Magellan: Toward a System-Building Agenda for Semantic Matching

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Joint work with many students & colleagues

Informatica

Motivation

- **Worked in academia from 2000-2010**
  - developed many algorithmic solutions for schema/ontology matching
- **Worked in industry 2010-2014**
  - realized that many of these solutions were not applicable
  - no open-source code that could be immediately used
  - impact of academic work was very limited
- **Back in academia in 2015**
  - decided to focus on building systems that real users can immediately use
  - hoped that if such systems were built, academic work would follow, I can make more impacts
- **Decided to focus on entity matching**
  - was easier to get data
  - but eventually want to consider other semantic matching tasks too

Entity Matching (EM)

Table A

Name	City	State
Dave Smith	Madison	WI
Joe Wilson	San Jose	CA
Dan Smith	Middleton	WI

Table B

Name	City	State
David D. Smith	Madison	WI
Daniel W. Smith	Middleton	WI

The Magellan Project @ UW-Madison

- **Started in 2015**
- **Develop a general-purpose EM platform**
- **Inspired by**
  - PostgreSQL for relational data management
  - Scikit-learn for machine learning
  - Hadoop/Spark for big data processing

Significant Progress in Past Five Years

- **Deployed at 12 companies and domain science groups**
  - 8 companies: Walmart, Recruit Holdings, Johnson Control, AF Insurance, Informatica, etc.
  - 4 domain sciences: Economics, Limnology, Biomedicine, Land Use
  - Pushed into production in 8 cases
- **Contributed to several high-profile projects**
  - saving Amazon forest, managing water quality in the Greater Lake region of the US
- **Used by 500+ students in 6 data science courses at UW-Madison**
- **Commercialized by GreenBay Technologies**
  - Acquired by Informatica in Aug 2020
  - Pushed into an EM platform to be used by thousands of customers
  - Influencing solutions for schema matching and knowledge graph construction
- **Multiple research papers, SIGMOD/ACM Research Highlight Awards**

The R&D Template of Magellan

1. **Identify the problem and user populations**
2. **Understand how a user typically does EM**
3. **Identify pain points and develop tools/guidance**
   - Goal is to improve productivity of the user
4. **Build tools into three data science ecosystems**
   - On-prem, cloud, mobile
   - Make tools atomic and easy to combine
   - Combine tools to build easy-to-use EM systems for users
5. **Work with real users, learn, and repeat**

- **Radically different from prior system building efforts**
- **Can be applied to other problems: IE, schema/ontology matching, etc.**

1. Identify Problems & User Populations

- Focus on simple but common problems
- Focus on user populations we can easily work with

Identify Problems

Table A

Name	City	State
Dave Smith	Madison	WI
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Name	City	State
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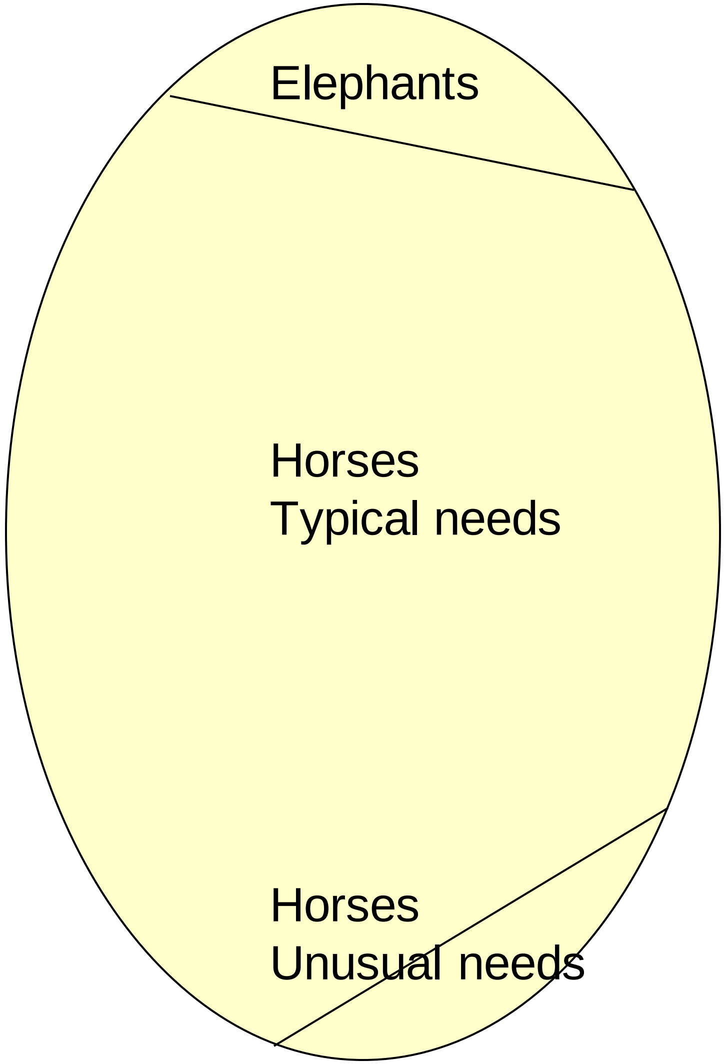
- **Use supervised machine learning**

