Building Mashups by Example

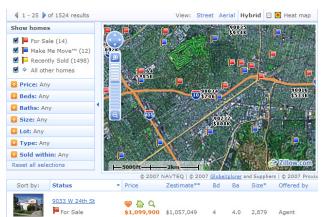
Craig A. Knoblock
University of Southern California

Work in collaboration with Rattapoom Tuchinda and Pedro Szekeley

What's a Mashup?

A website or application that combines content from more than one source into an integrated experience [wikipedia]







- a) LA crime map
 - -Crime Report from different counties
 - -Map

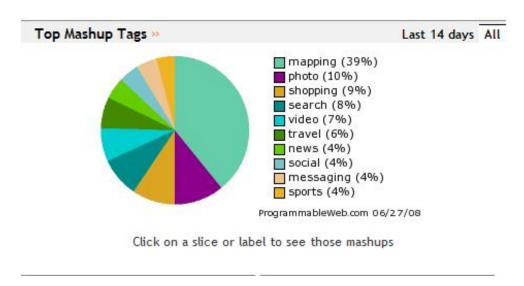
- b) zillow.com
- -Real Estate Listing
- -Property Tax

- c) Ski bonk
- -Weather
- -Snow Report
- -Snow Resorts

Combined Data gives new insight / provides new services

Statistics and Trends

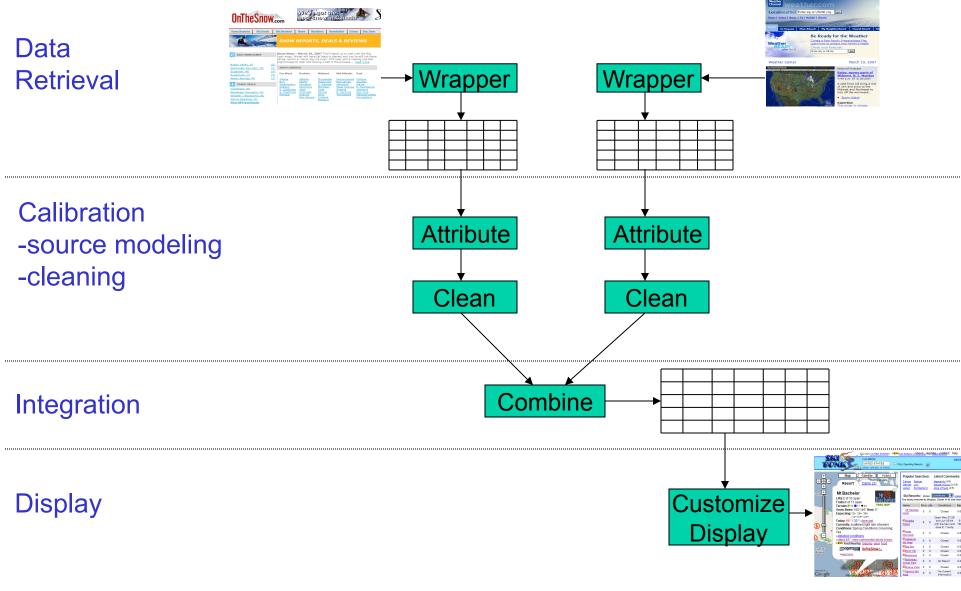




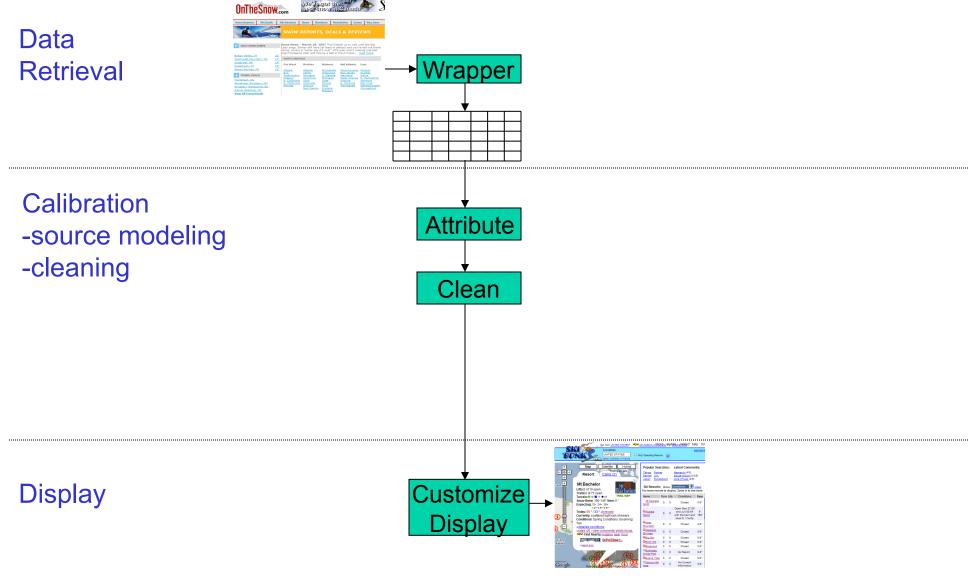
Survey of top 50 Mashups

- Divide into five categories based on programming structures
- Focus of this work is on the first four categories which account for 47% of the most popular Mashups

