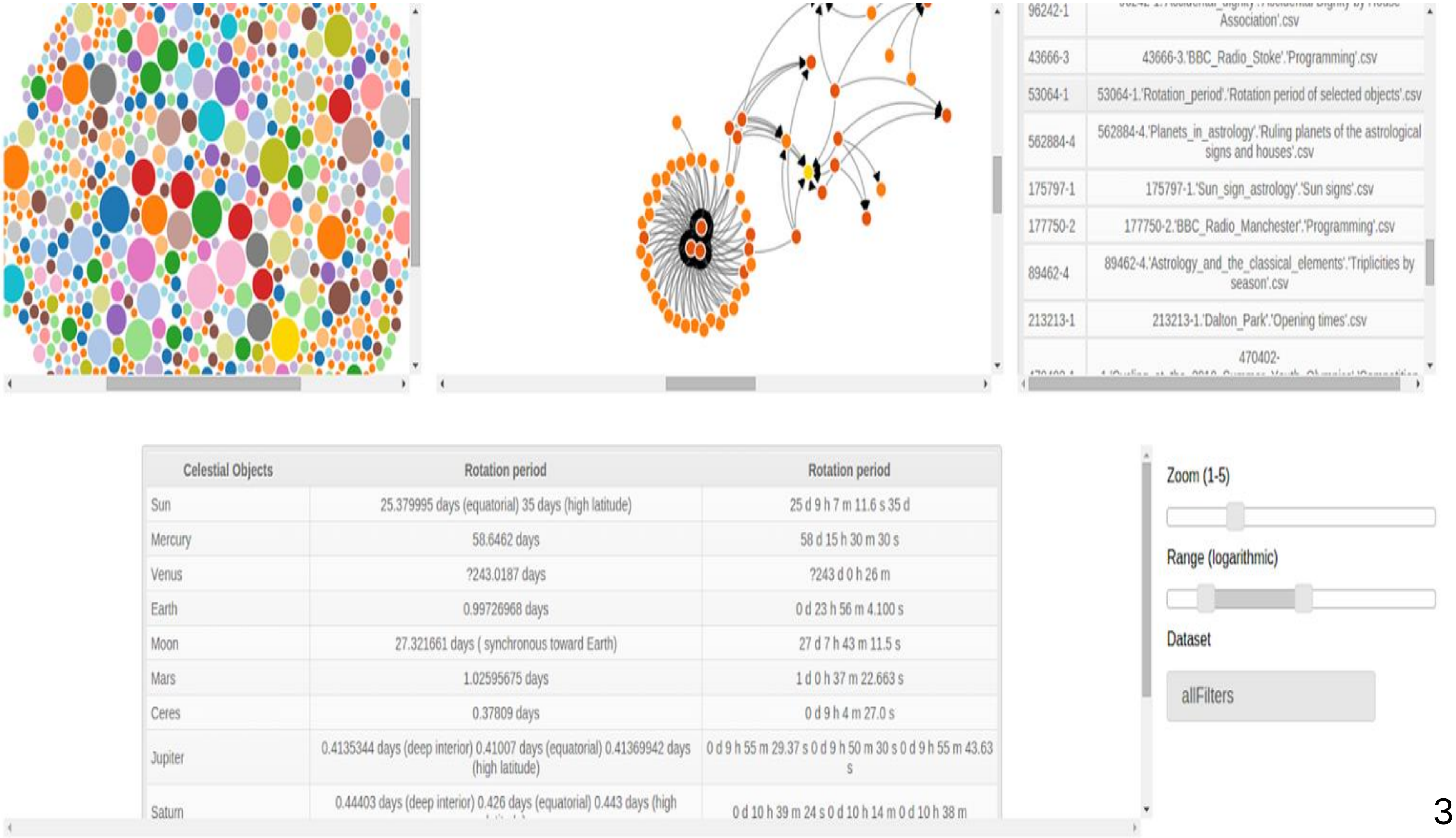
Visualisation



make G undirected

find Connected components

Interactive Application



96242-1	Association'.csv
43666-3	43666-3.'BBC_Radio_Stoke'.'Programming'.csv
53064-1	53064-1.'Rotation_period'.'Rotation period of selected objects'.csv
562884-4	562884-4.'Planets_in_astrology'.'Ruling planets of the astrological signs and houses'.csv
175797-1	175797-1.'Sun_sign_astrology'.'Sun signs'.csv
177750-2	177750-2.'BBC_Radio_Manchester'.'Programming'.csv
89462-4	89462-4.'Astrology_and_the_classical_elements'.'Triplicities by season'.csv
213213-1	213213-1.'Dalton_Park'.'Opening times'.csv
	470402-

Celestial Objects	Rotation period	Rotation period
Sun	25.379995 days (equatorial) 35 days (high latitude)	25 d 9 h 7 m 11.6 s 35 d
Mercury	58.6462 days	58 d 15 h 30 m 30 s
Venus	?243.0187 days	?243 d 0 h 26 m
Earth	0.99726968 days	0 d 23 h 56 m 4.100 s
Moon	27.321661 days (synchronous toward Earth)	27 d 7 h 43 m 11.5 s
Mars	1.02595675 days	1 d 0 h 37 m 22.663 s
Ceres	0.37809 days	0 d 9 h 4 m 27.0 s
Jupiter	0.4135344 days (deep interior) 0.41007 days (equatorial) 0.41369942 days (high latitude)	0 d 9 h 55 m 29.37 s 0 d 9 h 50 m 30 s 0 d 9 h 55 m 43.63 s
Saturn	0.44403 days (deep interior) 0.426 days (equatorial) 0.443 days (high	0 d 10 h 39 m 24 s 0 d 10 h 14 m 0 d 10 h 38 m

Zoom (1-5)

Range (logarithmic)

Dataset

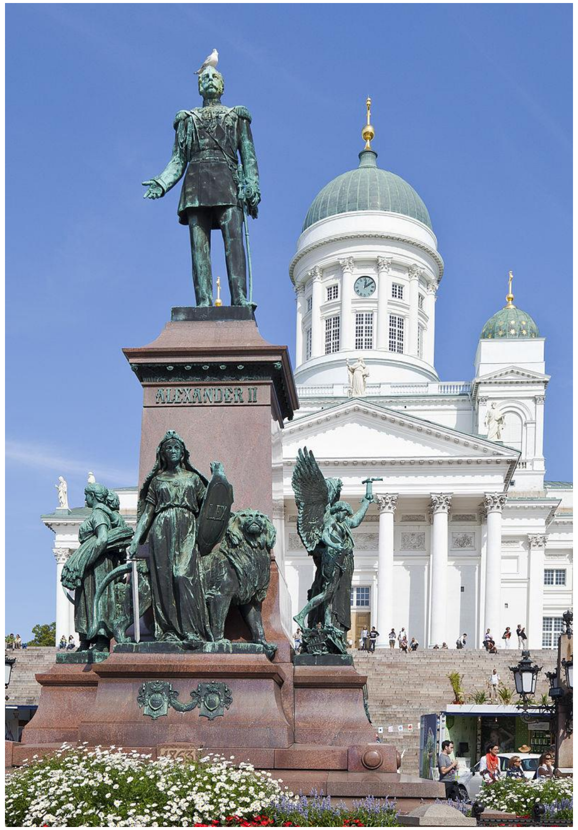
allFilters

More Dependencies

- Conditional …
  - Uniques
  - FDs
  - INDs
- Approximate ..
  - ..
- Order dependencies [Langer, Naumann: Discovering Order Dependencies, VLDBJ’15]
- Matching dependencies [Fan et al.:Reasoning about record matching rules, VLDB’09]

Tutorial Overview

- Motivation
  - Task classification
  - Use cases
- Tools
  - Research and industry
  - Shortcomings
- Single and Multiple Column Analysis
  - Cardinalities and datatypes
  - Co-occurrences and summaries
- Dependencies
  - UCCs, INDs, FDs
  - and their discover algorithms
- **Outlook**
  - **Functionality**
  - **Semantics**