A "Very Boring" Problem

- **Received very little attention**
  - judged trivial, hard to develop novel technical solutions, hard to publish
- **Most academic works focus on more complex problems**
  - e.g., how to exploit a knowledge graph to improve the accuracy of EM
  - easier to develop novel technical solutions
- **We selected the above problem because many users need to solve it**
  - especially the "horses"



“Horse” Populations That We Target

- **Domain scientists**
  - Biomedicine, land use, limnology, economics, etc.
  - They are within walking distance
  - Domain experts, some coding skills (e.g., Python, R, SQL)
- **Students, educators, researchers in data integration, data science**
  - Students form teams to do class project, we asked each team to solve an EM problem
- **Data scientists at companies**
  - Often work in a way similar to domain scientists
- **Lay users, data enthusiasts**
  - Journalists, citizen data scientists; domain experts, but often no coding skills
- **We do not target enterprise customers**
  - They often want “hardcore” stuff: proprietary code, big/complex processes, lot of support
  - But we ended up working with a few

2. Understand How a User Typically Does EM

- Observe how real users do it
- Observe how students do it in class projects

Existing Work Has a Relatively Simple View of How User Does EM

Table A

	Name	City	State
a_1	Dave Smith	Madison	WI
a_2	Joe Wilson	San Jose	CA
a_3	Dan Smith	Middleton	WI

Table B

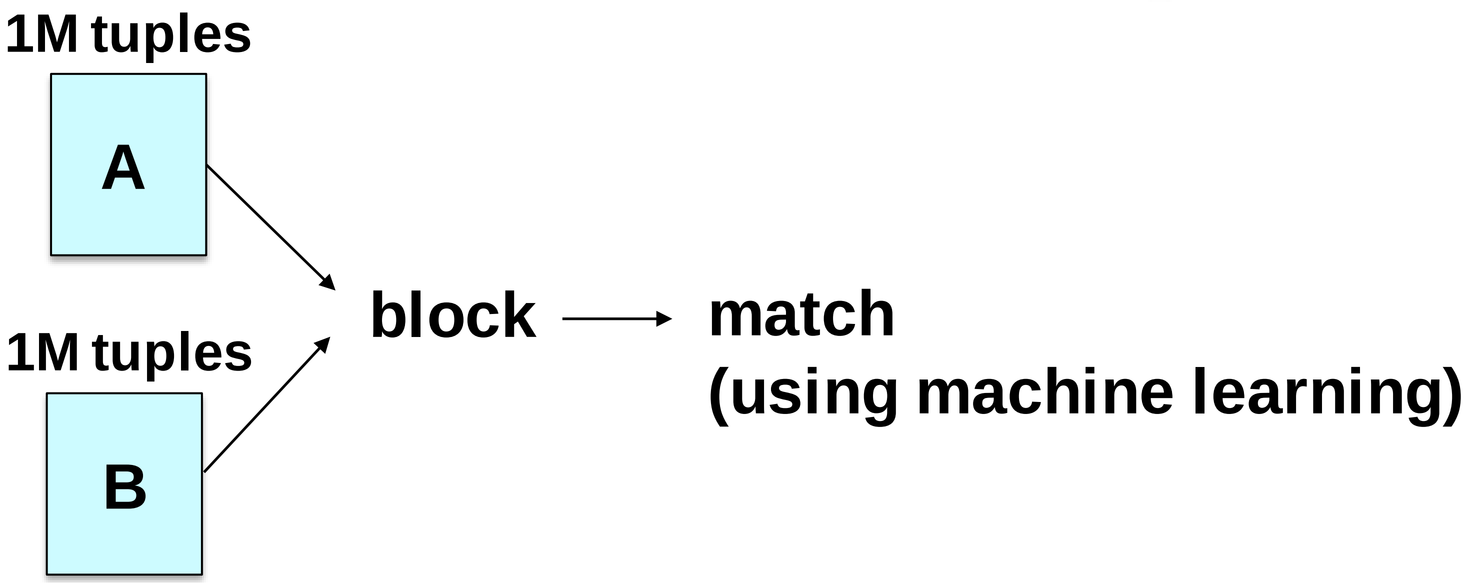
	Name	City	State
b_1	David D. Smith	Madison	WI
b_2	Daniel W. Smith	Middleton	WI

block on state = state → (a_1, b_1), (a_1, b_2), (a_3, b_1), (a_3, b_2) → **match** →