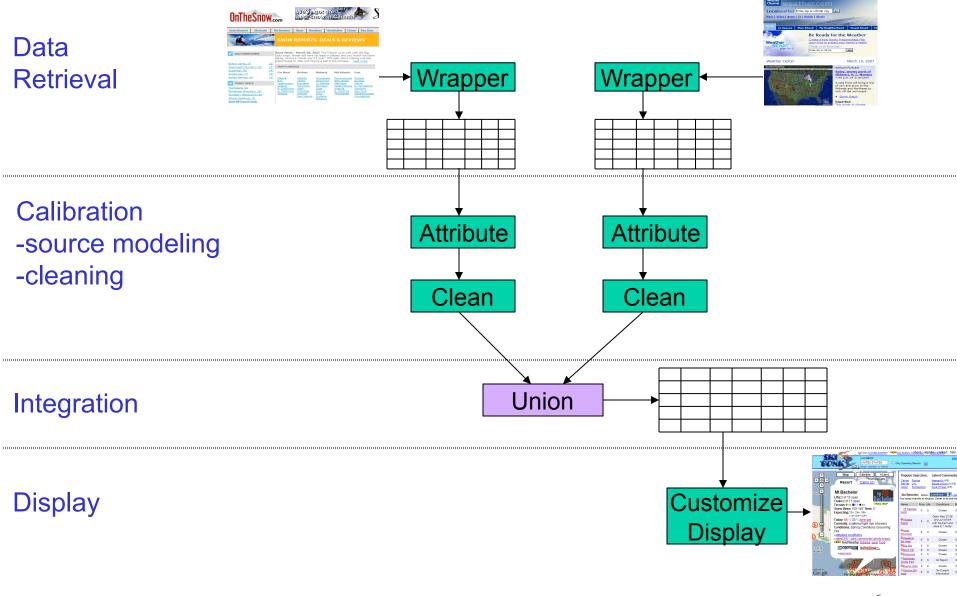
Mashup Building Issues



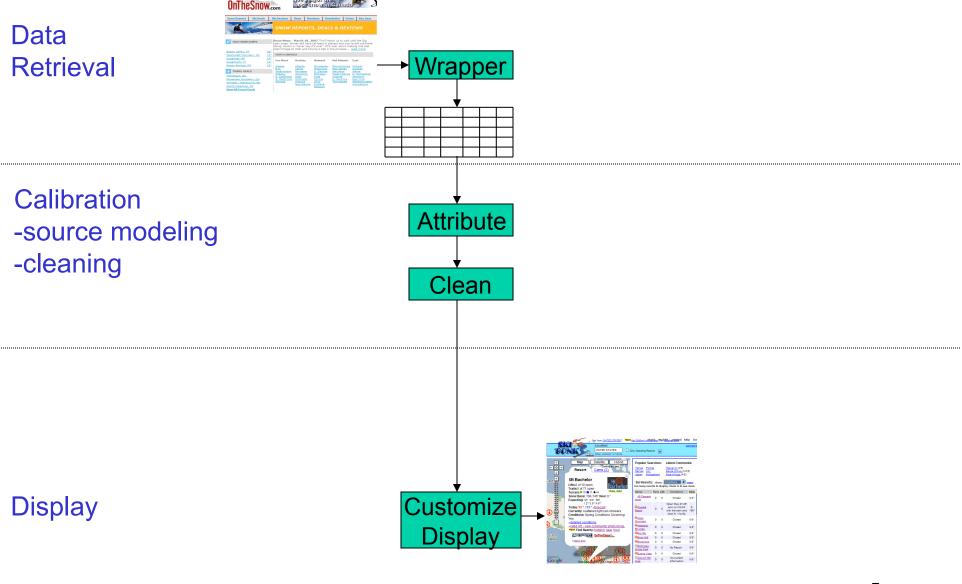
Type 1: One Simple Source



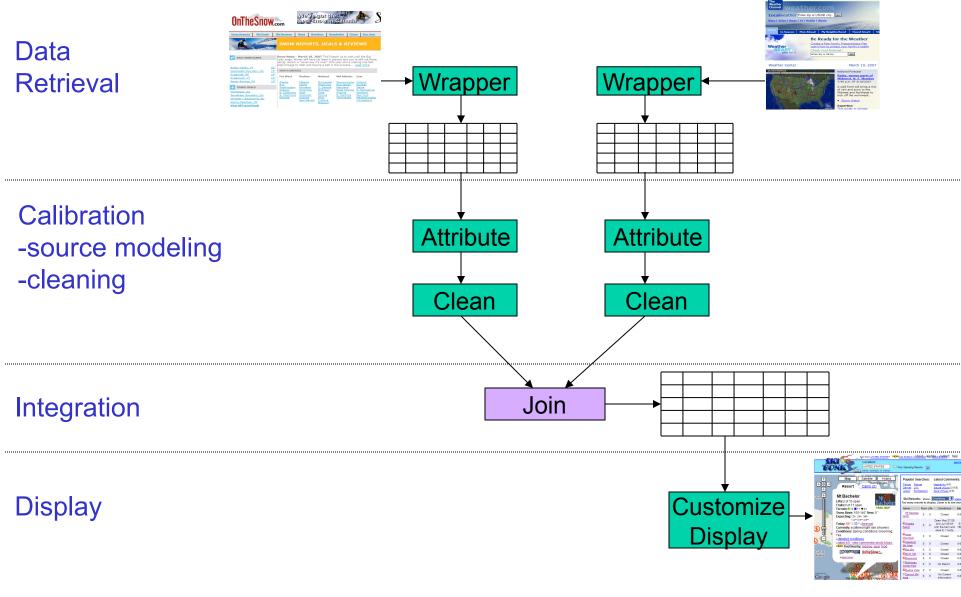
Type 2: Union



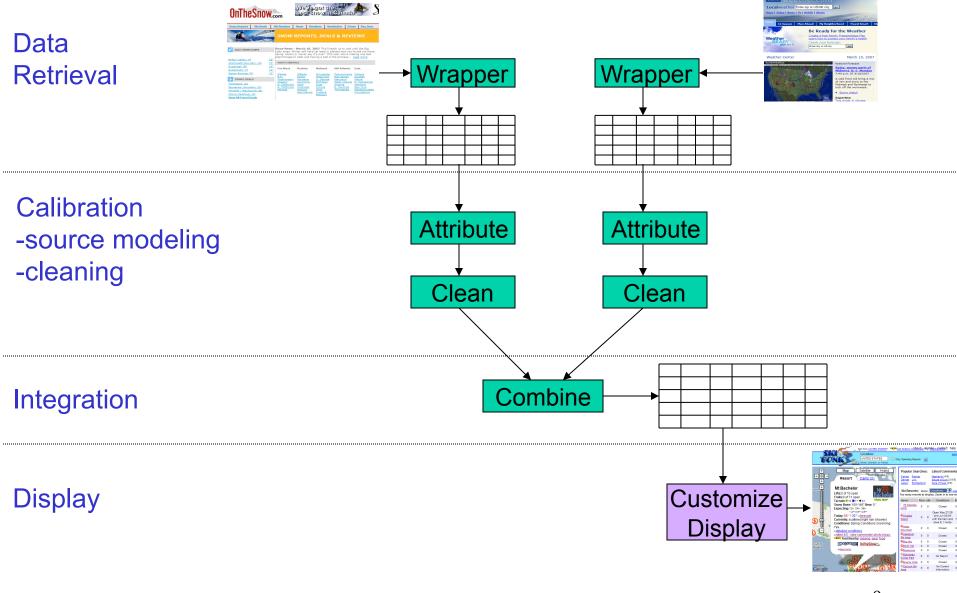
Type 3: One Source with Form



Type 4: Database Join



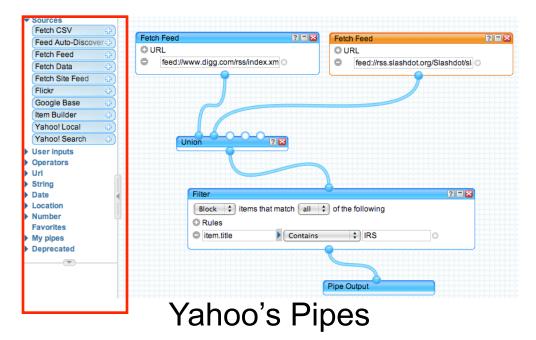
Type 5: Customized Display



Existing Approaches

Goal: Create Mashups without Programming

• Doesn't translate to not having to understand programming.



Widget Paradigm

- Widgets (i.e., 43 for Pipes, 300+ for MS) represents an operation on the data.
- Locating and learning to customize widget can be time consuming
- Most tools focus on particular issues and ignore others.

Can we come up with a framework that addresses all of the issues while still making the Mashup building process easy?

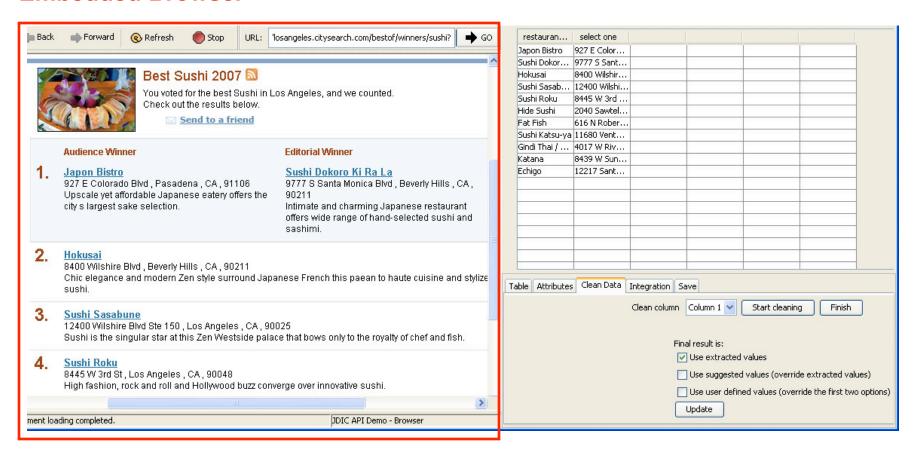
Key Contributions

- A programming by demonstration approach that uses a single table for building a Mashup
- An integrated approach that links data extraction, source modeling, data cleaning, and data integration together.
- A query formulation technique that allows users to specify examples to build complicated queries.

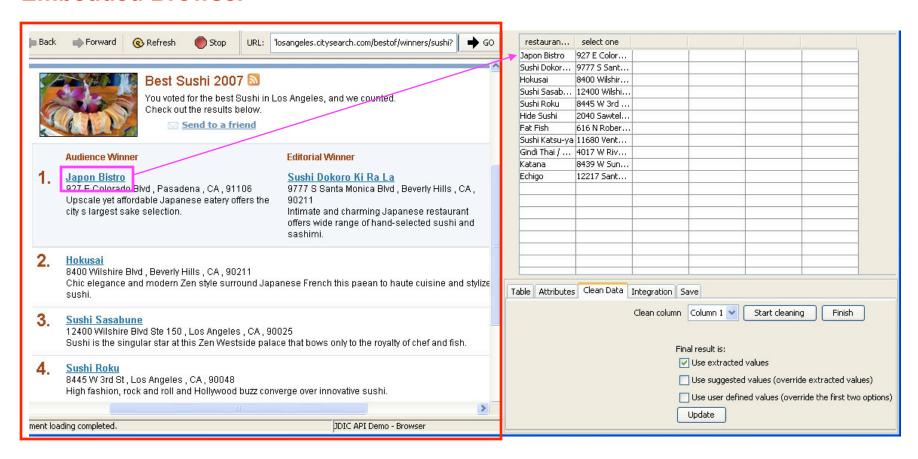
Key Ideas

- Focus on data, not operations
 - Users are more familiar with data.
- Leverage existing data
 - Help source modeling, cleaning, and data integration.
- Consolidate as opposed to Divide-And-Conquer
 - Solving a problem in one issue can help solve another issue.
 - Interacting within a single spreadsheet platform