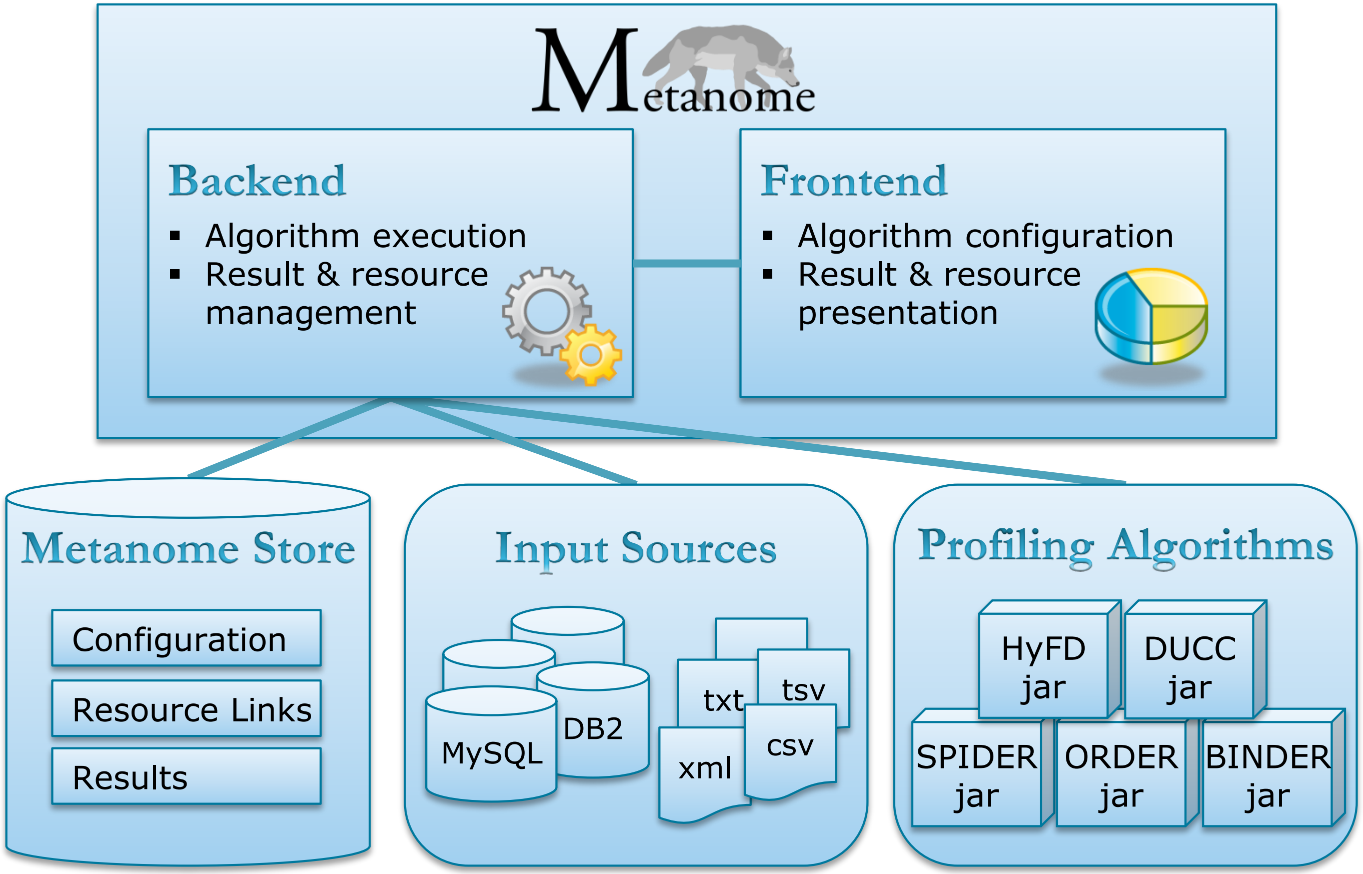


Part Overview

- The Metanome
  Data Profiling Framework
- Functional challenges
- Non-functional challenges
- Semantics of Dependencies

The Metanome Data Profiling Framework

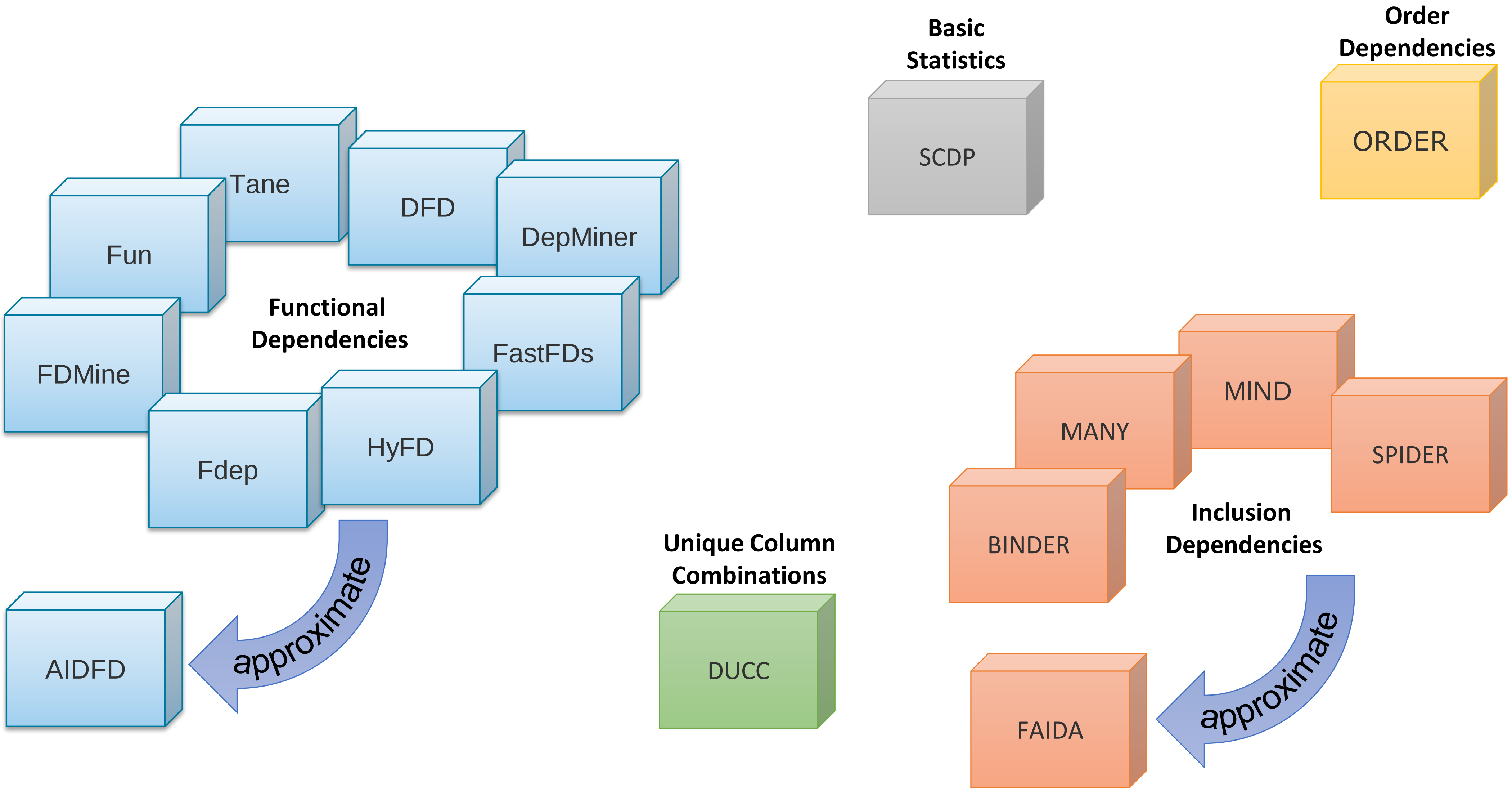
Metanome Data Profiling Tool



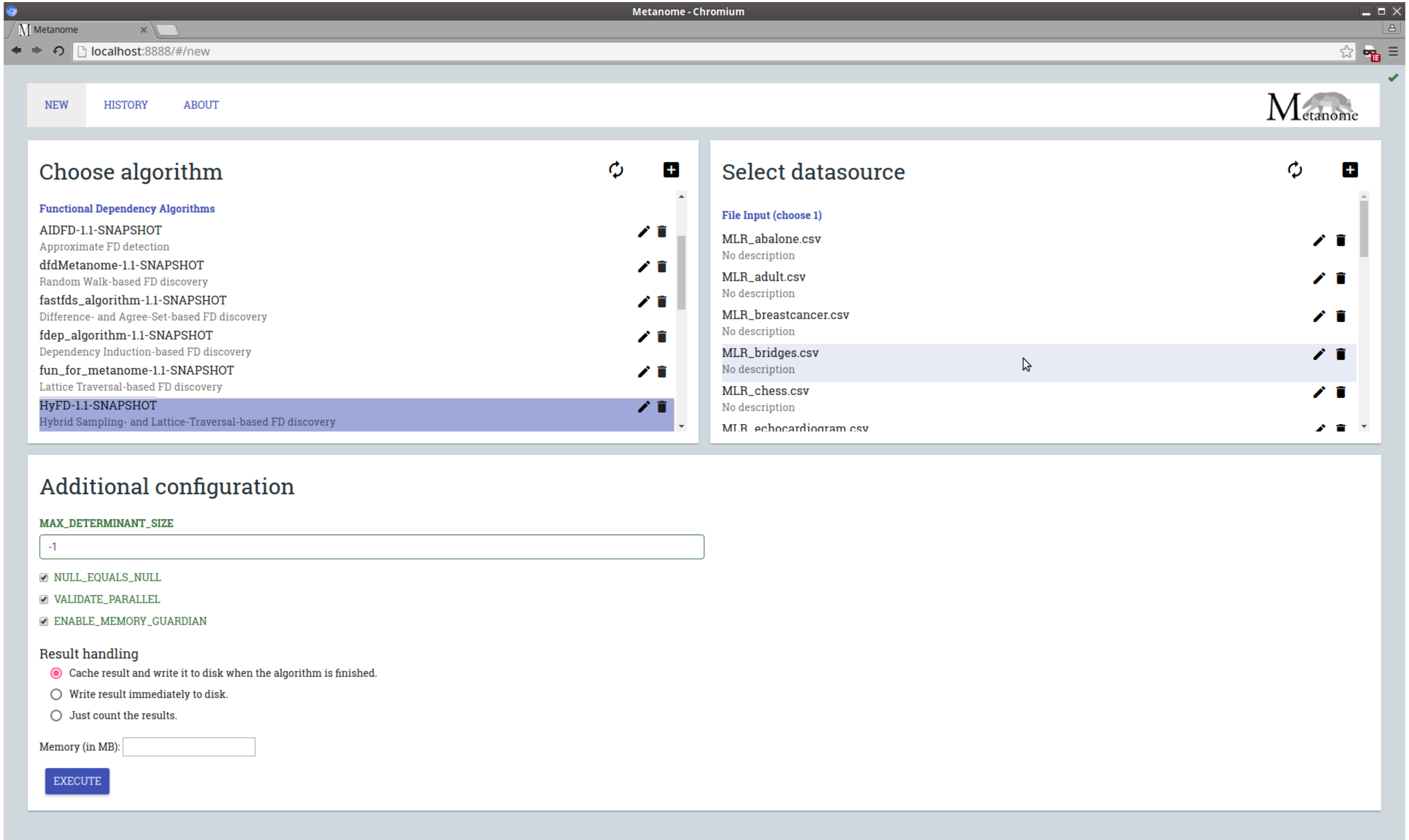
Open source framework, tool plus many algorithms