(a_1, b_1) +
(a_1, b_2) -
(a_3, b_1) -
(a_3, b_2) +

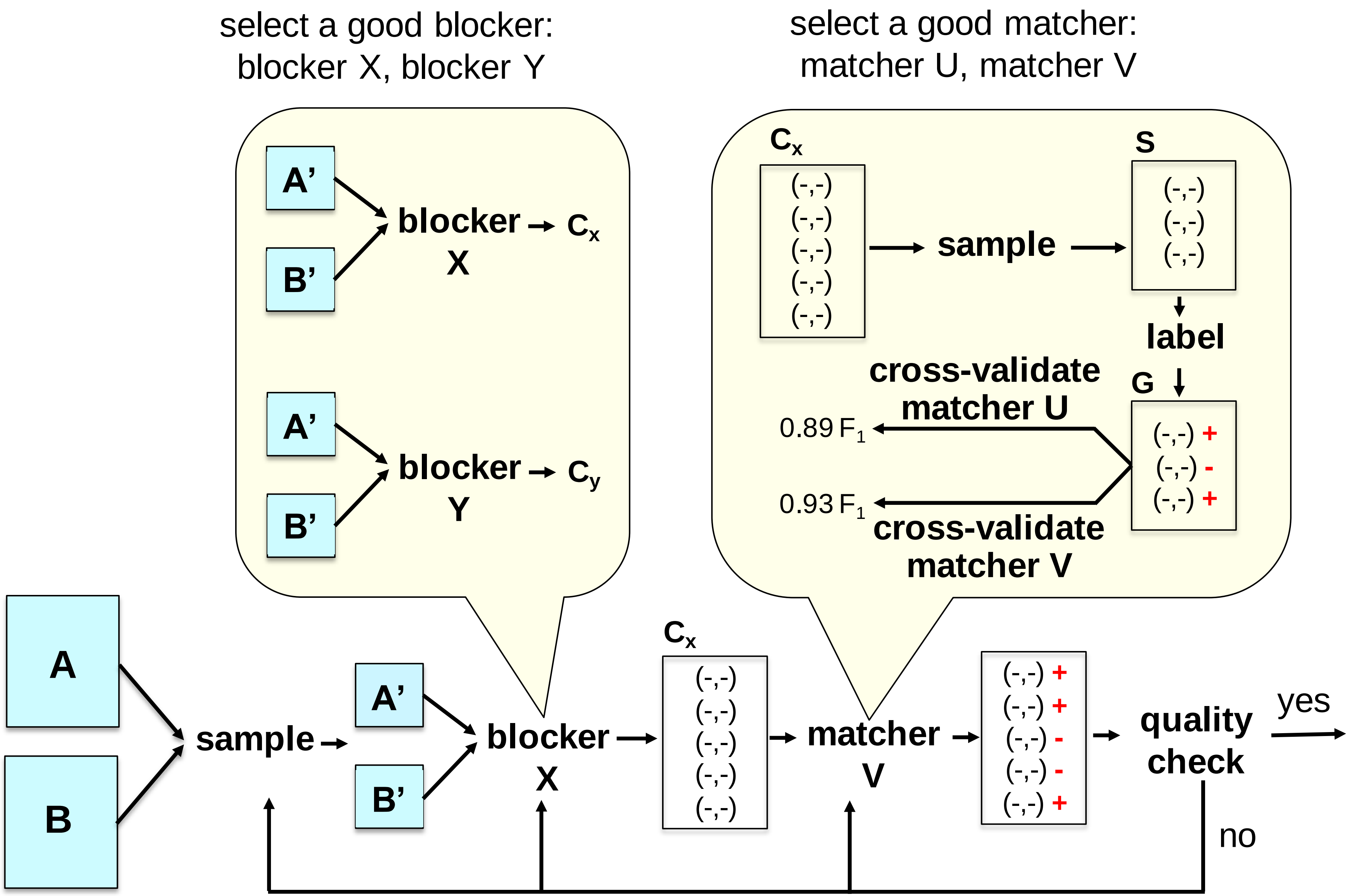
- **Focuses on developing blockers and matchers**