Embedded Browser

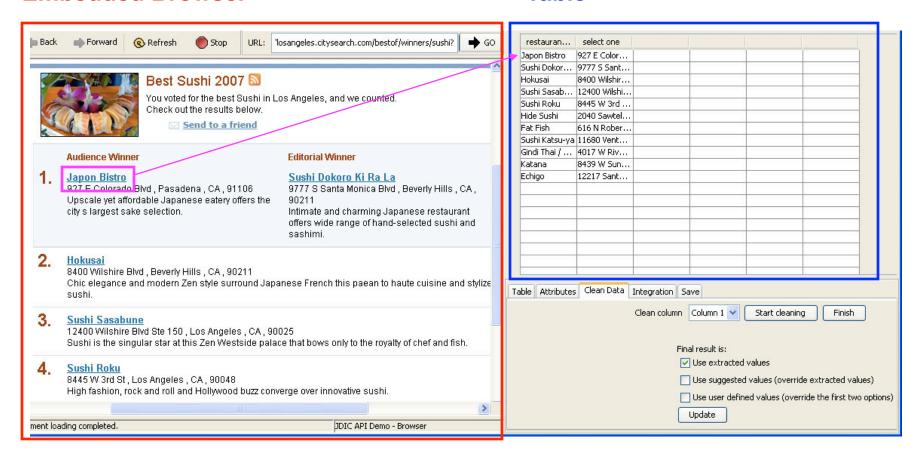


Embedded Browser



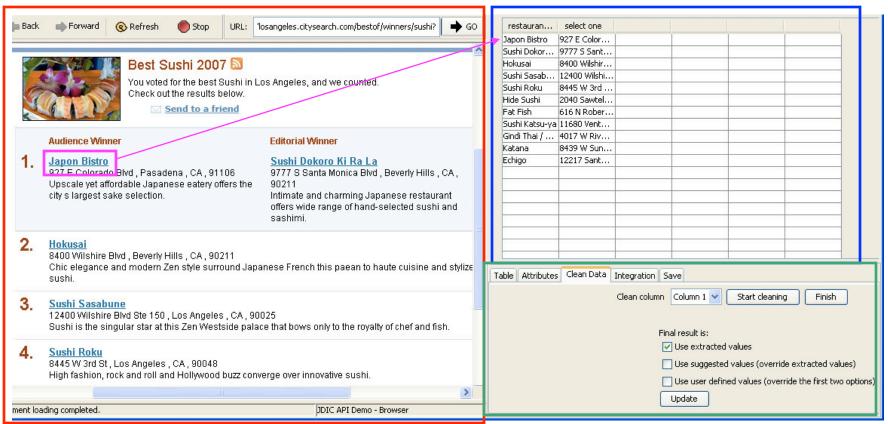
Embedded Browser

Table

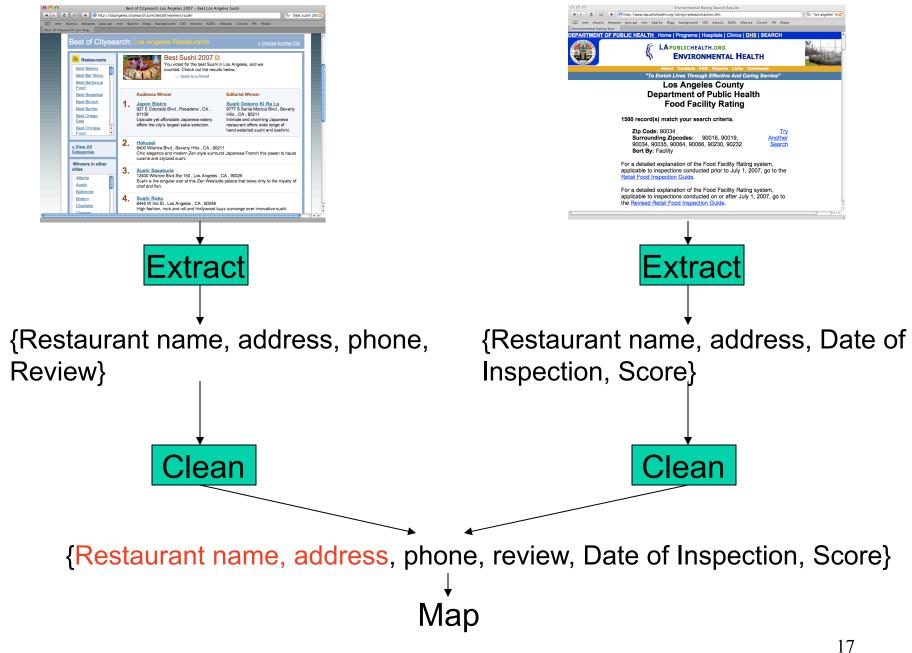


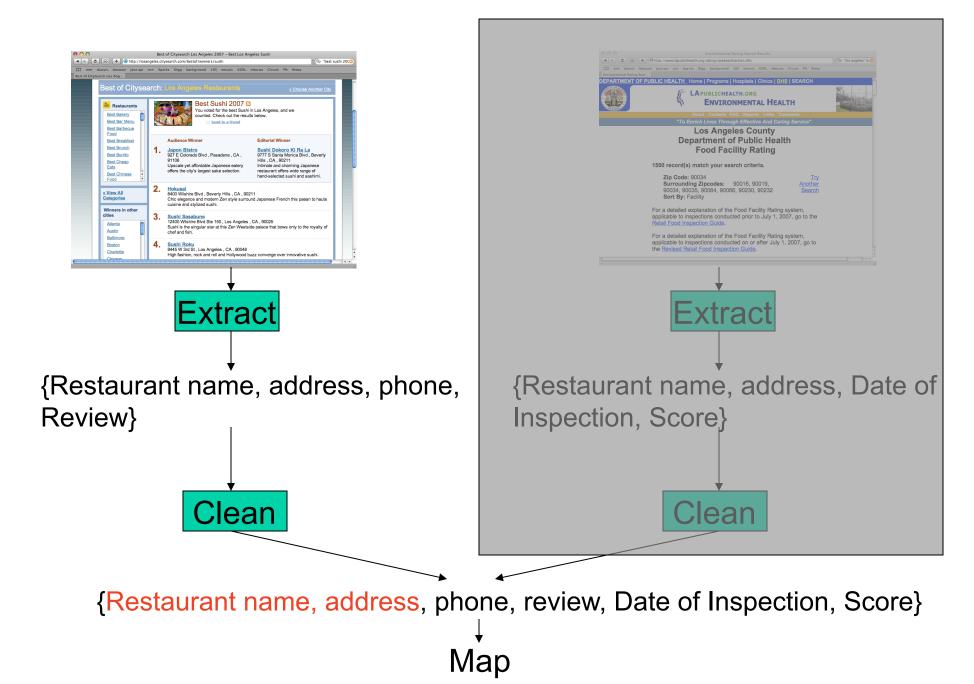
Embedded Browser

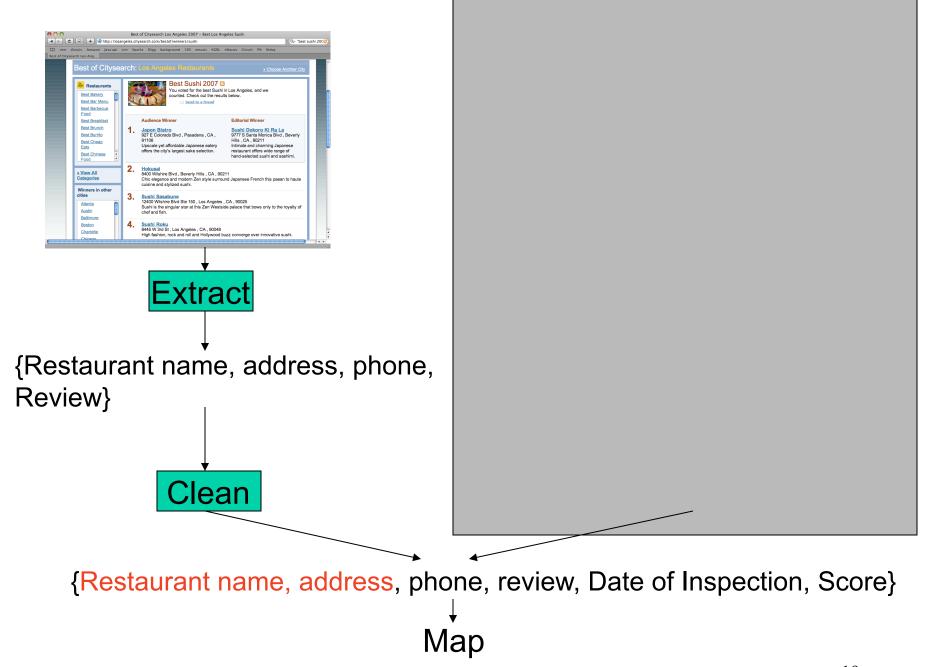
Table

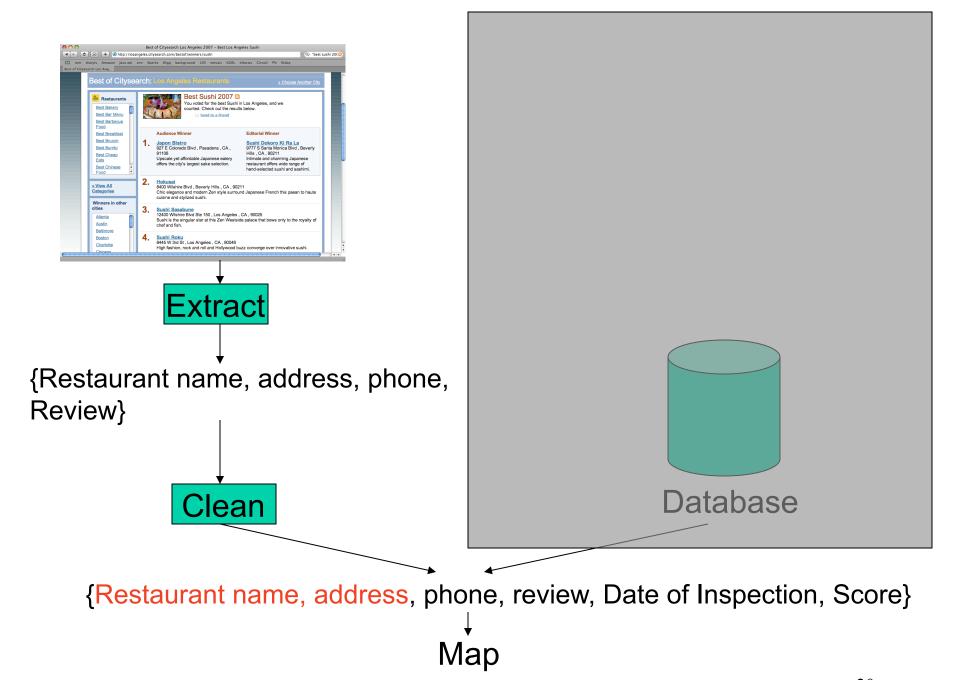


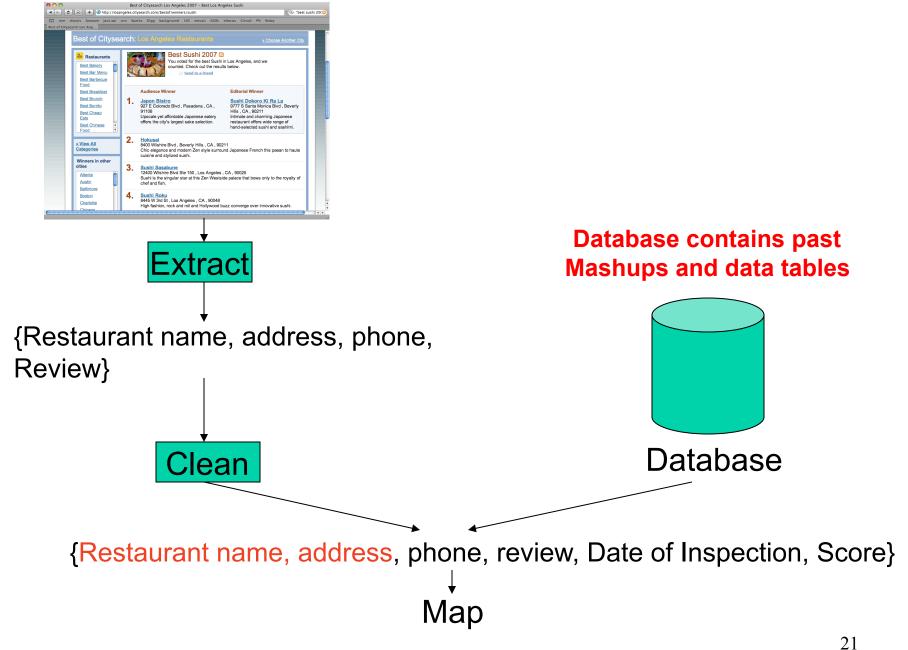
Interaction Modes











Data Retrieval: Extraction

1. Japon Bistro
927 E Colorado B
Vd , Pasadena , CA , 91106
Upscale yet affordable Japanese eatery offers the city's largest sake selection.

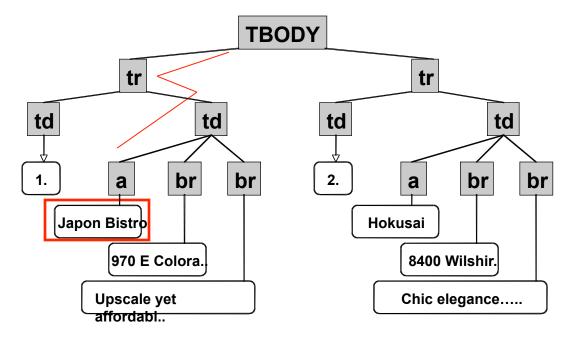
Sushi Dokoro Ki Ra La 9777 S Santa Monica Blvd , Beverly Hills , CA , 90211 Intimate and charming Japanese restaurant

Intimate and charming Japanese restaurant offers wide range of hand-selected sushi and sashimi.

2. Hokusai

8400 Wilshire Blvd , Beverly Hills , CA , 90211
Chic elegance and modern Zen style surround Japanese French this paean to haute cuisine and stylized sushi.

- 3. Sushi Sasabune 12400 Wilshire Blvd Ste 150, Los Angeles, CA, 90025 Sushi is the singular star at this Zen Westside palace that bows only to the royalty of chef and fish.
- 4. Sushi Roku
 8445 W 3rd St , Los Angeles , CA , 90048
 High fashion, rock and roll and Hollywood buzz converge over innovative sushi.



Japon Bistro

Tbody/tr[1]/td[2]/a

Data Retrieval: Extraction

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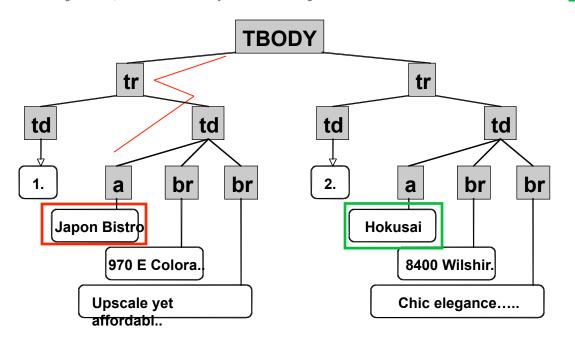
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 High fashion, rock and roll and Hollywood buzz converge over innovative sushi.



select one
Japon Bistro
Sushi Dokor..
Hokusai
Sushi Sasab..
Sushi Roku
Hide Sushi
Fat Fish
Sushi Katsu-ya
Gindi Thai /..
Katana
Echigo

Tbody/tr[1]/td[2]/a

Tbody/tr*/td*/a

Data Retrieval: Navigation

<u>Japon Bistro</u> 927 E Colorado Blvd , Pasadena , CA , 91106 Upscale yet affordable Japanese eatery offers the city's largest sake selection.

Sushi Dokoro Ki Ra La

9777 S Santa Monica Blvd , Beverly Hills , CA

Intimate and charming Japanese restaurant offers wide range of hand-selected sushi and sashimi.

Hokusai

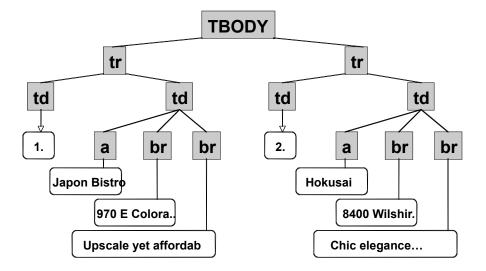
8400 Wilshire Blvd , Beverly Hills , CA , 90211

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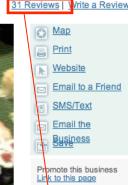
Sushi Roku 8445 W 3rd St , Los Angeles , CA , 90048 High fashion, rock and roll and Hollywood buzz converge over innovative sushi.