www.metanome.de

Profiling Algorithms



Metanome User Experience



Choose algorithm

Functional Dependency Algorithms

AIDFD-1.1-SNAPSHOT
Approximate FD detection

dfdMetanome-1.1-SNAPSHOT
Random Walk-based FD discovery

fastfds_algorithm-1.1-SNAPSHOT
Difference- and Agree-Set-based FD discovery

fdep_algorithm-1.1-SNAPSHOT
Dependency Induction-based FD discovery

fun_for_metanome-1.1-SNAPSHOT
Lattice Traversal-based FD discovery

HyFD-1.1-SNAPSHOT
Hybrid Sampling- and Lattice-Traversal-based FD discovery

Select datasource

File Input (choose 1)

MLR_abalone.csv
No description

MLR_adult.csv
No description

MLR_breastcancer.csv
No description

MLR_bridges.csv
No description

MLR_chess.csv
No description

MLR_echocardiogram.csv

Additional configuration

MAX_DETERMINANT_SIZE

-1

☑ NULL_EQUALS_NULL

☑ VALIDATE_PARALLEL

☑ ENABLE_MEMORY_GUARDIAN

Result handling

● Cache result and write it to disk when the algorithm is finished.

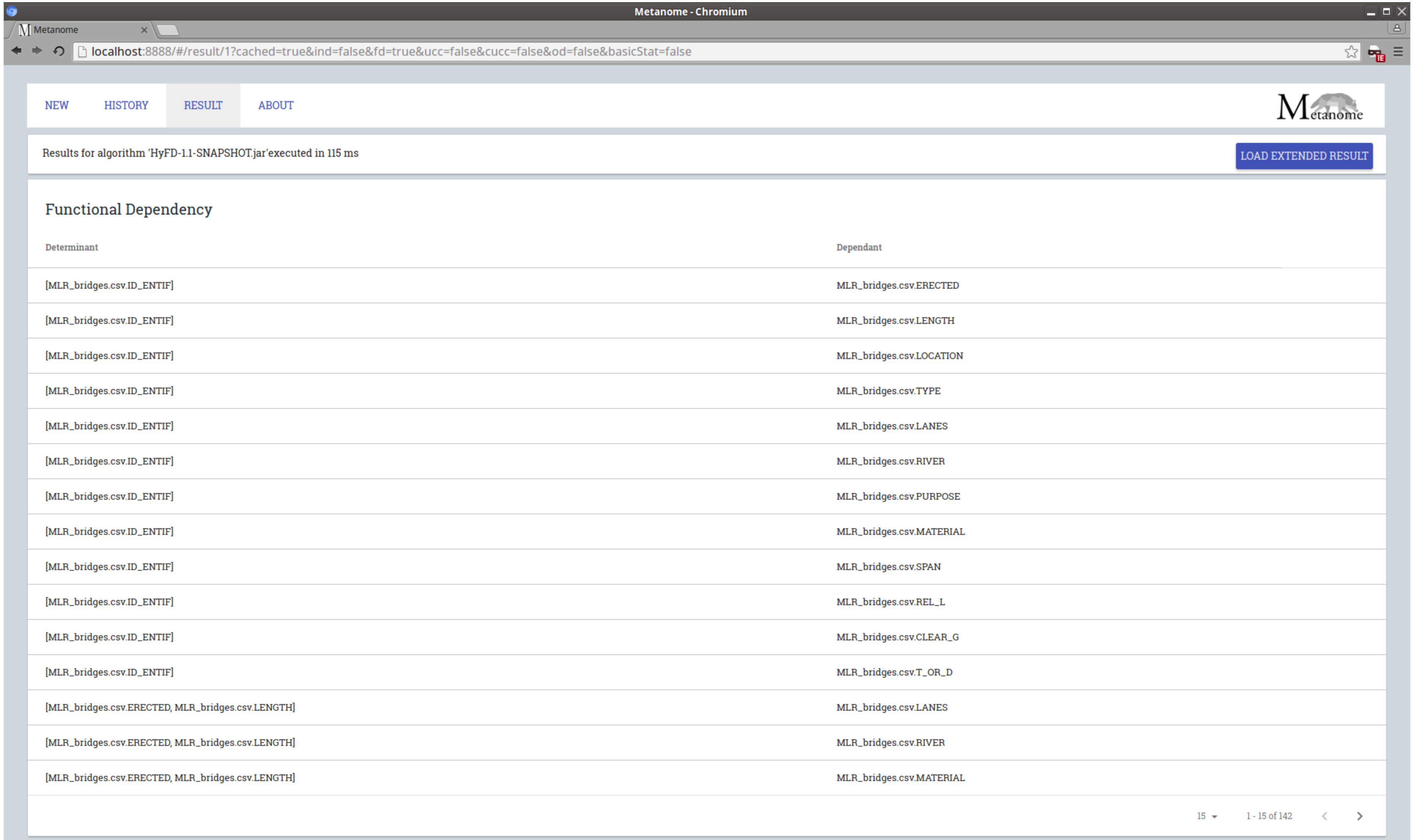
○ Write result immediately to disk.

○ Just count the results.

Memory (in MB):

EXECUTE

Metanome User Experience



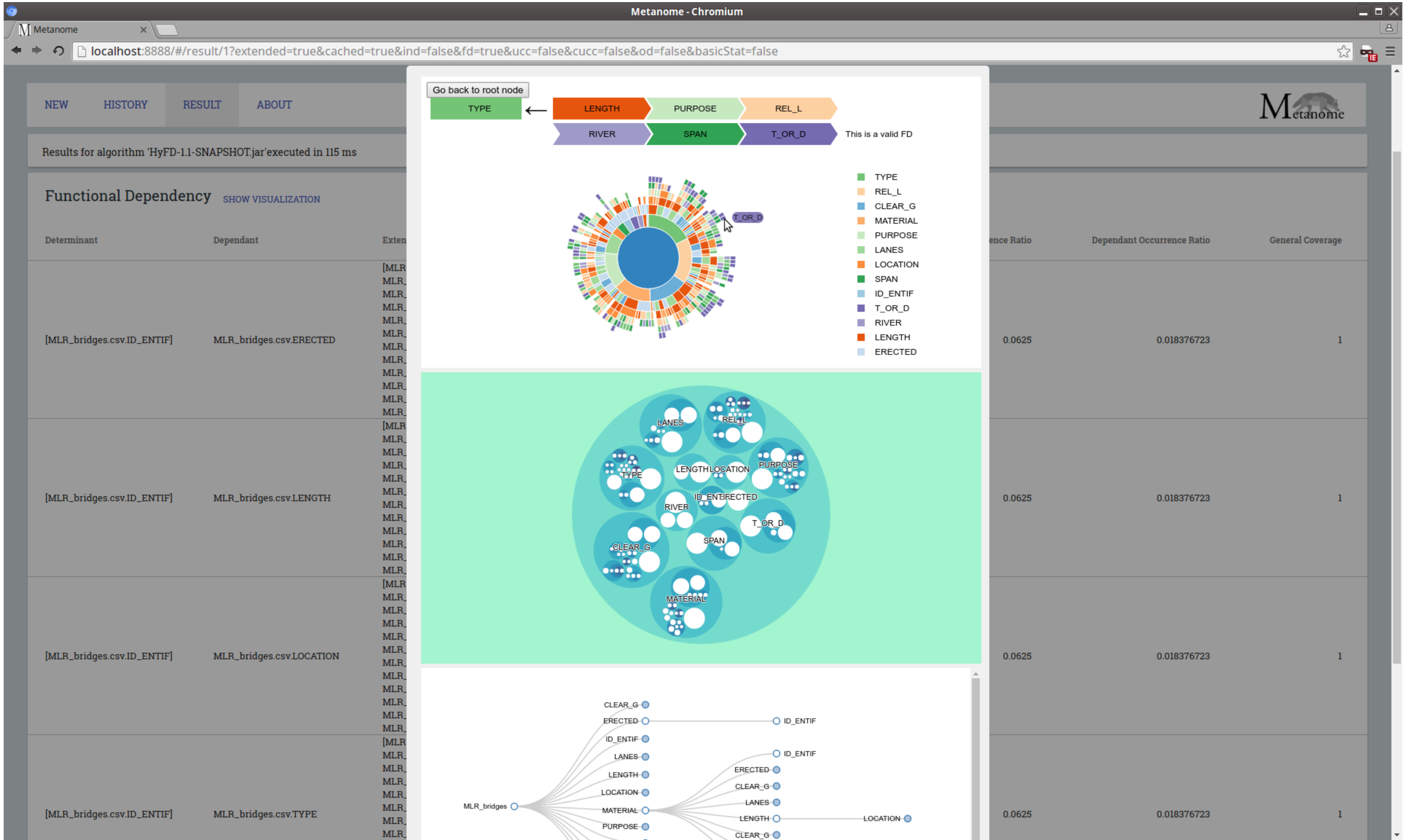
localhost:8888/#/result/1?cached=true&ind=false&fd=true&ucc=false&cucc=false&od=false&basicStat=false