We Observe That Real-World EM Processes Are Far More Complex

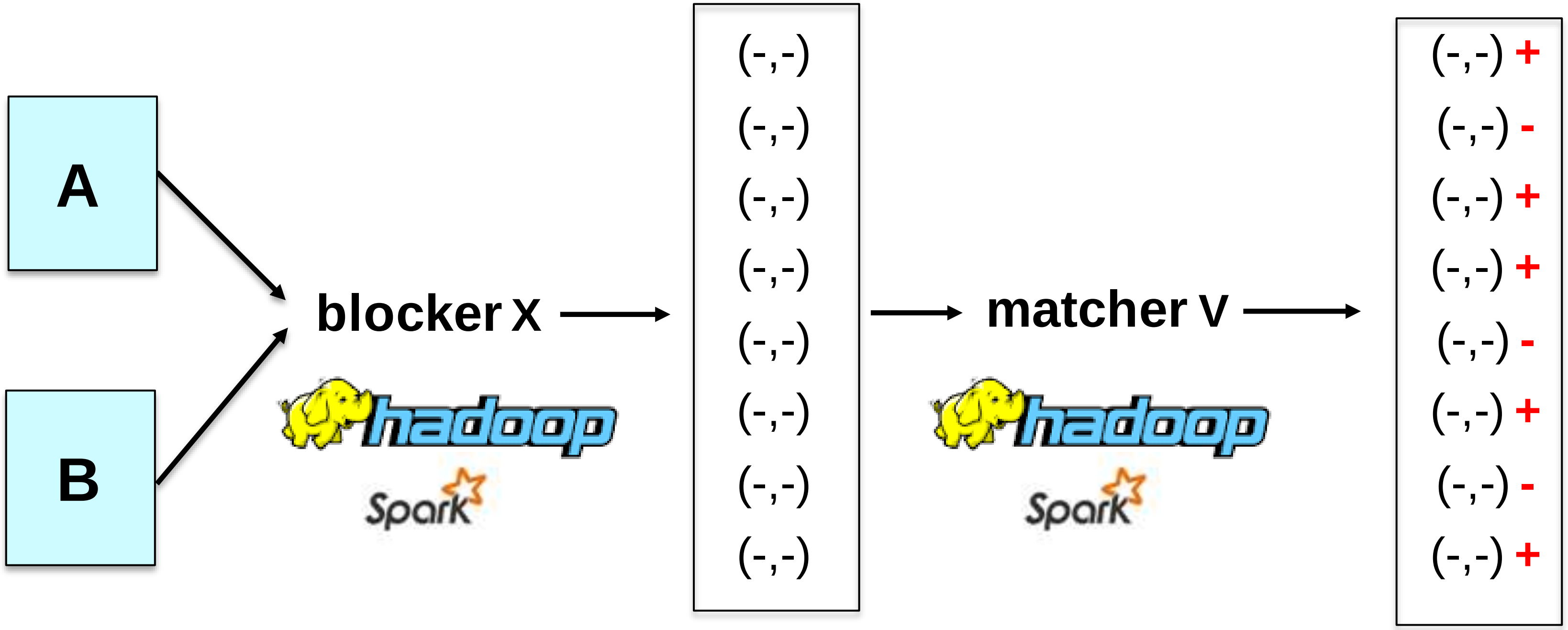


- **Development stage**
  - finds an accurate workflow, using data samples
- **Production stage**
  - executes workflow on entirety of data
  - focuses on scalability