927 E Colorado Blvd Pasadena, CA 91106 Phone: (626) 744-1751

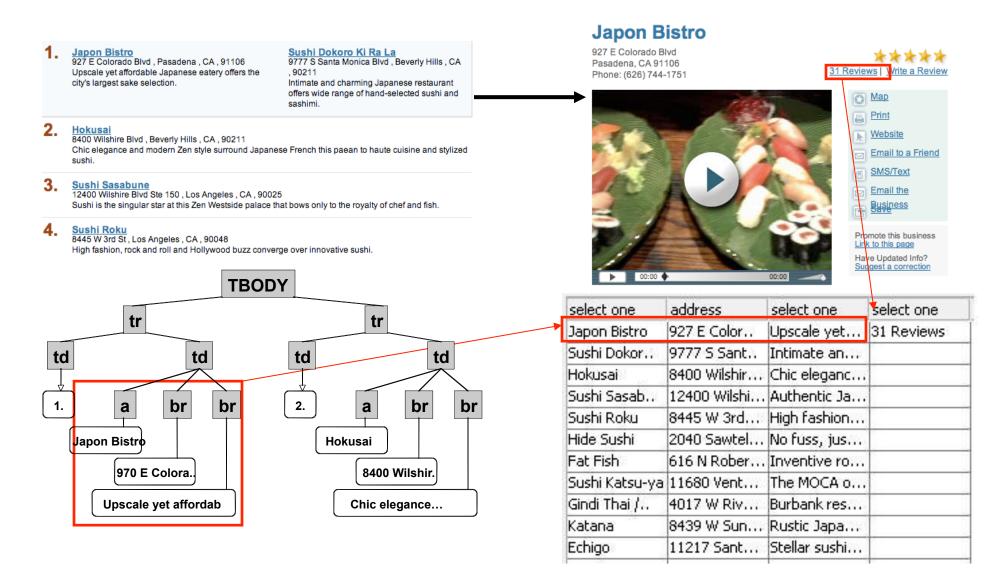




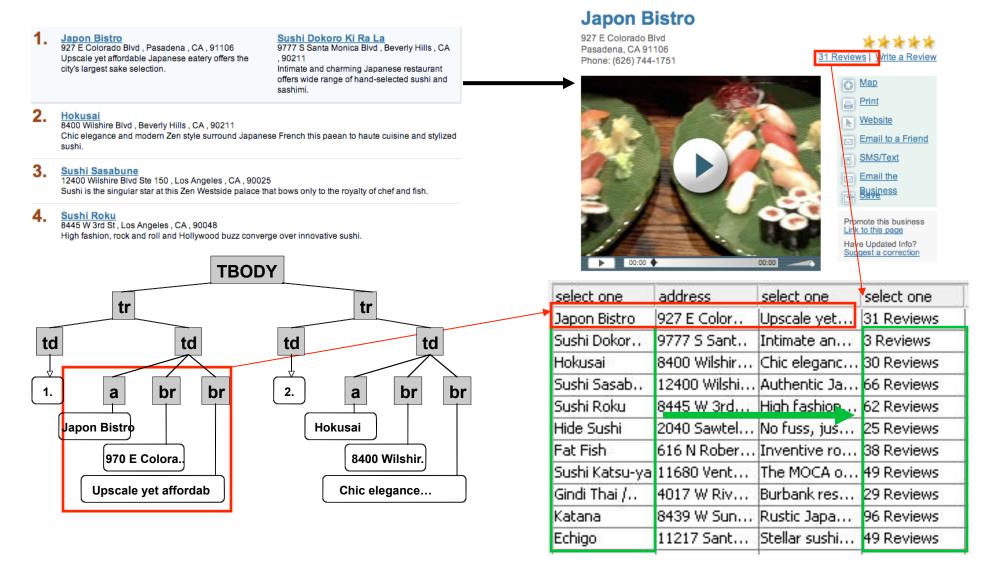
Have Updated Info? Suggest a correction

select one	address	select one	select one
Japon Bistro	927 E Color	Upscale yet	31 Reviews
Sushi Dokor	9777 S Sant	Intimate an	
Hokusai	8400 Wilshir	Chic eleganc	
Sushi Sasab	12400 Wilshi	Authentic Ja	
Sushi Roku	8445 W 3rd	High fashion	
Hide Sushi	2040 Sawtel	No fuss, jus	
Fat Fish	616 N Rober	Inventive ro	
Sushi Katsu-ya	11680 Vent	The MOCA o	
Gindi Thai /	4017 W Riv	Burbank res	
Katana	8439 W Sun	Rustic Japa	
Echigo	11217 Sant	Stellar sushi	

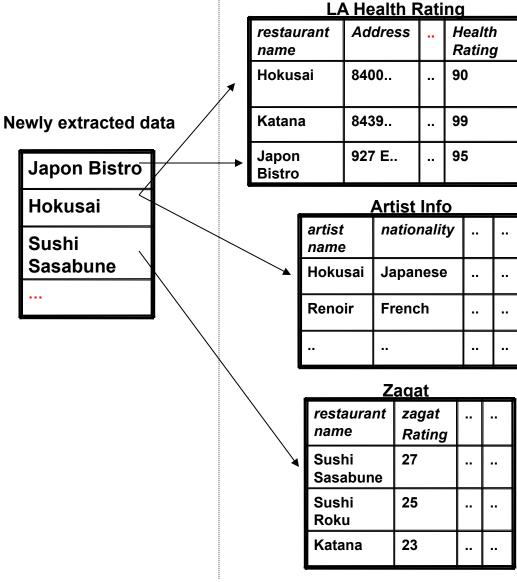
Data Retrieval: Navigation



Data Retrieval: Navigation



Source Modeling (Attribute selection)



Possible Attribute

 $\{a \mid a,s: a \in att(s) \land (val(a,s) \subset V)\}$

restaurant name (3) artist name (1)