Results for algorithm 'HyFD-1.1-SNAPSHOT.jar'executed in 115 ms

Functional Dependency

Determinant	Dependant
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.ERECTED
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.LENGTH
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.LOCATION
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.TYPE
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.LANES
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.RIVER
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.PURPOSE
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.MATERIAL
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.SPAN
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.REL_L
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.CLEAR_G
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.T_OR_D
[MLR_bridges.csv.ERECTED, MLR_bridges.csv.LENGTH]	MLR_bridges.csv.LANES
[MLR_bridges.csv.ERECTED, MLR_bridges.csv.LENGTH]	MLR_bridges.csv.RIVER
[MLR_bridges.csv.ERECTED, MLR_bridges.csv.LENGTH]	MLR_bridges.csv.MATERIAL

Metanome User Experience



Metanome - Chromium

Metanome

localhost:8888/#/result/1?extended=true&cached=true&ind=false&fd=true&ucc=false&cucc=false&od=false&basicStat=false

NEW HISTORY RESULT ABOUT

Results for algorithm 'HyFD-1.1-SNAPSHOT.jar'executed in 115 ms

Functional Dependency SHOW VISUALIZATION

Determinant	Dependant	Exten	ence Ratio	Dependant Occurrence Ratio	General Coverage
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.ERECTED	[MLR MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_	0.0625	0.018376723	1
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.LENGTH	[MLR MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_	0.0625	0.018376723	1
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.LOCATION	[MLR MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_	0.0625	0.018376723	1
[MLR_bridges.csv.ID_ENTIF]	MLR_bridges.csv.TYPE	[MLR MLR_ MLR_ MLR_ MLR_ MLR_ MLR_ MLR_	0.0625	0.018376723	1

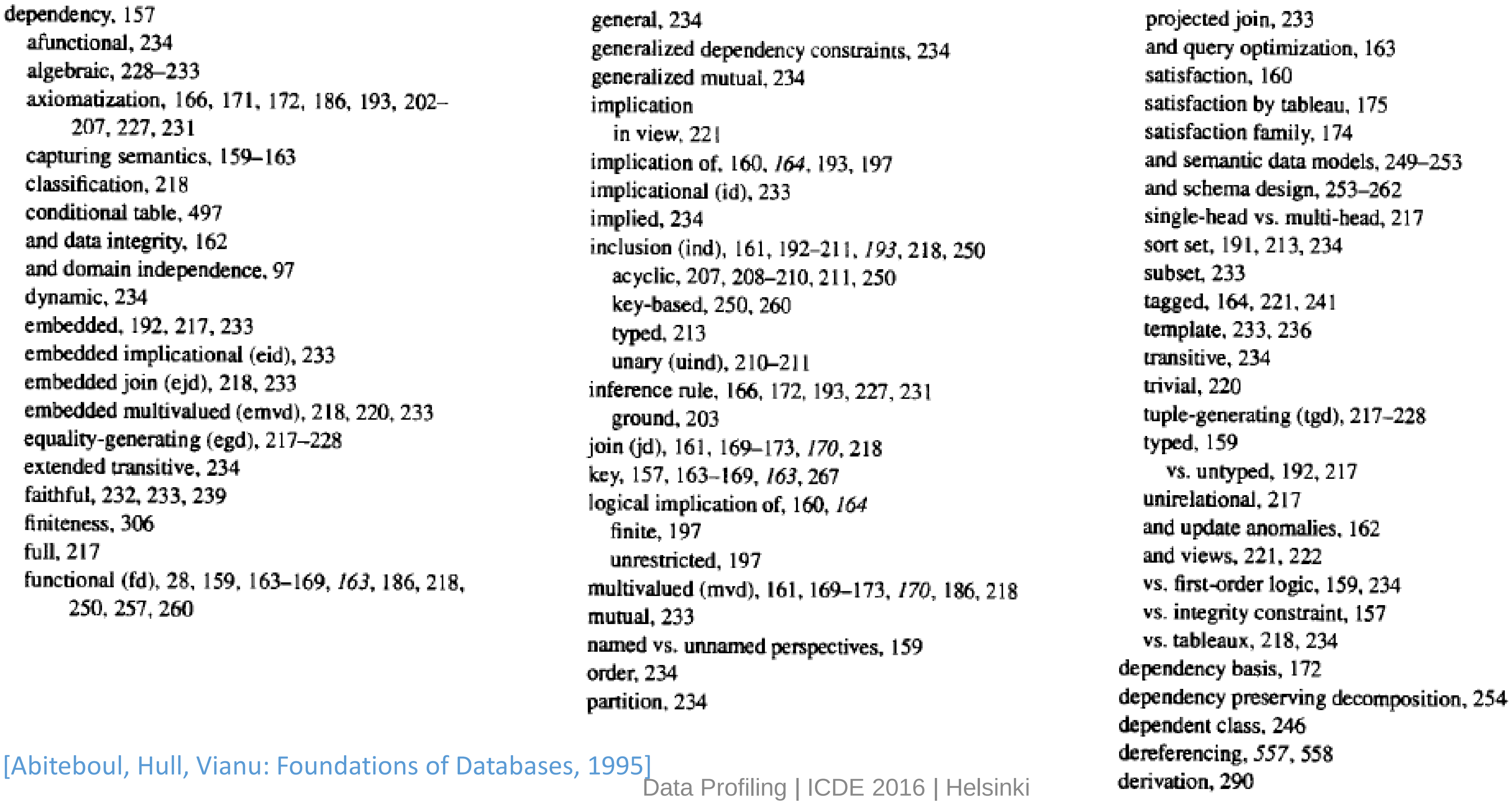
Go back to root node

TYPE ← LENGTH PURPOSE REL_L RIVER SPAN T_OR_D

This is a valid FD

Extending the Functionality of Data Profiling

Many Other Kinds of Dependencies



- dependency, 157
  - afunctional, 234
  - algebraic, 228–233
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  - embedded join (ejd), 218, 233
  - embedded multivalued (emvd), 218, 220, 233
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  - implied, 234
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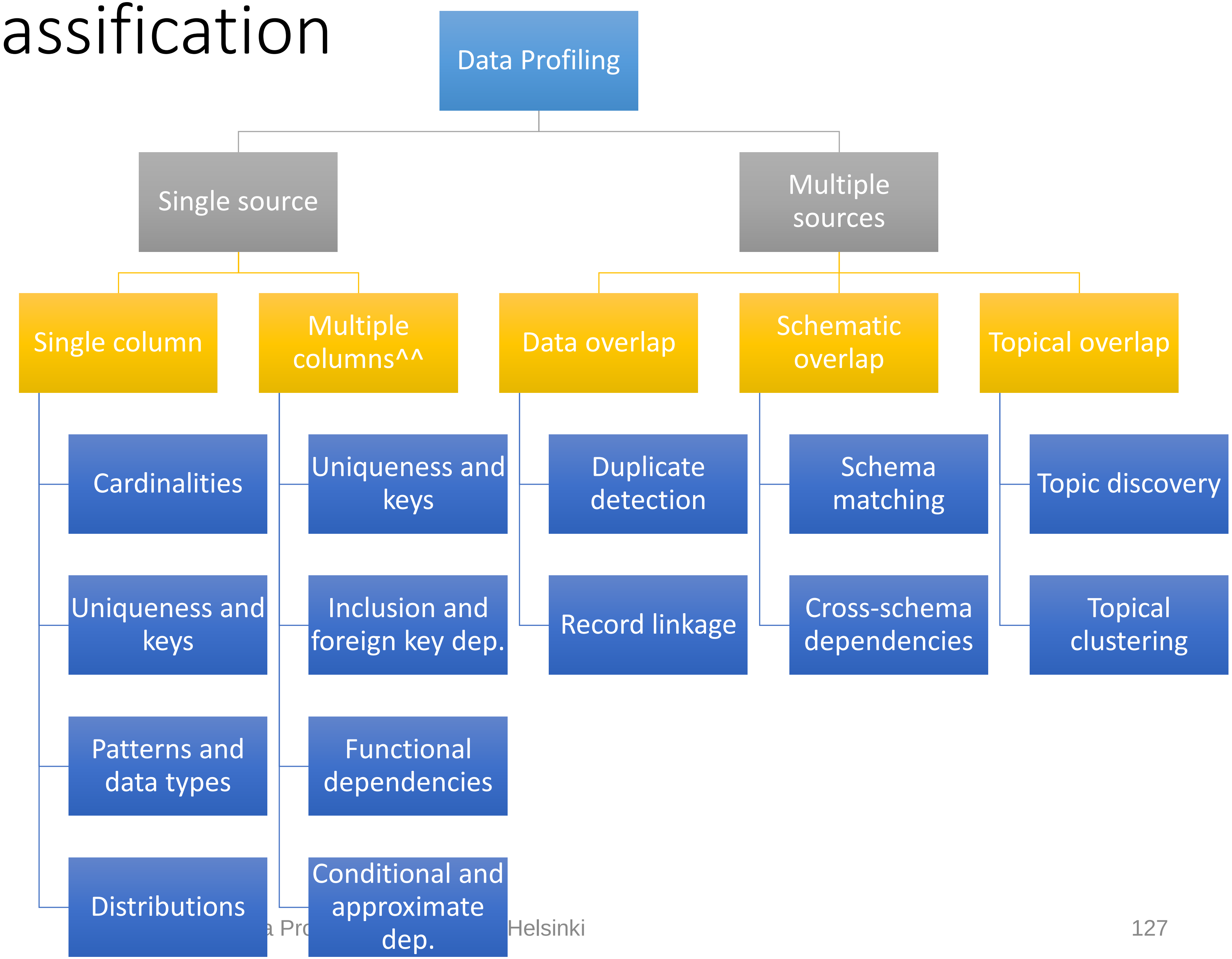
[Abiteboul, Hull, Vianu: Foundations of Databases, 1995]