Development Stage



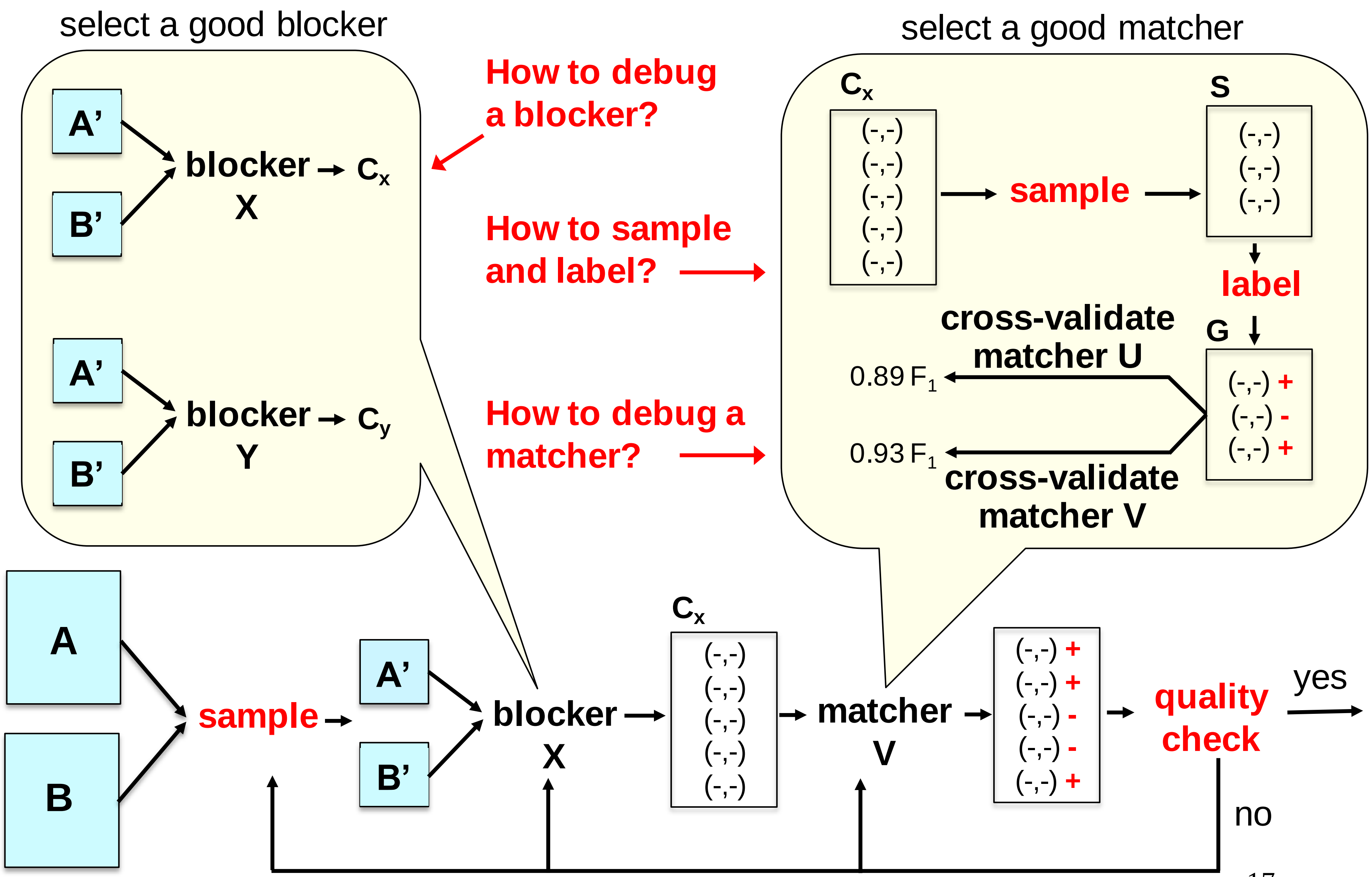
Production Stage



Scaling, quality monitoring, exception handling, crash recovery, …

3. Identify Pain Points and Develop Tools/Guidance

Example Pain Points



Debugging a Blocker

Table A

	Name	City	Age
a_1	Dave Smith	Altanta	18
a_2	Daniel Smith	LA	18
a_3	Joe Welson	New York	25
a_4	Charles Williams	Chicago	45
a_5	Charlie William	Atlanta	28

Table B

	Name	City	Age
b_1	David Smith	Atlanta	18
b_2	Joe Wilson	NY	25
b_3	Daniel W. Smith	LA	30
b_4	Charles Williams	Chicago	45