Database

Data Cleaning: using existing values

Newly extracted data

Japon Bistro

Hokusai

Sushi

Sasabune

Sushi

Roka

Restaurant name

Data repository

restaurant Address .. Health name Rating

Hokusai 8400.. .. 90

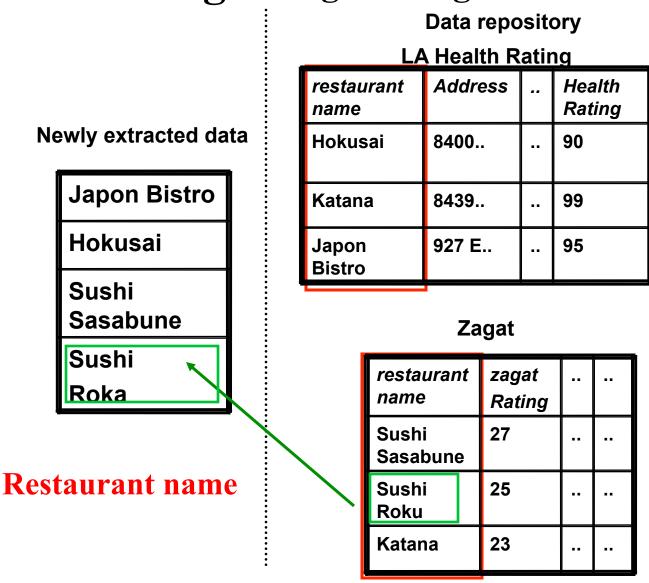
Katana 8439.. .. 99

Japon 927 E.. .. 95 Bistro

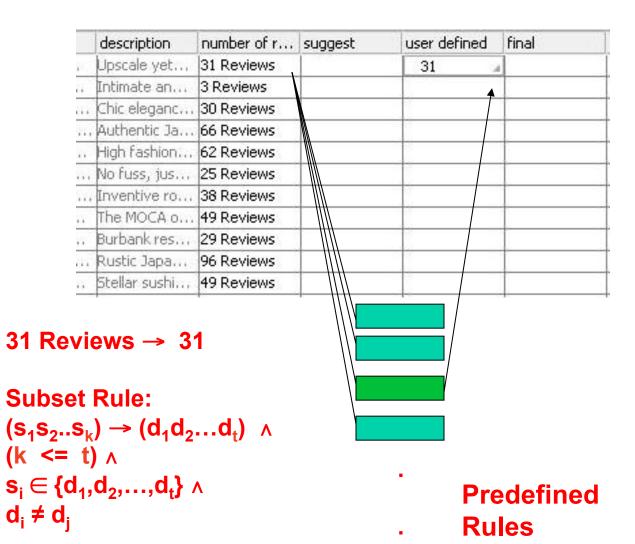
Zagat

restaurant name	zagat Rating		
Sushi Sasabune	27	:	
Sushi Roku	25	:	:
Katana	23		

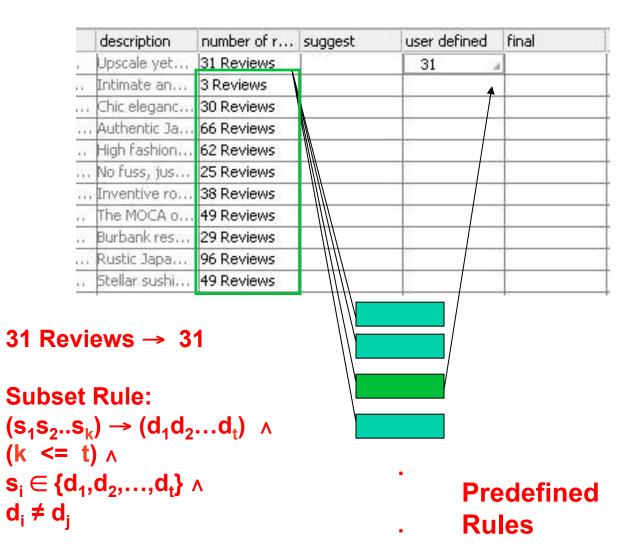
Data Cleaning: using existing values



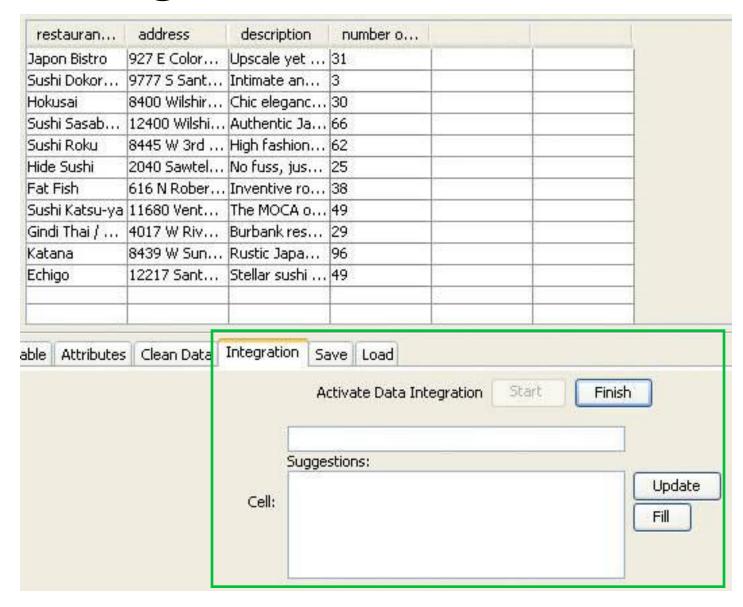
Data Cleaning: using predefined rules



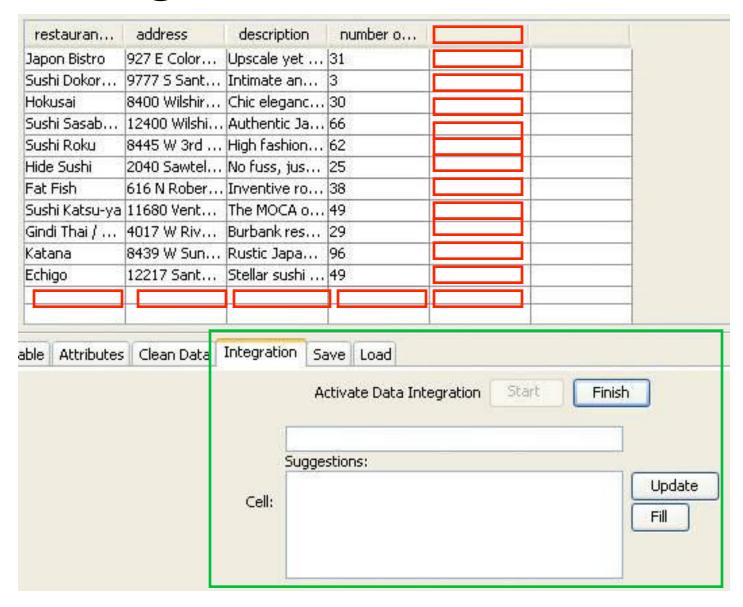
Data Cleaning: using predefined rules



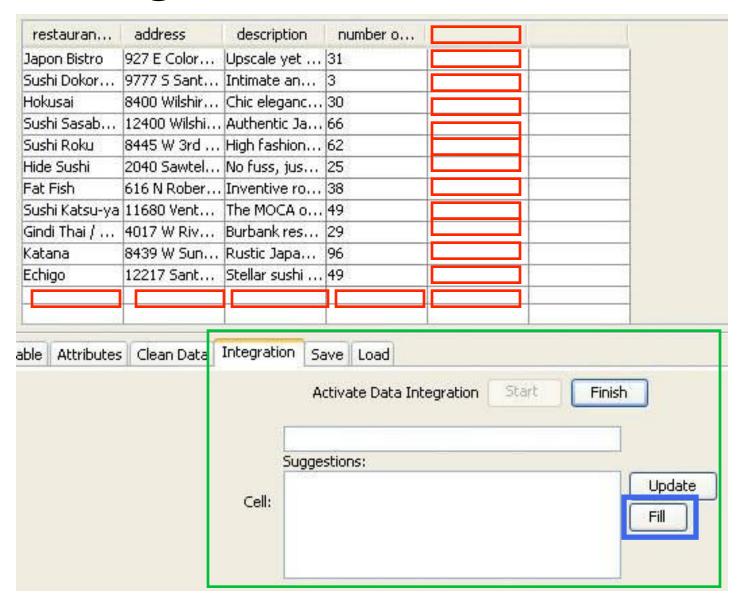
Data Integration [tuchinda 2007]



Data Integration [tuchinda 2007]



Data Integration [tuchinda 2007]



Data Integration (cont.)

restaurant	address	description	number of r	•
Japon Bistro	927 E Color	Upscale yet	31	
Sushi Dokor	9777 S Sant	Intimate an	3	
Hokusai	8400 Wilshir	Chic eleganc	30	
Sushi Sasab	12400 Wilshi	Authentic Ja	66	
Sushi Roku	8445 W 3rd	High fashion	62	
Hide Sushi	2040 Sawtel	No fuss, jus	25	
Fat Fish	616 N Rober	Inventive ro	38	
Sushi Katsu-ya	11680 Vent	The MOCA o	49	
Gindi Thai /	4017 W Riv	Burbank res	29	
Katana	8439 W Sun	Rustic Japa	96	
Echigo	11217 Sant	Stellar sushi	49	

Data repository

LA Health Rating

EATIOUITI KULHI					
restaurant name	Address		Health Rating		
Hokusai	8400		90		
Katana	8439		99		
Japon Bistro	927 E		95		

Zagat

Eugut					
restaurant name	zagat Rating				
Sushi Sasabune	27	:	:		
Sushi Roku	25	:	:		
Katana	23	••			

Data Integration (cont.)

restaurant	address	description	number of r	_
Japon Bistro	927 E Color	Upscale yet	31	
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Gindi Thai /	4017 W Riv	Burbank res	29	
Katana	8439 W Sun	Rustic Japa	96	
Echigo	11217 Sant	Stellar sushi	49	

Data repository

LA Health Rating

1			
	restaurant name	Address	 Health Rating
•	Hokusai	8400	 90
	Katana	8439	 99
	Japon Bistro	927 E	 95

Zagat

	<u> agat</u>		
restaurant name	zagat Rating		
Sushi Sasabune	27	:	
Sushi Roku	25		
Katana	23		

Data Integration (cont.)

restaurant	address	description	number of r	
Japon Bistro	927 E Color	Upscale yet	31	
Sushi Dokor	9777 S Sant	Intimate an	3	Î
Hokusai	3400 Wilshir	Chic eleganc	30	Î
Sushi Sasab	12400 Wilshi	Authentic Ja	66	Ĵ
Sushi Roku	3445 W 3rd	High fashion	62	Ĵ
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Fat Fish	516 N Rober	Inventive ro	38	Ĵ
Sushi Katsu-ya	11680 Vent	The MOCA o	49	Ĩ
Gindi Thai /	1017 W Riv	Burbank res	29	
Katana	3439 W Sun	Rustic Japa	96	
Echigo	11217 Sant	Stellar sushi	49	

Data repository

LA Health Rating

restaurant name	Address	 Health Rating
Hokusai	8400	 90
Katana	8439	 99
Japon Bistro	927 E	 95

Zagat

	<u>-ugut</u>		
restaurant name	zagat Rating		
Sushi Sasabune	27		:
Sushi Roku	25	:	:
Katana	23	••	••

Data Integration (cont.)

restaurant	address	description	number of r	
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Sushi Katsu-ya	11680 Vent	The MOCA o	49	
Gindi Thai /	1017 W Riv	Burbank res	29	
Katana	3439 W Sun	Rustic Japa	96	
Echigo	11217 Sant	Stellar sushi	49	
79				

 $\{a\}_R$ = possible new attribute selection for row *i*.

 $\{x\}$ = Set intersection($\{a\}$) over all the value rows.

 $\{v\} = \text{val}(a,s) \text{ where } a \{x\}$

s is any source where $att(s) \{x\} \neq \{\}$

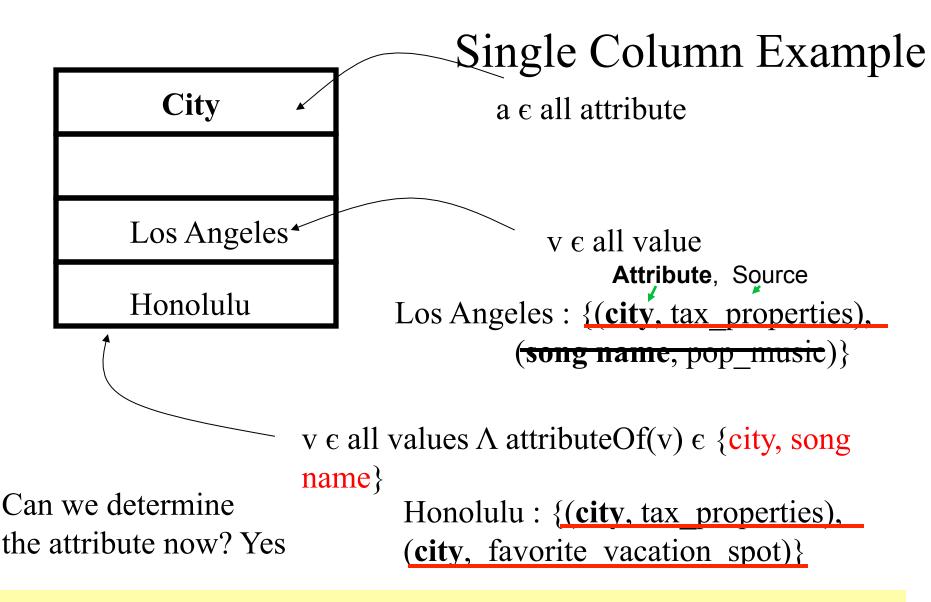
Data repository

LA Health Rating

-			tot th	
	restaurant name	Address		Health Rating
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	Katana	8439		99
	Japon Bistro	927 E		95

Zagat

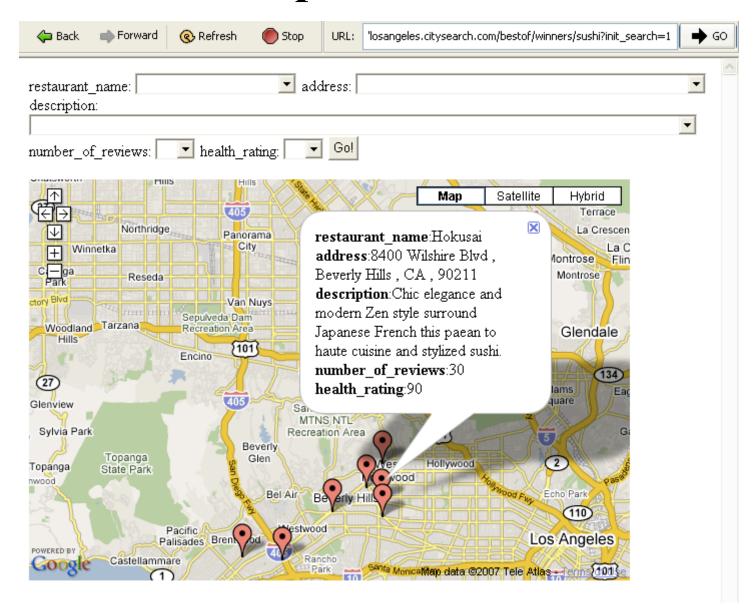
	<u>-agat</u>		
restaurant name	zagat Rating		
Sushi Sasabune	27		
Sushi Roku	25	:	
Katana	23		



 $\{x\}$ = Set intersection($\{a\}$) over all the value rows.