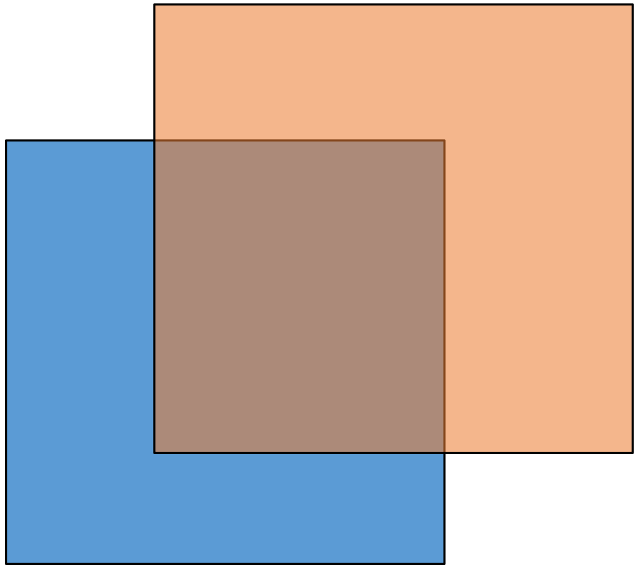
Extended Classification of Profiling Tasks



- Data Profiling
  - Single source
    - Single column
      - Cardinalities
      - Uniqueness and keys
      - Patterns and data types
      - Distributions
    - Multiple columns^^
      - Uniqueness and keys
      - Inclusion and foreign key dep.
      - Functional dependencies
      - Conditional and approximate dep.
  - Multiple sources
    - Data overlap
      - Duplicate detection
      - Record linkage
    - Schematic overlap
      - Schema matching
      - Cross-schema dependencies
    - Topical overlap
      - Topic discovery
      - Topical clustering

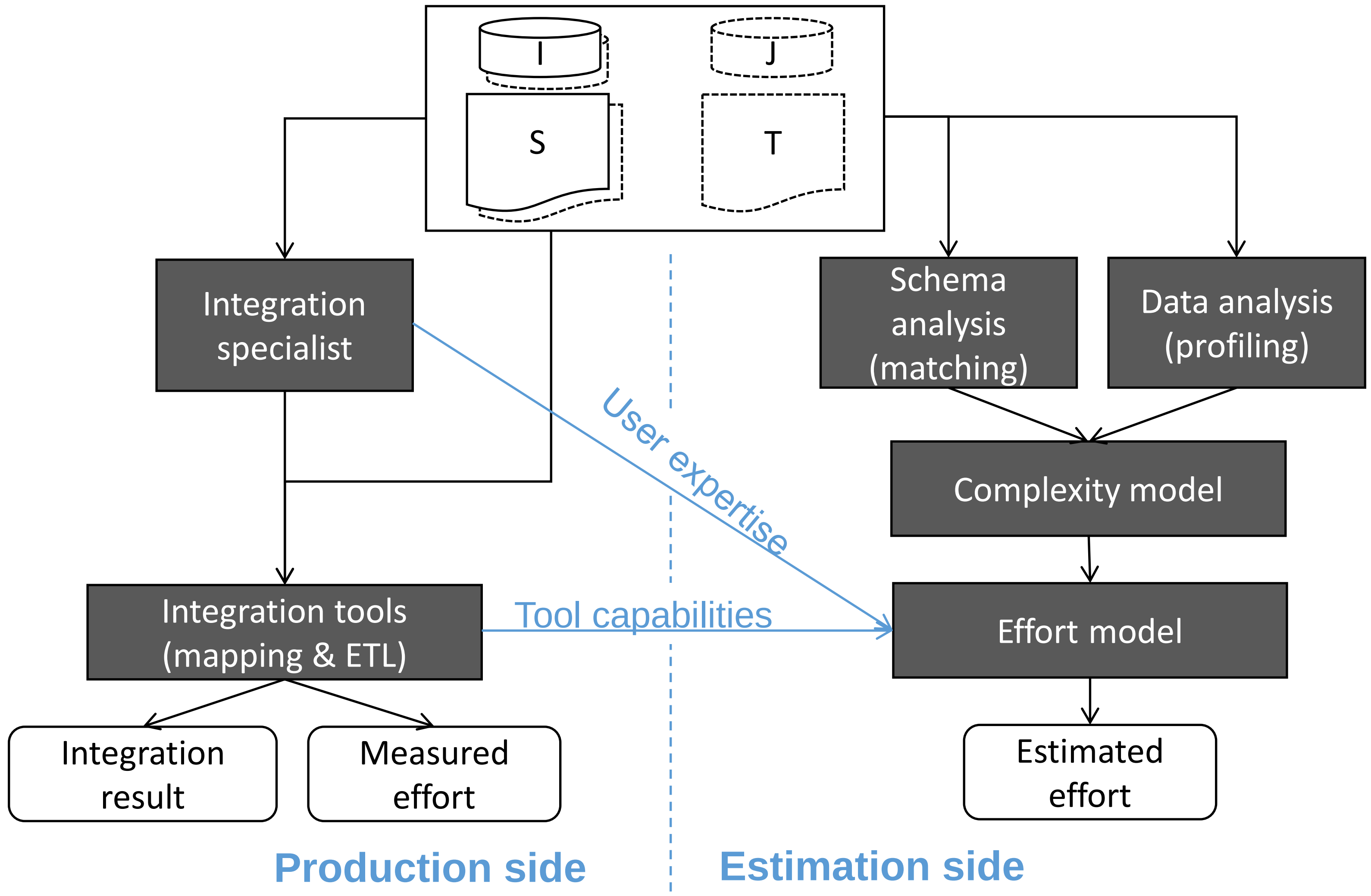
Profiling for Integration

- Create measures to estimate integration (and cleansing) effort
  - Schema and data overlap
  - Severity of heterogeneity
- Schema matching/mapping
  - What constitutes the “difficulty” of matching/mapping?
- Duplicate detection
  - Estimate data overlap
  - Estimate fusion effort



- Overall: Determine integration complexity and integration effort
  - Intrinsic complexity: Schema and data
  - Extrinsic complexity: Tools and expertise

Integration Effort Estimation



[Kruse, Papotti, Naumann: Estimating Data Integration and Cleaning Effort. EDBT 2015]