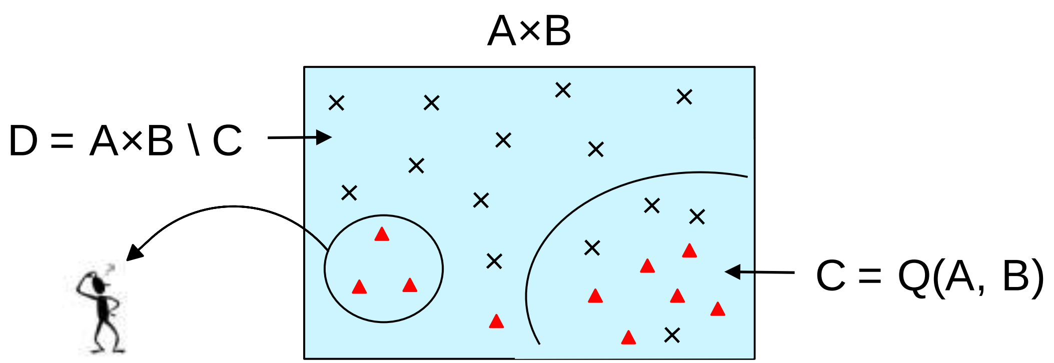
blocker Q
a.City = b.City →

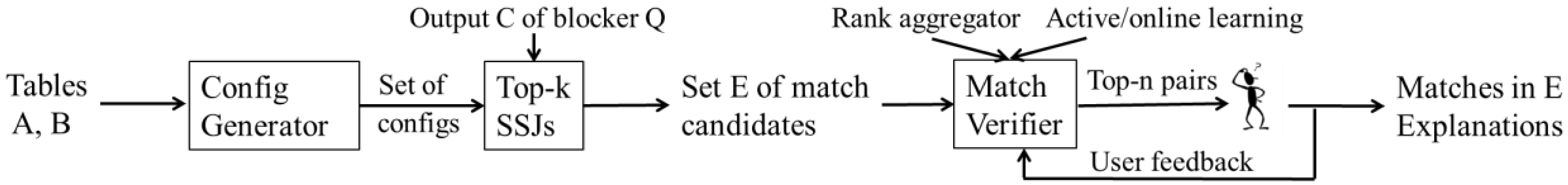
C
(a_2, b_3)
(a_4, b_4)
(a_5, b_1)

- **Does blocker Q kill off too many matches?**
- **What are the killed-off matches?**
- **Why are they killed off by Q?**

Debugging a Blocker

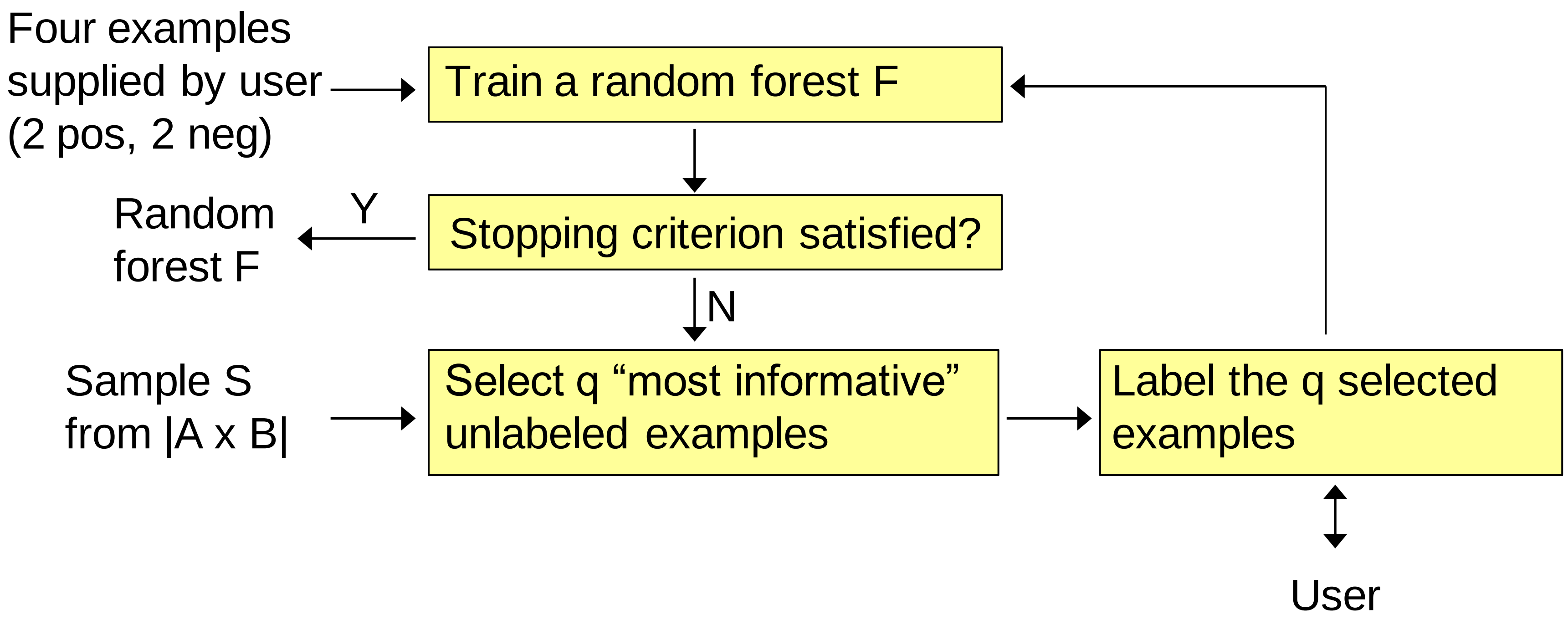
- Debugger quickly finds matches killed-off by the blocker
- User examines these matches and improves the blocker





Learning a Blocker

- **Take sample S from A x B (without materializing A x B)**
- **Train a random forest F on S (to match tuple pairs)**
  - using active learning, where user labels pairs



Learning a Blocker

CloudMatch Home Job Statistics Job Progress Task Monitoring Logout

Train Model

Do these pairs refer to the same real world entity?