 $\{v\} = \text{val}(a,s) \text{ where } a \in \{x\} \land s \text{ is any source where } att(s) \cap \{x\} \neq \{\}$

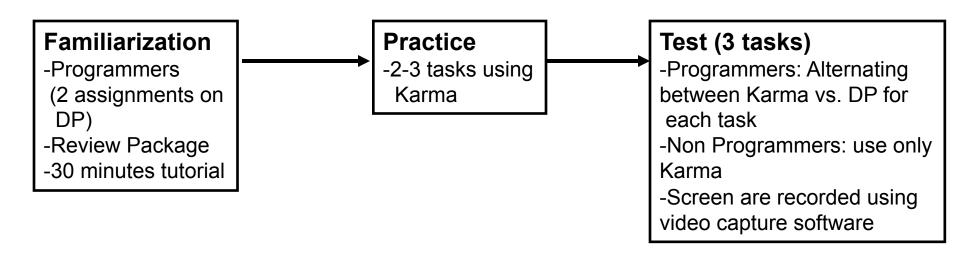
Map Generation



Evaluation

- Baseline: A combination of Dapper/Pipes
- Claims:
 - 1. Users with no programming experiences can build all four Mashup types.
 - 2. Karma takes less time to complete each subtask and scales better as the tasks get harder
 - 3. Overall, the user takes less time to build the same Mashup in Karma compared to Dapper/Pipes
- Users:
 - Programmers (20)
 - Non-programmers (3)

Evaluation: Setup



Task2	Dapper/Pipes				Karma					
Subject	E	M	С	I	Total	Е	M	С	I	Total
No.1	4:38	0:22	2:45	1:15	9:00	1:26	0:43	0:43	0:00	2:52
No.2	1:35	0:12	3:30	0:12	5:29	0:50	0:57	0.57	0:00	2:44
No.3	*5:00	0:25	*5:00	*5:00	15:25	2:52	1:00	3:00	0:00	5:52
No.4	4:49	0:17	3:29	0:38	9:14	1:26	0:48	1:03	0:00	3:18
No.5	*5:00	0:29	1:44	1:16	8:29	1:43	0:45	1:20	0:00	3:48
No.6	*5:00	0:20	*5:00	*5:00	15:20	2:07	0:30	0:50	0:00	3:27

5 minute cut off time

Evaluation: Tasks

Task No.	Mashup Type	Data Extraction	Source Modeling	Data Cleaning	Data Integration
1	1 (1 source)	Moderate	Simple	Difficult	N/A
2	2,3 (union+form)	Difficult	Simple	Simple	Union (simple)
3	4 (join 2 sources)	Simple	Simple	N/A	Join (difficult)

Claim 1 Claim 2 Claim 3

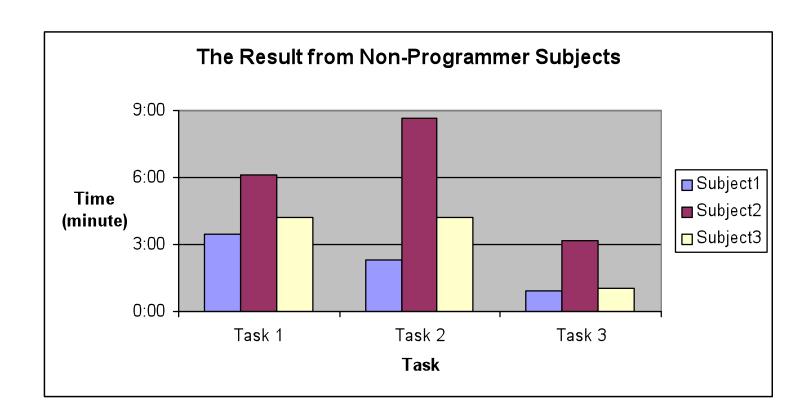
Users with no programming experiences can build all four Mashup types.

Karma takes less time to complete that subtask and scales better as the get harder

Overall, the user takes less time to build the same Mashup in Karma compared to Dapper/Pipes

Claim 1: Users with no programming experiences can build all four Mashup types

Evaluation: Non-Programmers



Claim 2: Karma takes less time to complete each subtask

Karma (programmer)

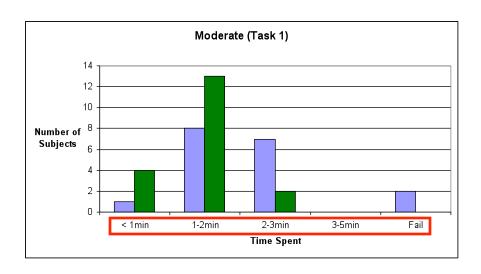
Evaluation: Extraction

Number of Subjects

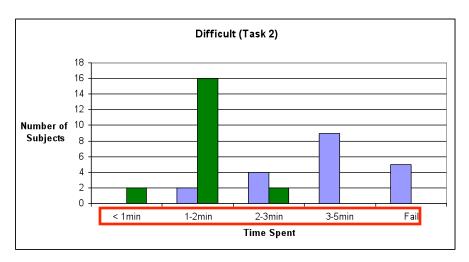
Number of Subjects

0-30 sec 30-60sec 60-90sec

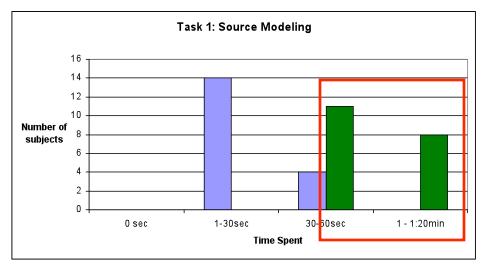
Time Spent

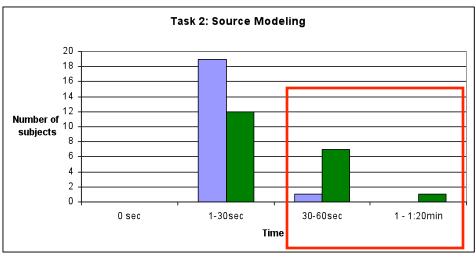


- As the extraction task gets more difficult, Dapper/Pipes takes
 - longer
 - more subjects failing to complete the task (11% for moderate and 25% for difficult)

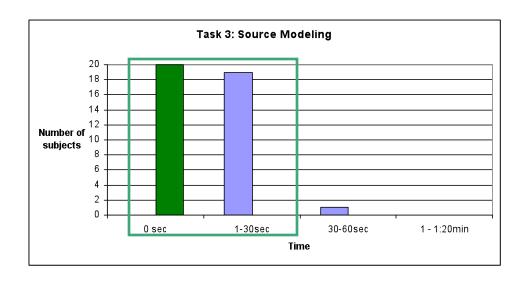


Evaluation: Source Modeling





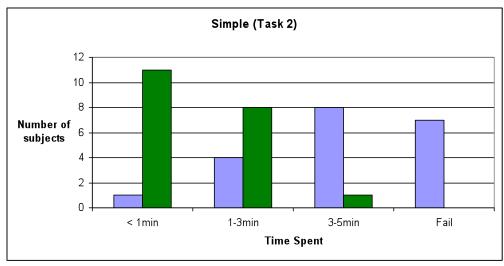
- Karma performed worse in task 1 and tasks 2
 - only 30 sec difference
 - -subjects take times selecting attributes
 - the saving will be realized in the data integration step.
- Karma performed better in task 3 because of it can automatically identify the attribute

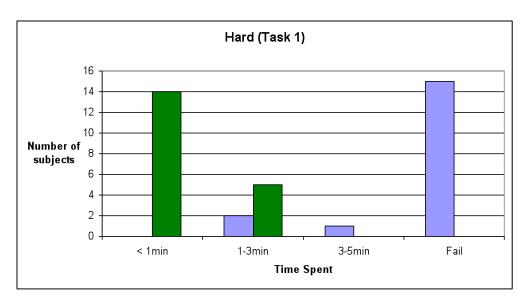


48

Dapper/Pipes

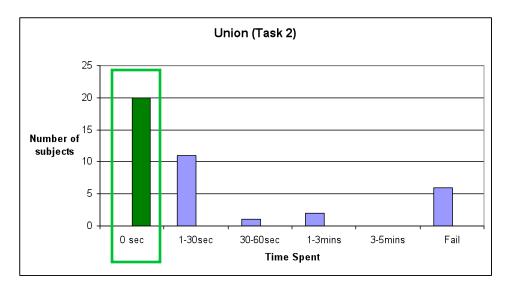
Evaluation: Data Cleaning

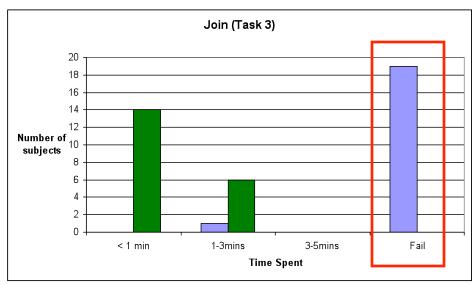




- Karma performed better in both tasks
- When the cleaning task gets harder, more subjects are failing in Dapper/ Pipes (35% for simple and 83% in hard)

Evaluation: Data Integration

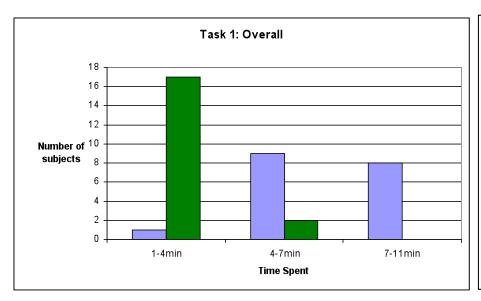


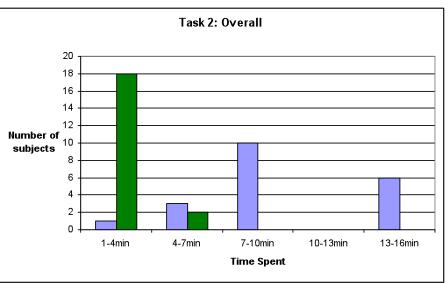


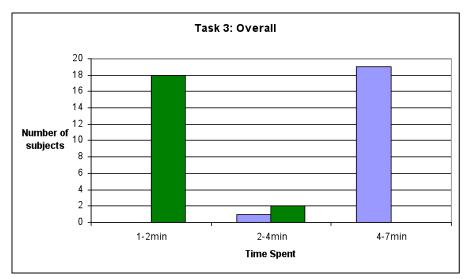
- Because of the table structure, subjects can specify union indirectly by dropping data into the right cell
- The time spent in source modeling step allows Karma to suggest the linking source
- Dapper/Pipes: 30% fail in the union case and 95% fail in the join case

Claim 3: Overall, the user takes less time to build the same Mashup in Karma compared to Dapper/Pipes

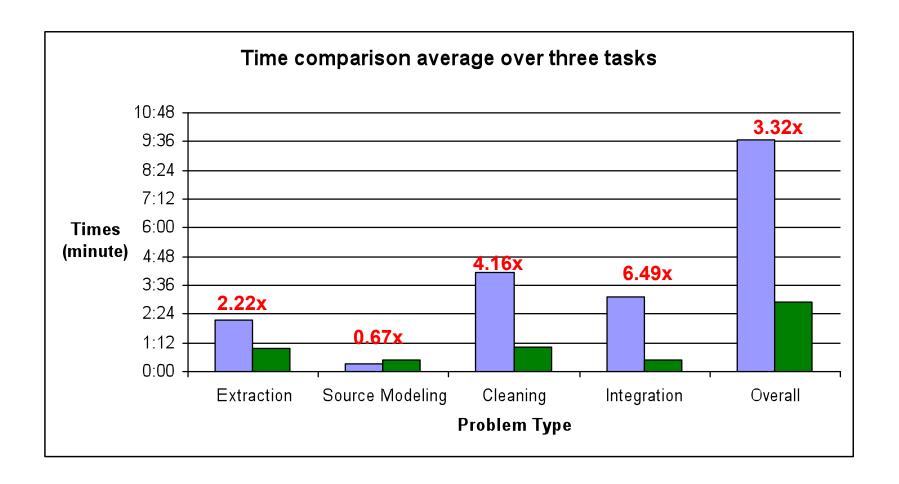
Evaluation: Overall







Evaluation: Average



Evaluation: T-test

- Karma is faster than DP in data extraction subtasks
 - t=5.35, df = 114, p < 0.01
- DP is faster than Karma in source modeling subtasks
 - t=2.54, df=114, p < 0.01
- Karma is faster than DP in data cleaning subtasks
 - t=13.54, df=74, p < 0.01
- Karma is faster than DP in data integration subtasks
 - t=7.05, df=78, p < 0.01
- Karma is faster than DP overall
 - t=13.24, df=114, p < 0.01

Not susceptible to time-bound bias because only DP's result (and not Karma) contains time-bound values.

