Tackling The Challenges of Big Data Big Data Collection	
Michael Stonebraker	
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Tackling The Challenges of Big Data Big Data Collection	
Data Cleaning & Integration	
Introduction	
Michael Stonebraker	
Professor	
Massachusetts Institute of Technology	
THIT MANAGEMENT	
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Data Curation	
• Ingest	
Validate	
• Transform	
• Correct	
Consolidate (dedup)	
 And visualize information to be integrated 	
- And visualize information to be integrated	

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Data Warehouse Roots	
Retail sector started integrating sales data into a data warehouse in the early 1990's	
Average system was 2X budget and 2X late	
Because of data integration headaches	
However, warehouse paid for itself within 6 months with smarter buying decisions!	
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Issues	
sold \$100K of widgets to IBM, Inc.sold 800K Euros of m-widgets to IBM, SA	
Translate currencies	
 Is IBM, SA the same as IBM, Inc? Are m-widgets the same as widgets?	
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The Pile On	
The Pile-On	
 Essentially all enterprises followed suit and built warehouses of customer facing data 	
Serviced by so-called Extract-Transform-and Load (ETL) tools	
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Architecture	
http://on.wikipodia.org/wiki/Data_intogration	
http://en.wikipedia.org/wiki/Data_integration	
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Traditional Wisdom - ETL	
Human defines a global schema	
Assign a programmer to each data source to:	
Assign a programmer to each data source to.	
- Understand it	
 Write local to global mapping (in a scripting language) 	
- Write cleaning routine	
- Run the ETL	
Scales to (maybe) 25 data sources	
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Traditional ETL Methodology – Schema Mapping	
Schema Mapping	
http://www.google.com/imgres?imgurl=http://	
www.xmlschema.info/images/shots/	
map_xml_thumb.gif&imgrefurl=http:// www.xmlschema.info/	
www.xmiscnema.info/ xml_schema_mapping.html&h=469&w=600&sz=63&tb	
nid=70oECAvg0TMwkM:&tbnh=102&tbnw=131&zoom=	
1&usg=AsYa- CEcZeR6MX9IV8JqvdpX9RM=&docid=MbKKOGXt3LED1	
M&sa=X&ei=XDGJUpi9OYevsQT5IYGAAg&ved=0CDQQ9	
QEwAg	
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Traditional ETL Methodology – Data Transformation	
http://www.informatica.com/	
us/products/enterprise-data- integration/powercenter/	
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Current Situation	
Enterprises want to integrate more and more data sources	
Miller beer example Novartis example	
- Goby example (we will see this again) • Traditional ETL won't scale!!!!	
Point-projects in departments Staffed by a data scientist	
Brand manager deciding marketing spend Augmenting demographic customer data for department use	
Traditional ETL way too heavy-weight	
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The Rest of This Module	
The Rest of This Floudie	-
Curation example	
Low end (individual data scientist) support	
Enterprise support	
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Issues	
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The Duelder	
The Problem	-
Demo of Goby.com	
No.	
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In Summary	
In Sammary	
Data is distribut	
Data is dirty!!!!!	
Sometimes not clear how to clean it	
- 2 restaurants at the same address: food court or	-
one went out of business??	
Transformations may be a big problem	
Tanoromations may be a big problem	
17	
17 THITTS TOTAL	
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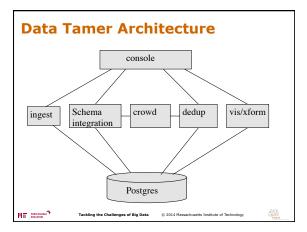
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Data Cleaning & Integration New Ideas - 1	
New Ideas 1	
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HIL months Girls	
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Startups in This Space (probably a	
bunch more)	
Paxata Trifacta (commercial Data Wrangler)	
Cambridge Semantics	
Data Tamer ClearStory	
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At Least Two Foci	
Support for the individual data scientist	
Enterprise data integration	
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Command for the Date Colordist]
Support for the Data Scientist	
• Wrangler video	
http://vis.stanford.edu/wrangler/	
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Summary	
Expect more systems in this space	
At low prices	
Market will be gated by the availability of data	
scientists - Insurance example	
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Big Data Collection	Jala _		
Data Cleaning & Integration	_		
New Ideas - 1			
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Data Cleaning & Integration			
New Ideas - 2	-		
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Michael Stonebraker			
Professor Massachusetts Institute of Technology	-		
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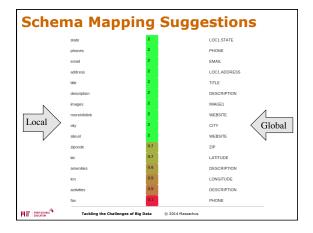
Data Tamer Goals • Do the "long tail" - Better/cheaper/faster than the ad-hoc techniques being used currently • By inverting the normal ETL architecture - Machine learning and statistics - Ask for human help only when automatic algorithms are unsure