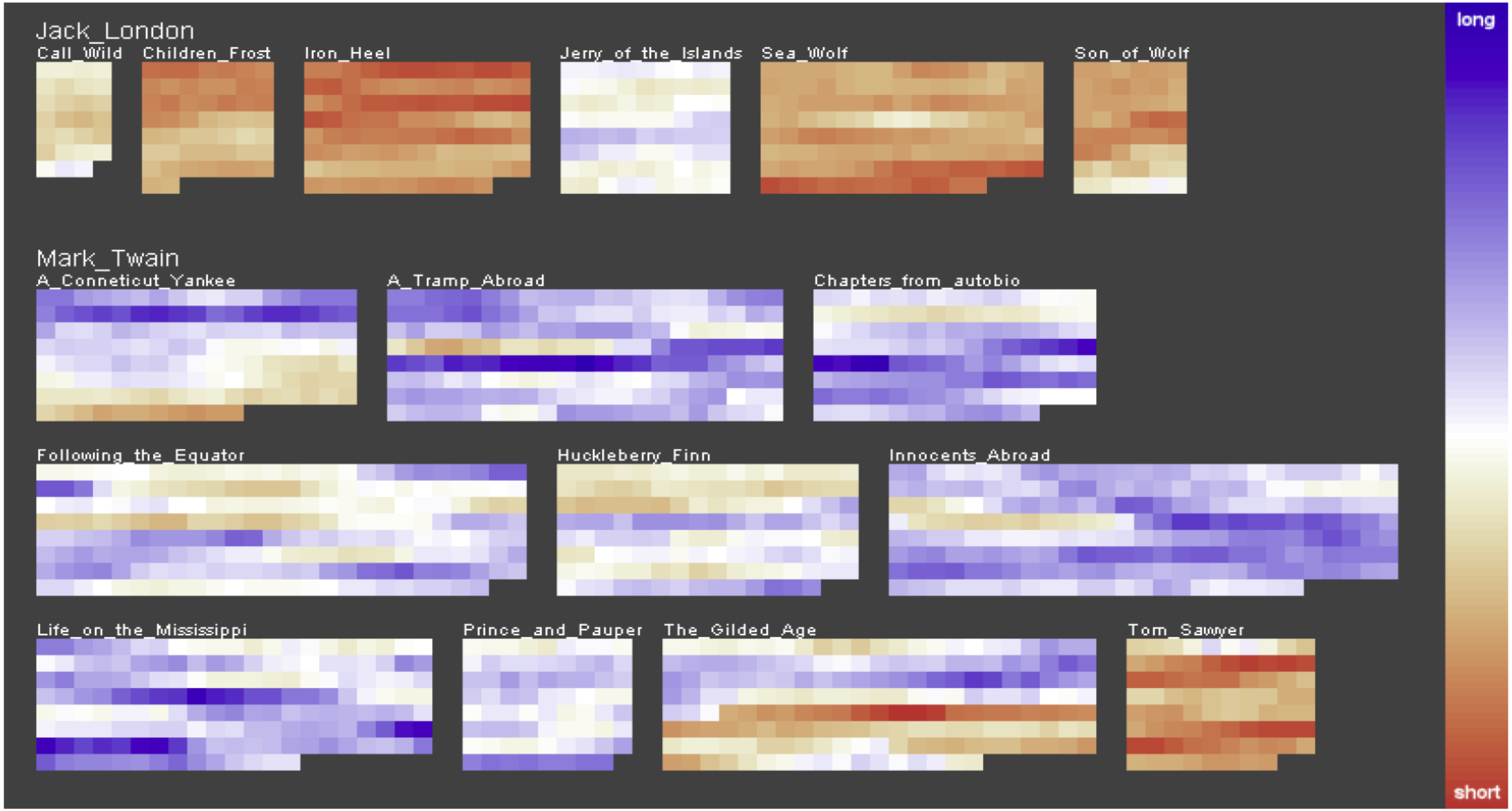
Profiling new Types of Data

- Traditional data profiling: Single table or multiple tables
- More and more data in other models
    - XML / nested relational / JSON
    - RDF triples
    - Textual data: Blogs, Tweets, News
    - Multimedia data
- Different models offer new dimensions to profile
    - XML: Nestedness, measures at different nesting levels
    - RDF: Graph structure, in- and outdegrees
    - Multimedia: Color, video-length, volume, etc.
    - Text: Sentiment, sentence structure, complexity, and other linguistic measures

Example: Text Profiling

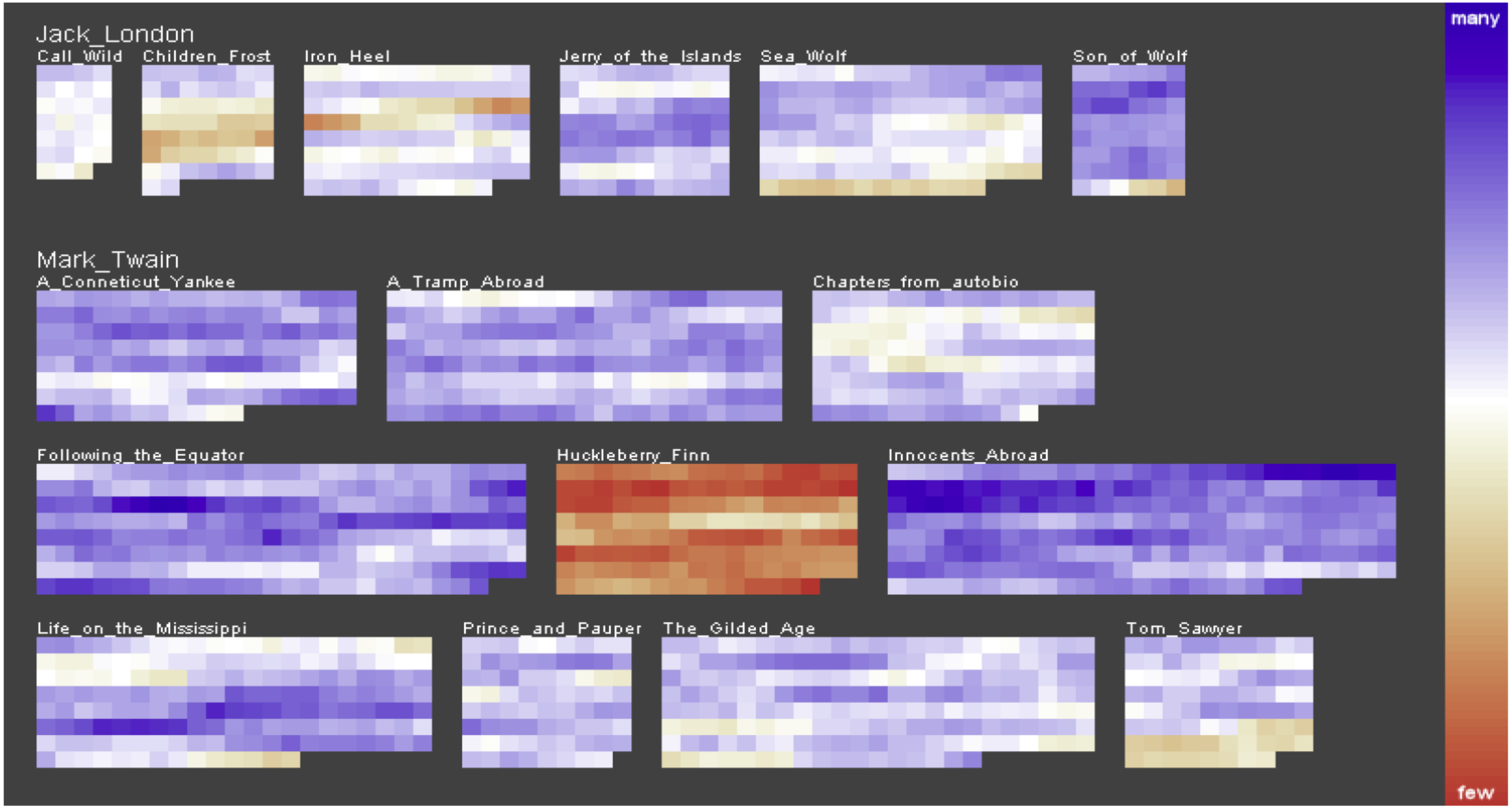
- Statistical measures
    - Syllables per word
    - Sentence length
    - Proportions of parts of speech
- Vocabulary measures
    - Frequencies of specific words
    - Type-token ratio
    - Simpson’s index (vocabulary richness)
    - Number of hapax (dis)legomena
        - Token that occurs exactly once (twice) in the corpus
        - Characterize style of an author

Average Sentence Length



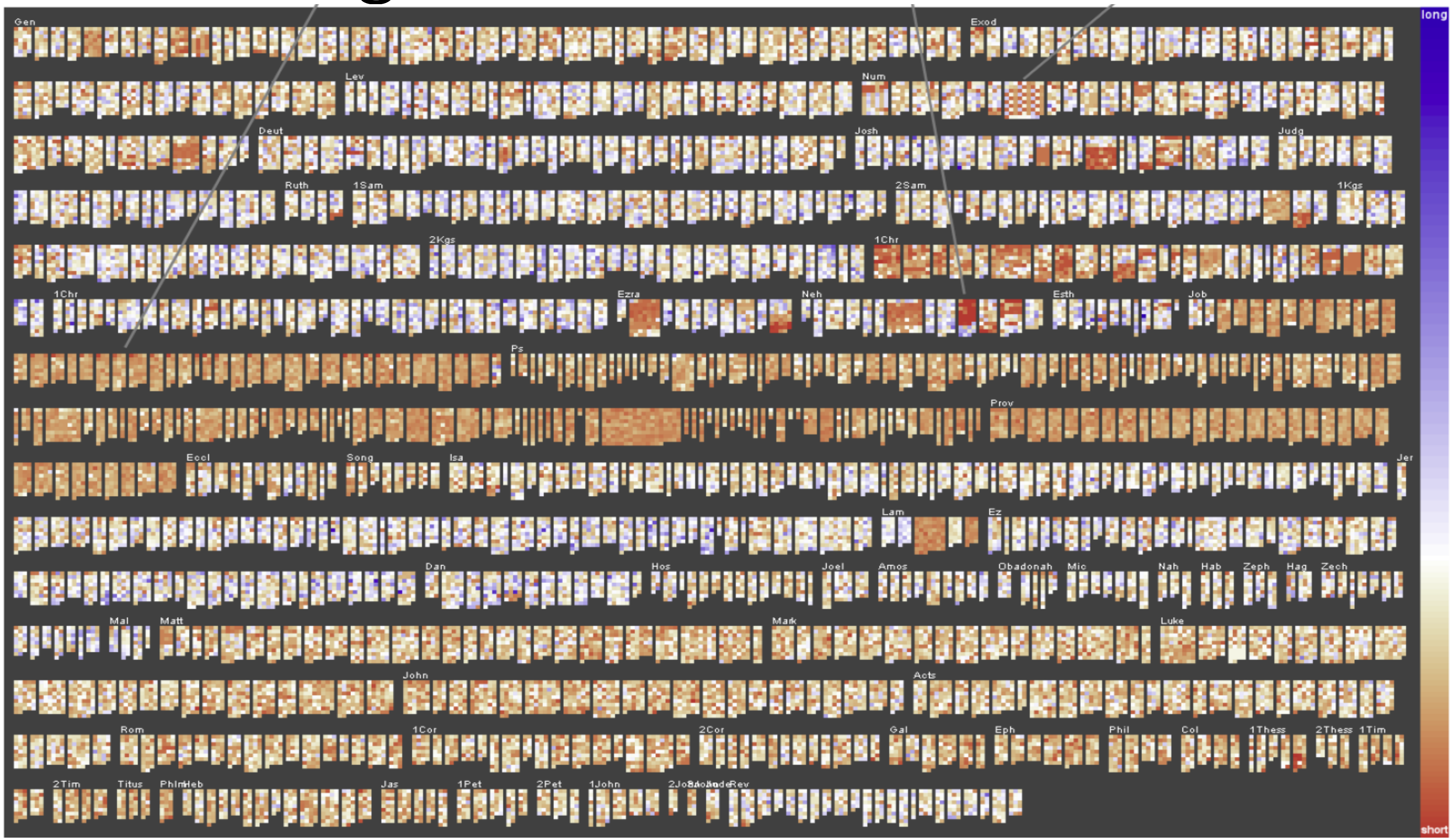
[Keim and Oelke: Literature Fingerprinting: A New Method for Visual Literary Analysis. IEEE VAST 2007]