System	Data	Source	Data	Data	Mashup Type
	Retrieval	Modeling	Cleaning	Integration	Supported
MIT's Simile	Early wo	rk. Focus	on DOM,	too basic	1
MIT's Pot Luck	RDF	/ Manually	specify d	ata int	1,3,4
Dapper	Mainly	focus on	extraction	/ linear	1,2,4
Yahoo's Pipes			1,2,3		
MS's Popfly] Fa	ancier UI/ r	nore widg	ets	1,2,4
CMU's Marmite				n workflow	1,2,4
Intel's Mashmaker		_	an expert		1,2,3,4
Google MyMap		Create poi		p	1,2
Agent Wizard	Q/A a	1,3,4			
Cards	Tuple = c	1,2,4			
Karma	DOM	Database	PBD	PBD	1,2,3,4

System	Data	Source	Data	Data	Mashup Type
	Retrieval	Modeling	Cleaning	Integration	Supported
MIT's Simile	DOM	Manual	N/A	N/A	1
MIT's Pot Luck	RDF	Manual	PBD	Manual	1,3,4
Dapper	DOM	Manual	Manual	Join only	1,2,4
Yahoo's Pipes	Widgets	Manual	Widgets	Union only	1,2,3
MS's Popfly	Widgets	Manual	Widgets	Widgets	1,2,4
CMU's Marmite	Widgets	Manual	Widgets	Widgets	1,2,4
Intel's Mashmaker	Dapper	Manual	Widgets	Expert	1,2,3,4
Google MyMap	Widgets	Manual	N/A	Union only	1,2
Agent Wizard	Q/A	Q/A	Q/A	Q/A	1,3,4
Cards	DOM	Manual	N/A	Manual	1,2,4
Karma	DOM	Database	PBD	PBD	1,2,3,4

System	Data	Source	Data	Data	Mashup Type
	Retrieval	Modeling	Cleaning	Integration	Supported
MIT's Simile	DOM	Manual	N/A	N/A	1
MIT's Pot Luck	RDF	Manual	PBD	Manual	1,3,4
Dapper	DOM	Manual	Manual	Join only	1,2,4
Yahoo's Pipes	Widgets	Manual	Widgets	Union only	1,2,3
MS's Popfly	Widgets	Manual	Widgets	Widgets	1,2,4
CMU's Marmite	Widgets	Manual	Widgets	Widgets	1,2,4
Intel's Mashmaker	Require	an expert			1,2,3,4
Google MyMap	Widgets	Manual	N/A	Union only	1,2
Agent Wizard	Q/A	Q/A	Q/A	Q/A	1,3,4
Cards	DOM	Manual	N/A	Manual	1,2,4
Karma	DOM	Database	PBD	PBD	1,2,3,4

System	Data	Source	Data	Data	Mashup Type
	Retrieval	Modeling	Cleaning	Integration	Supported
MIT's Simile	Early wo	rk. Focus	on DOM, t	oo basic	1
MIT's Pot Luck	RDF	Manual	PBD	Manual	1,3,4
Dapper	DOM	Manual	Manual	Join only	1,2,4
Yahoo's Pipes	Widgets	Manual	Widgets	Union only	1,2,3
MS's Popfly	Widgets	Manual	Widgets	Widgets	1,2,4
CMU's Marmite	Widgets	Manual	Widgets	Widgets	1,2,4
Intel's Mashmaker	Require a	an expert			1,2,3,4
Google MyMap	Widgets	Manual	N/A	Union only	1,2
Agent Wizard	Q/A	Q/A	Q/A	Q/A	1,3,4
Cards	DOM	Manual	N/A	Manual	1,2,4
Karma	DOM	Database	PBD	PBD	1,2,3,4

System	Data	Source	Data	Data	Mashup Type				
	Retrieval	Modeling	Cleaning	Integration	Supported				
MIT's Simile	Early wo	Early work. Focus on DOM, too basic							
MIT's Pot Luck	RDF / Ma	anually spe	ecify data	int	1,3,4				
Dapper	DOM	Manual	Manual	Join only	1,2,4				
Yahoo's Pipes	Widgets	Manual	Widgets	Union only	1,2,3				
MS's Popfly	Widgets	Manual	Widgets	Widgets	1,2,4				
CMU's Marmite	Widgets	Manual	Widgets	Widgets	1,2,4				
Intel's Mashmaker	Require a	an expert			1,2,3,4				
Google MyMap	Widgets	Manual	N/A	Union only	1,2				
Agent Wizard	Q/A	Q/A	Q/A	Q/A	1,3,4				
Cards	DOM	Manual	N/A	Manual	1,2,4				
Karma	DOM	Database	PBD	PBD	1,2,3,4				

System	Data	Source	Data	Data	Mashup Type				
	Retrieval	Modeling	Cleaning	Integration	Supported				
MIT's Simile	Early wo	Early work. Focus on DOM, too basic							
MIT's Pot Luck		anually spe			1,3,4				
Dapper	Mainly fo	Mainly focus on extraction / linear							
Yahoo's Pipes	Widgets	Manual	Union only	1,2,3					
MS's Popfly	Widgets	Manual	Widgets	Widgets	1,2,4				
CMU's Marmite	Widgets	Manual	Widgets	Widgets	1,2,4				
Intel's Mashmaker	Require a	an expert			1,2,3,4				
Google MyMap	Widgets	Manual	N/A	Union only	1,2				
Agent Wizard	Q/A	Q/A	Q/A	Q/A	1,3,4				
Cards	DOM	Manual	N/A	Manual	1,2,4				
Karma	DOM	Database	PBD	PBD	1,2,3,4				

System	Data	Source	Data	Data	Mashup Type			
	Retrieval	Modeling	Cleaning	Integration	Supported			
MIT's Simile	Early wo	rk. Focus	on DOM, t	oo basic	1			
MIT's Pot Luck		anually spe			1,3,4			
Dapper	Mainly fo	cus on ext	traction / I	inear [1,2,4			
Yahoo's Pipes	Widgets	Widgets						
MS's Popfly	Fancier l	Fancier UI/ more widgets						
CMU's Marmite			•	n workflow	1,2,4			
Intel's Mashmaker		an expert			1,2,3,4			
Google MyMap	Widgets	Manual	N/A	Union only	1,2			
Agent Wizard	Q/A	Q/A	Q/A	Q/A	1,3,4			
Cards	DOM	Manual	1,2,4					
Karma	DOM	Database	PBD	PBD	1,2,3,4			

System	Data Source		Data	Data	Mashup Type			
	Retrieval	Modeling	Cleaning	Integration	Supported			
MIT's Simile	Early wo	Early work. Focus on DOM, too basic						
MIT's Pot Luck	RDF / Ma	anually spe	ecify data	int	1,3,4			
Dapper	Mainly fo	cus on ext	traction / I	inear [1,2,4			
Yahoo's Pipes	Widgets	Widgets						
MS's Popfly	Fancier U	ال/ more w	idaets		1,2,4			
CMU's Marmite			•	n workflow	1,2,4			
Intel's Mashmaker		an expert			1,2,3,4			
Google MyMap	Create p	<u>oints on M</u>	ap		1,2			
Agent Wizard	Q/A	Q/A	Q/A	Q/A	1,3,4			
Cards	DOM	Manual	N/A	Manual	1,2,4			
Karma	DOM	Database	PBD	PBD	1,2,3,4			

System	Data	Source	Data	Data	Mashup Type			
	Retrieval	Modeling	Cleaning	Integration	Supported			
MIT's Simile	Early wo	Early work. Focus on DOM, too basic						
MIT's Pot Luck		anually spe			1,3,4			
Dapper	Mainly fo	cus on ext	traction / I	near	1,2,4			
Yahoo's Pipes	Widgets	Widgets						
MS's Popfly	Fancier l	ال/ more w	idgets		1,2,4			
CMU's Marmite			•	n workflow	1,2,4			
Intel's Mashmaker		an expert			1,2,3,4			
Google MyMap	Create p	<u>oints on M</u>	<u>ap</u>		1,2			
Agent Wizard	Q/A appr	oach / line	ar / scalal	oility	1,3,4			
Cards	DOM	Manual	N/A	Manual	1,2,4			
Karma	DOM	Database	PBD	PBD	1,2,3,4			

System	Data	Source	Data	Data	Mashup Type			
	Retrieval	Modeling	Cleaning	Integration	Supported			
MIT's Simile	Early wo	rk. Focus	on DOM, t	oo basic	1			
MIT's Pot Luck	RDF / Ma	anually spe	ecify data	int	1,3,4			
Dapper	Mainly fo	cus on ext	traction / I	inear [1,2,4			
Yahoo's Pipes	Widgets				1,2,3			
MS's Popfly	Fancier l	1,2,4						
CMU's Marmite			•	n workflow	1,2,4			
Intel's Mashmaker		an expert			1,2,3,4			
Google MyMap		<u>oints on M</u>	ap		1,2			
Agent Wizard	Q/A appr	oach / line	ar / scalal	oility	1,3,4			
Cards	Tuple = c	or relations	1,2,4					
Karma	DOM							

Related Work: Data Extraction

•	Automatic extraction: table and lists only	
	 RoadRunner (exploit HTML structure) [C1 	rescenzi et al., 2001]
	 Adel (grammer induction to detect rows) 	[Lerman+ 2001]
	 VisualWeb (OCR technique to detect tables) 	[Gatterbauer+ 2007]
•	Semi-Automatic: require more label examples	S
	 WIEN (inductive – less expressive than stalker) 	[Kushmerick 1997]
	Stalker (Cotesting)	[Muslea+ 1999]
	 SoftMealy (finite state transducer) 	[Hsu 1998]
	 WHISK (rigid format, exact delimiter) 	[Soderland 1998]
•	DOM: rely on well-formed HTML and less la	beling
	- Simile	[Huynh+ 2005]
	– Dapper	
	 Interactive Wrapper Generation (ML + prediction on DC 	M) [Irmak+ 2006]
	 PLOW (add natural language) 	[Allen+ 2007]
	- Cards	[Dontcheva+ 2007]
	- Karma	[Tuchinda+ 2008]

Related Work: Source Modeling

- 1:1 mapping, N:M mapping
 - Schema-level match

• TranScm	[Milo+ 98]
• DIKE	[Palopoli+ 99]
 Artemis 	[Castano+ 01]
• Delta	[Clifton+ 97]

+Instance-based matcher

• SemInt	[Li 00
• LSD	[Doan 01
• ILA	[Etzioni 95
• iMapp	[Dhamanka 04
• Clio (interactive)	[Ling 01
 Inducing Source Description 	[Carman 07