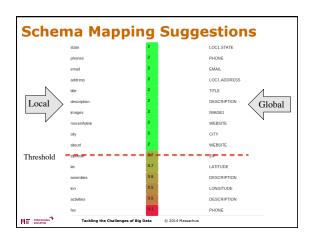
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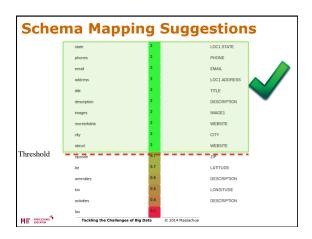


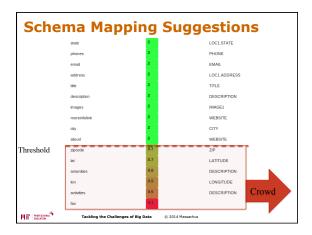
Data Tamer -- Ingest Assumes (for now) a data source is a collection of records, each a collection of (attribute-name, value) pairs. Loaded into Postgres Tackling the Challenges of Big Data © 2014 Massachusetts Institute of Technology

Data Tamer – Schema Integration	
Must be told whether there is a predefined partial or complete global schema or nothing	
Starts integrating data sources Using synonyms, templates, and authoritative tables for help	
1st couple of sources require asking the crowd for answers	
- System gets better and better over time	
HIT PARTIES TACKING THE Challenges of Big Data © 2014 Massachusetts Institute of Technology	
Data Tamer – Schema Integration	
Inner loop is a collection of experts T-test on the data	
- Cosine similarity on attribute names	
– Cosine similarity on the data	
Scores combined heuristically	
After modest training, get 90% of the matching attributes on Goby and Novartis automatically	
- Cuts human cost dramatically	
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Data Tamer – Crowd Sourcing	
Hierarchy of experts	
With specializations With algorithms to adjust the "expertness" of	
experts • And a marketplace to perform load balancing	
Currently doing a large scale evaluation at Novartis Late flash: it works!!!!	









Data Tamer – Entity Consolidation

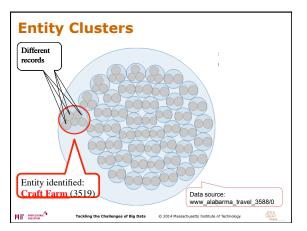
- On tables defined by schema integration module
- Entity matching on all attributes, weighted by value presence and distribution
- Basically a data clustering problem
- With a first pass to try to identify "blocks" of records

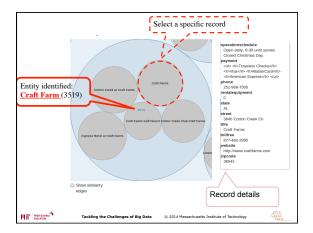
 Otherwise N ** 2 in the number of records
- Wildly better than Goby; a bit better than domainspecific Verisk module

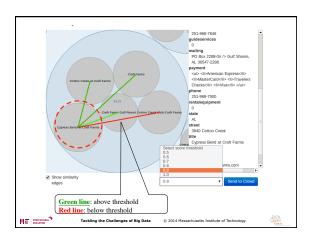
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Pata Tamer Future Text Relationships Hierarchical data (maybe) Adaptors Better algorithms User-defined operations Tackling the Challenges of Big Data © 2014 Massachusetts Institute of Technology

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New Ideas - 2	
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massachusetts institute of Technology	
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The Way Forward • Enterprises will want to integrate more and more data sources • This is the number one headache of most of them • Too expensive to do manually with a programmer • Remains to be seen what fraction of the market can be aided by Data Tamer-style tools • Initial results are encouraging Tackling the Challengee of Big Data • 2011 Messachusetts Institute of Technology The Way Forward

Cleaning will be a big issue forever How clean does your data need to be? I imagine a big database of transformations Pick the one that you need Data scientists will have to familiar with this stuff Not just stat and data management Tackling the Challenges of Big Data © 2014 Massachusetts Institute of Technology

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Summary

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