✔ Yes 2
✖ No 2

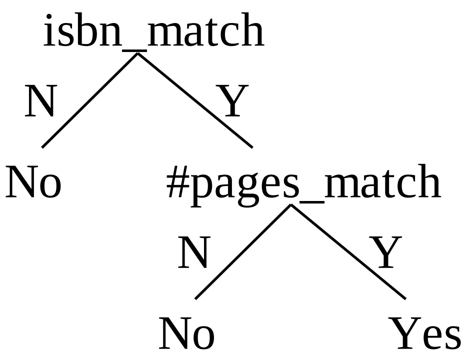
id	name	addr	city	phone	type	class
550	patina	'5955 melrose ave.'	'los angeles'	213/467-1108	californian	16
235	patina	'5955 melrose ave.'	'los angeles'	213-467-1108	californian	16
						✔Yes ✖No Unsure
555	valentino	'3115 pico blvd.'	'santa monica'	310/829-4313	italian	21
240	valentino	'3115 pico blvd.'	'santa monica'	310-829-4313	italian	21
						✔Yes ✖No Unsure
875	'sammy\'s roumanian steak house'	'157 chrystie st. at delancey st.'	'new york'	212/673-0330	'east european'	341
108	'sparks steak house'	'210 e. 46th st.'	'new york city'	212-687-4855	steakhouses	641
						✔Yes ✖No Unsure
962	'binion\'s coffee shop'	'128 fremont st.'	'las vegas'	702/382-1600	'coffee shops/diners'	428
9	'brighton coffee shop'	'9600 brighton way'	'beverly hills'	310-276-7732	'coffee shops'	542
						✔Yes ✖No Unsure
619	'la grotta'	'2637 peachtree rd. peachtree house condominium'	atlanta	404/231-1368	italian	85
304	'la grotta'	'2637 peachtree rd. ne'	atlanta	404-231-1368	italian	85
						✔Yes ✖No Unsure