- Karma leverages existing techniques to narrow candidate matches
 - String Similarities [Cohen+ 2003]

Related Work: Data Cleaning

• Commercial Tools: Focus on writing transformation

ACR/Data, Migration Architect

[Chaudhuri+ 1997]

 Discrepancy Detection: Use as a stepping stone for record linkage and cleaning system

_	Levenshtein distance	[Needleman+ 70]
_	Vector based	[Baeza-Yates+ 99]
_	EM	[Ristad+ 98]
_	SVM	[Bilenko+ 03]
Red	cord linkage & cleaning systems: Focus on ranking	[Winkler 06]
_	Fuzzy Match	[Chaudhuri+ 03]
_	Apollo	[Michalowski+ 05]
_	Phoebus	[Michelson+ 07]
_	Potter's wheel	[Raman+ 01]

- Karma
 - Gained reference sources through source modeling process
 - Provided predefined transformations

Related Work: Data Integration

- Universal Relation: Make it easier to formulate the query but users still need to formulate the query [Ullman 1980, 1988]
- Query by example: Need to know which data sources to use and the query may not return results
 - QBE [Zloof 1975]
- Retrieval by formulation: Need to understand domain model to formulate partial description
 - Helgon [Fischer 1989]
 - RABBIT [Williams 1982]
- Graphical Query Language: Users still need to navigate through sources (graphs)
 - Gql [Benzi 1998, Haw 1994, Papantonakis 1988]
- Question-Answering Technique: Understanding about database operations required.
 - Agent Wizard [Tuchinda+ 2004]
- Interactive Schema/data integration: Understanding about source schema required
 - Clio [Ling 01]
- Karma is based on Programming by Demonstration [Cyper 2001; Lau2001]

Conclusion

- Mashup is a fast growing area
 - Need an efficient way to for casual web users to build them
- Contributions
 - A PBD approach that uses a single table for building a Mashup
 - An integrated approach that solves four Mashup building issues
 - A query formulation technique that allows users to specify examples to build complicated queries
- Evaluated the validity of the Karma approach
 - Subjects were able to complete Mashup building tasks in Karma
 - The overall improvement is at least a factor of 3.5

Future Work

- Customizing display by examples
 - Interface today is limited to the table of data or a map if the points can be geocoded
- Learn and generalize over the task
 - Store the integration plan so that it can be reexecuted on new data
- Integrate in work on machine learning of extraction tasks
 - In collaboration with Fetch Technologies
- Integrate in work on automatic source modeling
 Introduction • Approach • Evaluation • Related Work • Conclusion

Papers

- Building mashups by example,
 Rattapoom Tuchinda, Pedro Szekely, and Craig A.
 Knoblock.
 - Proceedings of the 2008 International Conference on Intelligent User Interfaces, 2008
- Building data integration queries by demonstration, Rattapoom Tuchinda, Pedro Szekely, and Craig A. Knoblock.
 - In Proceedings of the International Conference on Intelligent User Interfaces, 2007

Thank You!

Backup Slides

Task1	Dapper/Pipes				Karma				
Subject	Е	Μ	C	Total	Е	M	С	Total	
No.1	*5:00	0:20	*5:00	10:20	2:19	1:08	1:00	4:27	
No.2	1:43	0:30	*5:00	7:13	1:00	0:40	0:29	2:09	
No.3	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	
No.4	0:52	0:48	*5:00	6:40	1:12	1:00	0:50	3:02	
No.5	5:00	0:35	*5:00	10:35	1:15	1:18	1:20	3:53	
No.6	2:30	0:15	*5:00	7:45	1:00	0:54	0:28	2:22	
No.7	1:20	0:22	*5:00	6:42	0:51	0.51	0:46	2:28	
No.8	1:40	0:14	*5:00	6:54	1:04	0:41	0:33	2:19	
No.9	1:26	0:16	*5:00	6:42	1:14	1:00	1:10	3:24	
No.10	1:39	0:10	*5:00	6:49	0:53	0:42	0:50	2:26	
No.11	2:00	0:19	*5:00	7:19	1:04	1:00	0:53	2:57	
No.12	2:00	0:49	2:00	4:49	1:07	1:00	0:40	2:47	
No.13	2:00	0:05	*5:00	7:05	0:58	0:50	0:56	1:44	
No.14	2:46	0:15	*5:00	8:01	1:12	0:45	0:48	2:45	
No.15	2:27	0:14	3:11	5:52	1:10	0:49	1:20	3:19	
No.16	1:16	0:12	*5:00	6:28	0:58	0:42	0:25	2:05	
No.17	n/a	n/a	n/a	n/a	2:00	1:00	0:50	3:50	
No.18	2:30	0:14	*5:00	7:44	1:06	1:10	1:46	4:02	
No.19	1:38	0:47	1:20	3:45	1:20	0:49	0:35	2:44	
No.20	1:30	0:16	*5:00	6:46	1:04	0:44	0:35	2:23	
No.21	n/a	n/a	n/a	n/a	1:11	1:17	0:59	3:27	
No.22	n/a	n/a	n/a	n/a	2:58	1:46	1:24	6:08	
No.23	n/a	n/a	n/a	n/a	1:19	1:40	1:14	4:13	

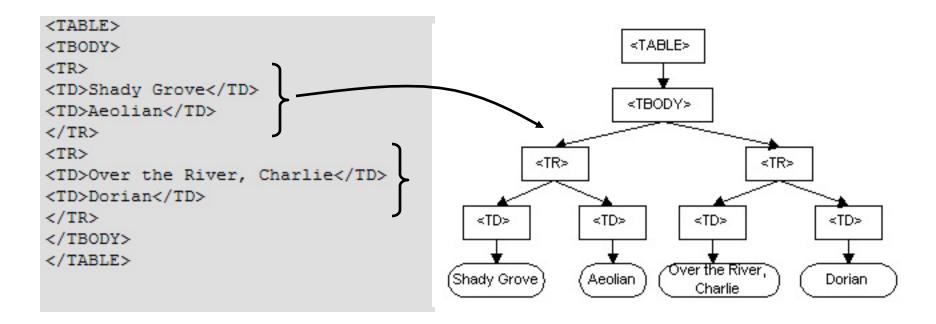
Task2		Dε	apper/P	ipes				Karm	a	
Subject	Е	M	С	I	Total	Е	M	С	I	Total
No.1	4:38	0:22	2:45	1:15	9:00	1:26	0:43	0:43	0:00	2:52
No.2	1:35	0:12	3:30	0:12	5:29	0:50	0:57	0.57	0:00	2:44
No.3	*5:00	0:25	*5:00	*5:00	15:25	2:52	1:00	3:00	0:00	5:52
No.4	4:49	0:17	3:29	0:38	9:14	1:26	0:48	1:03	0:00	3:18
No.5	*5:00	0:29	1:44	1:16	8:29	1:43	0:45	1:20	0:00	3:48
No.6	*5:00	0:20	*5:00	*5:00	15:20	2:07	0:30	0.50	0:00	3:27
No.7	2:17	0:15	4:46	0:18	7:36	1:13	0:25	0.52	0:00	2:31
No.8	3:23	0:21	*5:00	*5:00	13:44	1:10	0:21	0:24	0:00	1:55
No.9	4:11	0:21	*5:00	*5:00	14:32	1:22	0:47	2:11	0:00	4:20
No.10	2:16	0:07	3:14	0:20	5:50	1:04	0:20	1:06	0:00	2:30
No.11	3:04	0:17	*5:00	*5:00	13:21	1:06	0:34	0.53	0:00	2:33
No.12	2:00	0:27	*5:00	0:20	7:47	1:23	0:30	0:37	0:00	2:30
No.13	*5:00	0:07	1:43	0:10	7:00	1:42	0:32	0:41	0:00	2:55
No.14	3:03	0:23	4:42	0:10	8:21	1:40	0:31	0.56	0:00	3:07
No.15	2:06	0:12	3:13	0:22	5:53	1:30	0:24	2:05	0:00	3:59
No.16	3:58	0:11	3:29	0:27	8:05	0:51	0:17	1:00	0:00	2:08
No.17	4:15	0:28	3:39	0:30	8:52	1:04	0:28	1:18	0:00	2:50
No.18	*5:00	0:23	*5:00	*5:00	15:23	1:17	0:30	1:10	0:00	2:57
No.19	4:01	0:14	2:42	0:21	7:16	1:39	0:21	0:50	0:00	2:50
No.20	1:36	0:43	0:36	0:22	3:17	1:07	0:28	0:40	0:00	2:15
No.21	n/a	n/a	n/a	n/a	n/a	1:03	0:21	0:55	0:00	2:19
No.22	n/a	n/a	n/a	n/a	n/a	3:56	1:52	2:50	0:00	8:38
No.23	n/a	n/a	n/a	n/a	n/a	2:15	0:31	1:27	0:00	4:13

Task3	Dapper/Pipes				Karma			
Subject	Е	M	I	Total	Е	M	I	Total
No.1	1:30	0:26	*5:00	6:56	0:14	0:00	2:16	2:30
No.2	0:30	0:10	*5:00	5:40	0:25	0:00	0:26	0:54
No.3	1:00	0:15	*5:00	6:15	0:15	0:00	0:44	0:59
No.4	0:40	0:16	*5:00	5:56	0:20	0:00	1:06	1:26
No.5	0:40	0:14	*5:00	5:54	0:20	0:00	0:37	0:57
No.6	0:30	0:10	*5:00	5:40	0:20	0:00	0:31	0:51
No.7	0:27	0:10	*5:00	5:37	0:14	0:00	0:50	1:04
No.8	0:29	0:20	*5:00	5:49	0:30	0:00	0:51	1:21
No.9	0:40	0:23	*5:00	6:03	0:13	0:00	0:44	0:57
No.10	0:30	0:10	*5:00	5:40	0:20	0:00	0:35	0:55
No.11	0:51	0:20	*5:00	6:11	0:16	0:00	1:05	1:21
No.12	1:05	0:18	*5:00	6:23	0:30	0:00	0:46	1:16
No.13	0:31	0:14	*5:00	5:45	0:16	0:00	0:57	1:13
No.14	0:36	0:14	*5:00	5:50	0:14	0:00	2:00	2:14
No.15	0:26	0:21	*5:00	5:47	0:30	0:00	0:45	1:15
No.16	0:27	0:13	*5:00	5:40	0:15	0:00	0:56	1:11
No.17	0:33	0:38	1:56	3:07	0:30	0:00	0:46	1:16
No.18	1:03	0:07	*5:00	6:10	0:20	0:00	1:10	1:30
No.19	0:33	0:17	*5:00	5:50	0:25	0:00	1:20	1:45
No.20	0:18	0:13	*5:00	5:31	0:12	0:00	0:44	0:56
No.21	n/a	n/a	n/a	n/a	0:15	0:00	0:39	0:54
No.22	n/a	n/a	n/a	n/a	0:21	0:00	2:50	3:11
No.23	n/a	n/a	n/a	n/a	0:12	0:00	0:51	1:03

Table 8.7: Individual and Overall failure rate in Dapper/Pipes.

Task	Task 1	Task 2	Task 3
Data Extraction	5%	25%	0%
Source Modeling	0%	0%	0%
Data Cleaning	83%	35%	n/a
Data Integration	n/a	30%	95%
Overall	83%	45%	95%

Document Object Model (DOM)



Vertical Expansion