Hapax Legomena



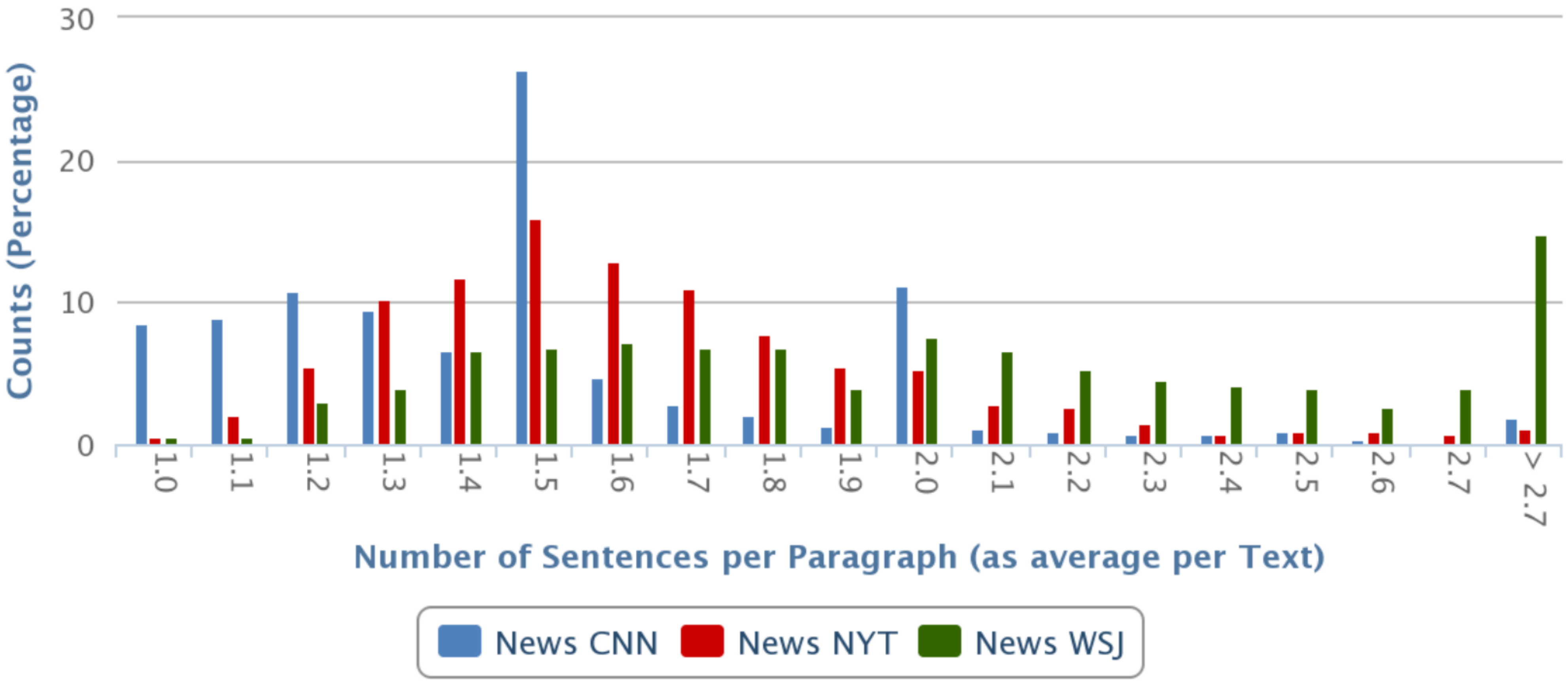
[Keim and Oelke: Literature Fingerprinting: A New Method for Visual Literary Analysis. IEEE VAST 2007]

Verse Length



[Keim and Oelke: Literature Fingerprinting: A New Method for Visual Literary Analysis. IEEE VAST 2007]

Example: News Article Statistics



Improving Non-Functional Properties of Data Profiling

Profiling Challenges

- Efficient profiling
- Scalable profiling
- Holistic profiling
- Incremental profiling
- Online profiling
- Temporal profiling
- Profiling query results
- Profiling new types of data
- Data generation and testing
- Data profiling benchmark

Holistic Profiling

- Various profiling methods for various profiling tasks
- Commonalities/similarities
  - Search space: All column combinations (or pairs thereof)
  - I/O: Read all data at least once
  - Data structure: Some index or hash table
  - Pruning and candidate generation: based on subset/superset relationships
  - Sortation: Benefit from sorted sets

- Challenge: Develop single method to output all/most profiling results

Incremental Profiling

- Data is dynamic
  - Insert (batch or tuple-based)
  - Updates
  - Deletes

- Problem: Keep profiling results up-to-date without reprofiling the entire data set
  - Easy examples: SUM, MIN, MAX, COUNT, AVG
  - Difficult examples: MEDIAN, uniqueness, FDs, etc.

Online Profiling

- Profiling is long procedure
  - Boring for developers
  - Expensive for machines (I/O and CPU)

- Challenge: Display intermediate results
  - … of improving/converging accuracy
  - Allows early abort of profiling run

- Gear algorithms toward that goal
  - Allow intermediate output
  - Enable early output: “progressive” profiling

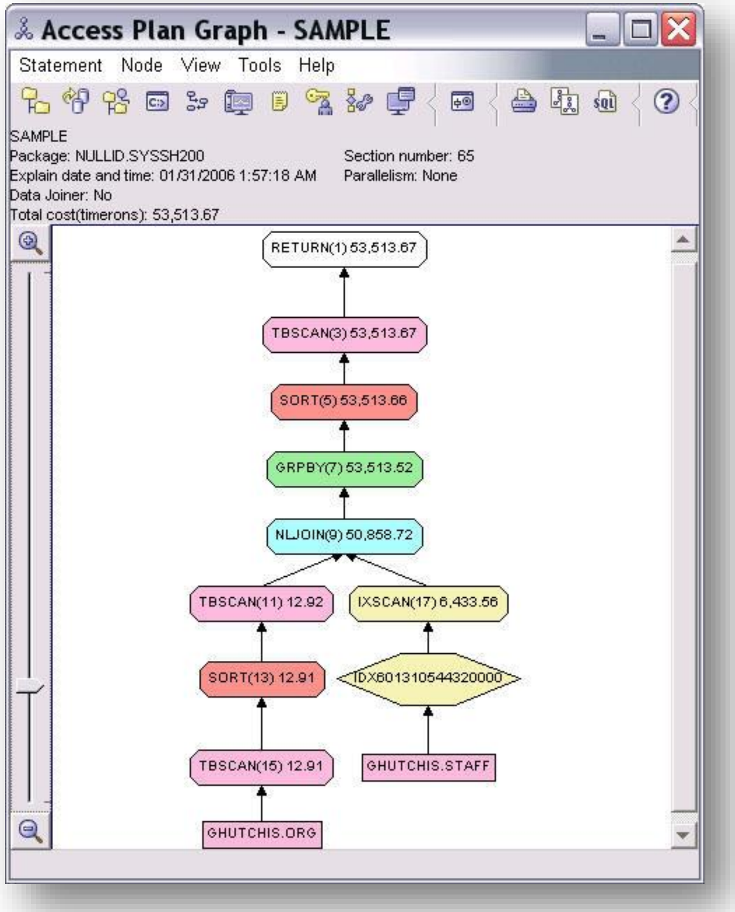
Temporal Profiling

- Observe behavior of dependencies over time
  - Do FDs appear and disappear?
  - Does a partial IND become less partial over time?
  - …
- Metadata monitoring
  - Meta-Metadata

Profiling Query Results

- Query results are boring: Spruce them up with some metadata
  - Usually only: Row count
  - For each column, give some statistics

- Idea: Piggy-back profiling on query execution
  - Re-use sortations, hash tables, etc.



SAMPLE
Package: NULLID.SYSSH200 Section number: 65
Explain date and time: 01/31/2006 1:57:18 AM Parallelism: None
Data Joiner: No
Total cost(timerons): 53,513.67

Data Generation and Testing

- Generate volumes of data with certain properties
  - Test extreme cases
  - Test scalability

- Problem: Interaction between properties
  - FDs vs. uniqueness
  - Patterns vs. conditional INDs
  - Distributions vs. all others…
- Problem: Create realistic data
  - Distributions, patterns
  - Placement of dependencies (tight or spread out)
  - Example: TPCH (next slide)

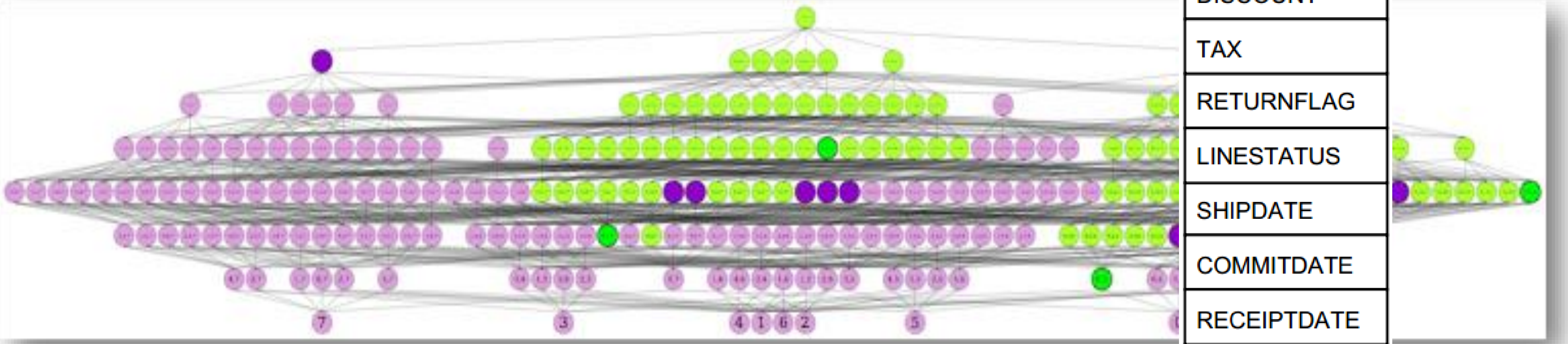
Recent work
[Arocena et al. : Messing Up with BART: Error Generation for Evaluating Data-Cleaning Algorithms. PVLDB 9(2), 2015]
[Arocena et al. : The iBench Integration Metadata Generator . PVLDB 9(3), 2015]

TPCH – Uniques and Non-Uniques

- Using the first 8 columns of the lineitems table
- Using a scale-factor of 0.1

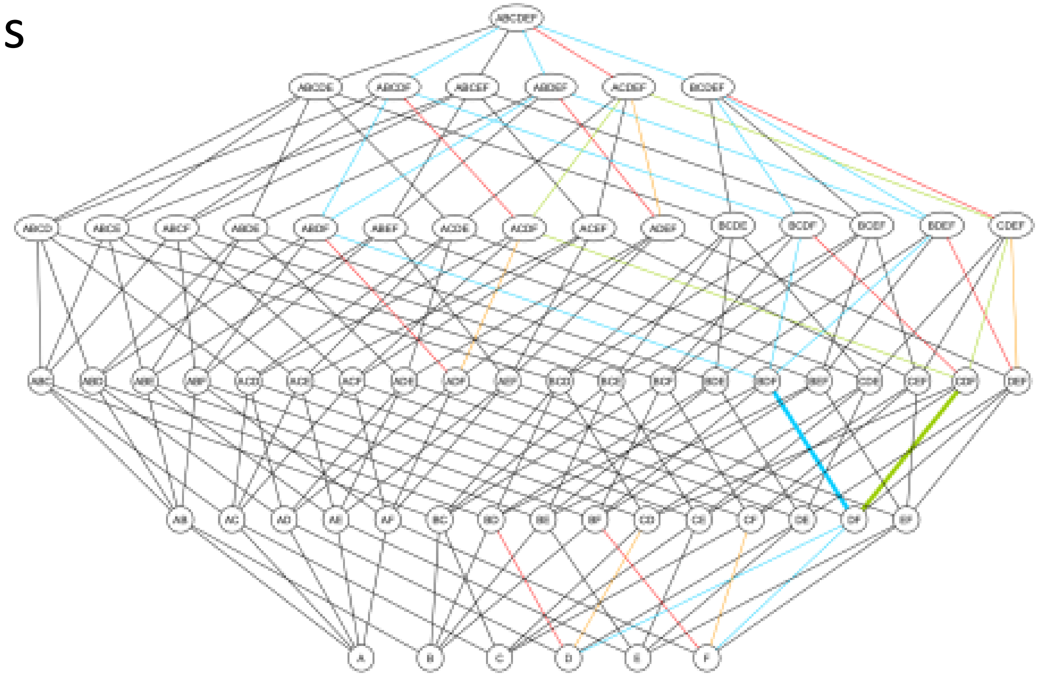
LINEITEM (L_)
SF*6,000,000

ORDERKEY
PARTKEY
SUPPKEY
LINENUMBER
QUANTITY
EXTENDEDPRICE
DISCOUNT
TAX
RETURNFLAG
LINESTATUS
SHIPDATE
COMMITDATE
RECEIPTDATE
SHIPINSTRUCT
SHIPMODE
COMMENT



Data Profiling Benchmark

- Define data
  - Data generation
  - Real-world dataset(s)
  - Different scale-factors: Rows and columns
- Define tasks
  - Individual tasks
  - Sets of tasks
- Define measures
  - Speed
  - Speed/cost
  - Minimum hardware requirements
  - Accuracy for approximate approaches



Semantic Interpretation of Profiling Results

Turning Instance-based Observations to Schema-based Constraints

- Hundreds of UCCs – which ones are keys?
- Thousands of FDs – which ones are true?
- Millions of INDs – which ones are foreign keys?

- User-driven interpretation:
  - Rank and visualize metadata
- Machine-driven interpretation
  - Machine learning

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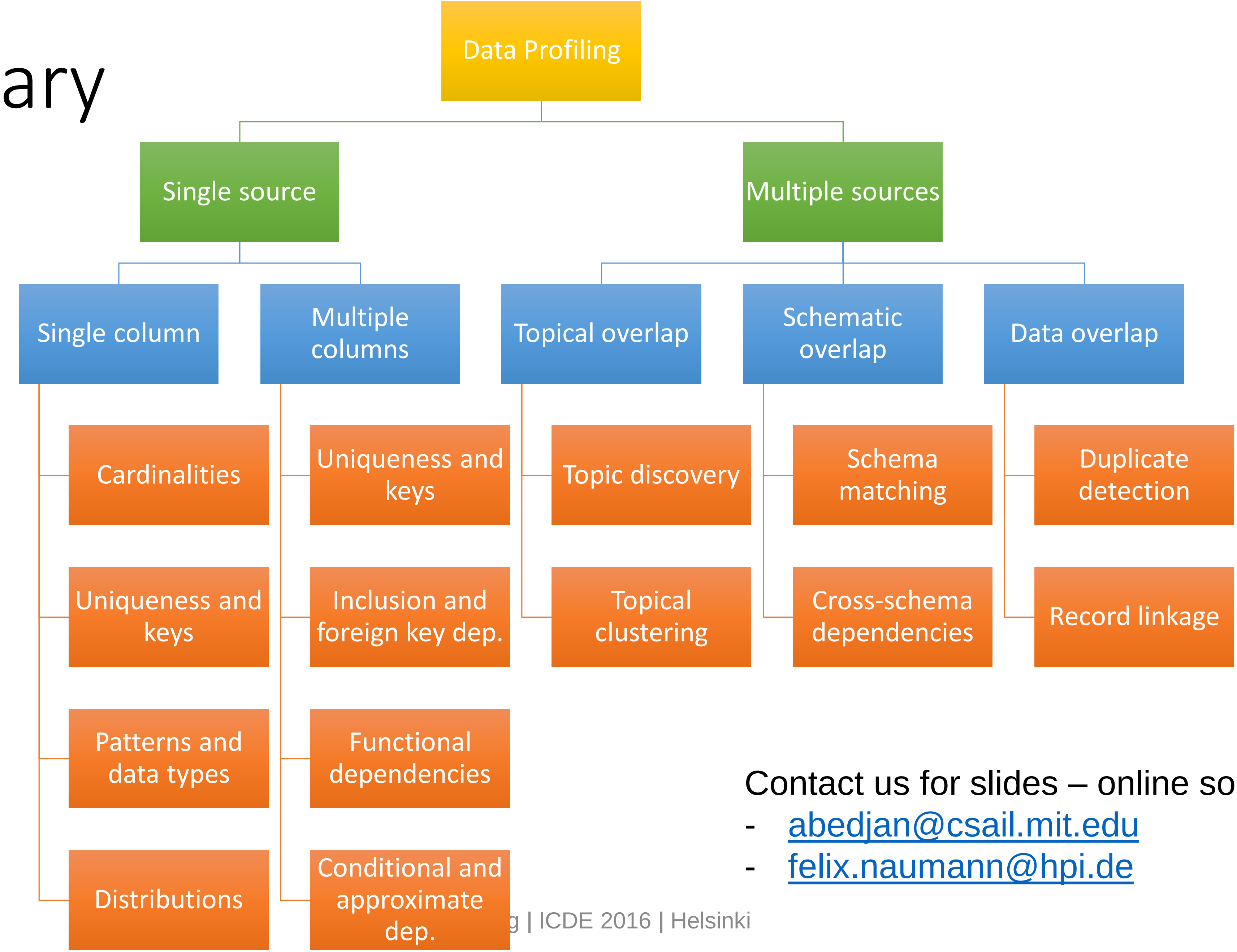
Summary



Data Profiling

Single source

Multiple sources

Single column

Multiple columns

Topical overlap

Schematic overlap

Data overlap

Cardinalities

Uniqueness and keys

Patterns and data types

Distributions

Uniqueness and keys

Inclusion and foreign key dep.

Functional dependencies

Conditional and approximate dep.

Topic discovery

Topical clustering

Schema matching

Cross-schema dependencies

Duplicate detection

Record linkage

Contact us for slides – online soon

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