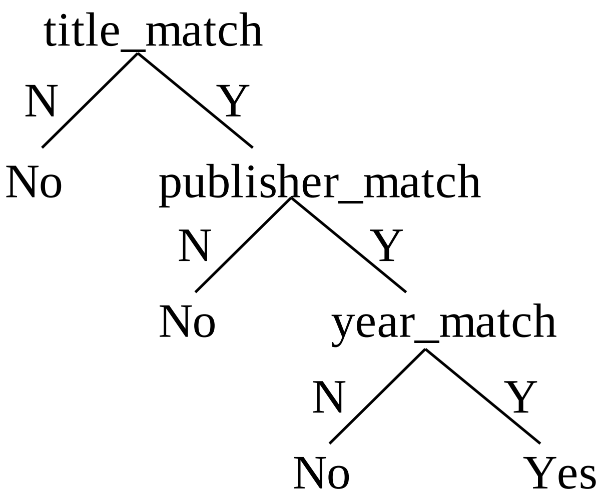
Home Submit

Learning a Blocker

- **Extract candidate blocking rules from random forest F**

Example random forest F for matching books





Extracted candidate blocking rules

(isbn_match = N) $\longrightarrow$ No

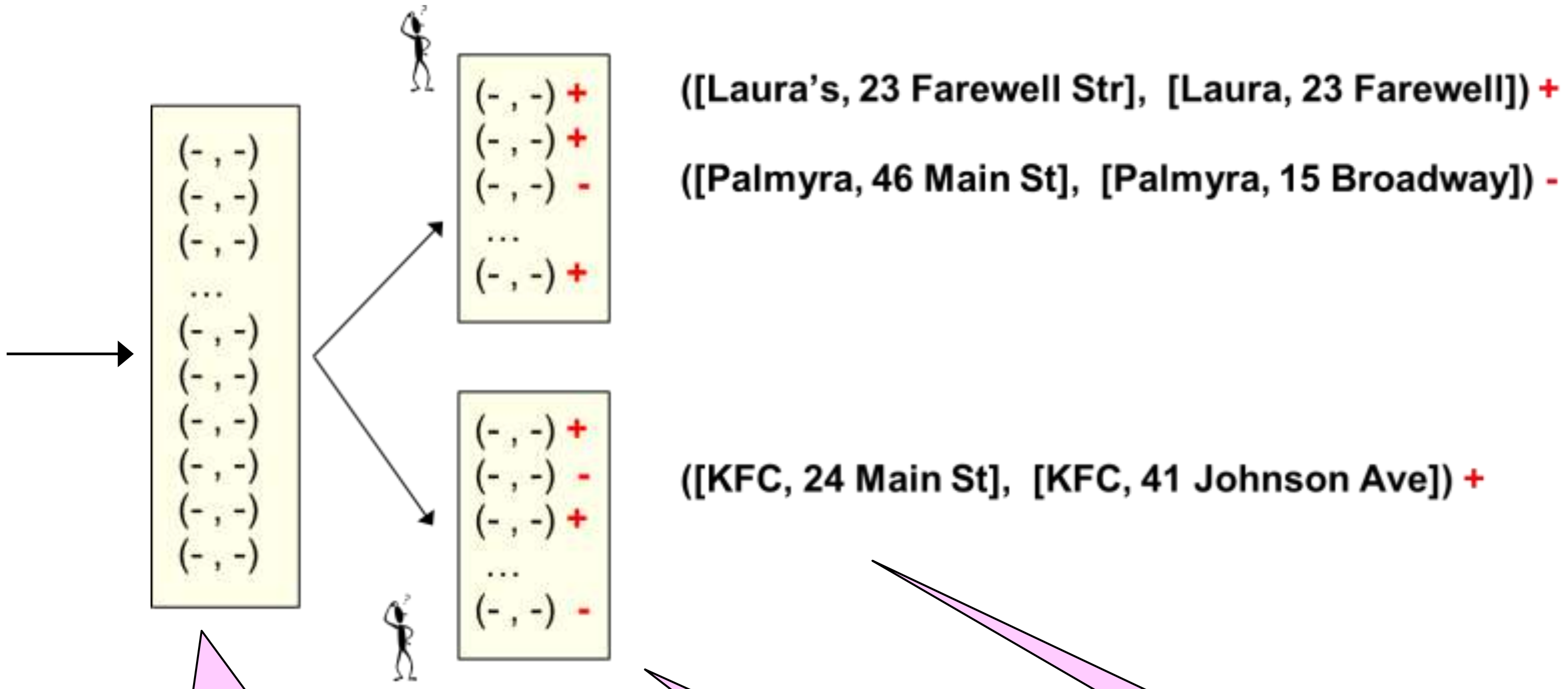
(isbn_match = Y) and (#pages_match = N) $\longrightarrow$ No

(title_match = N) $\longrightarrow$ No

(title_match = Y) and (publisher_match = N) $\longrightarrow$ No

(title_match = Y) and (publisher_match = Y) and (year_match = N) $\longrightarrow$ No

Collaborative Labeing



Tool to highlight possible matching definitions

Tool to debug labels

Tool to help revise labels

Tool to Highlight Possible Match Definitions

- **We do not have a tool yet, but we do have guidance for user**
  1. Take a small sample S of tuple pairs (say 50)
  2. All labelers must label S
  3. Compare their outputs, highlight discrepancies, discuss
  4. Repeat Steps 1-3 until no more discrepancies
  5. During above steps, document all possible match definitions that come up

- **In addition to above guidance, currently we also recommend the following**
  – Use blocking debugger to return pairs that are likely to be matches, collectively discuss them
  – Use an active learner to identify controversial pairs, collectively discuss them

What We Learn When Working with Users

- **They need to understand (and agree on) the match definition**
  - KFC on Univ Ave = KFC on Farewell Ave?
  - iPhone 6s black = iPhone 6s white?
  - The Amazon rain forest group has worked on EM for three years, and yet still have problems

- **They need to understand the data (tables A and B)**
  - How dirty? Lot of missing values? Any portion of data is unreliable?

- **They need to understand the limitations of tools**
  - Can random forests match textual data accurately?

- **Need to develop tools and guidance to help them gain this understanding**
  - As a part of the EM process

Summary

- **A user typically does EM in a multi-step iterative complex process**
  - Far more complicated than we thought, we do not fully understand it today
  - Need more work to completely specify this EM process
- **Cannot be completely automated, aims instead to improve user productivity**
  - Keep the same process, but make it easier for user to execute (far less ambitious goal)
- **Identify pain point steps in the process, for each such step**
  - Develop (semi-)automatic tools to help user if possible
  - If not, develop guidance telling user how to do the step

4. Build Tools into Three Data Science Ecosystems

- On-prem, cloud, mobile
- Make tools atomic & easy to combine
- Combine tools to build easy-to-use EM systems

Our First Observation

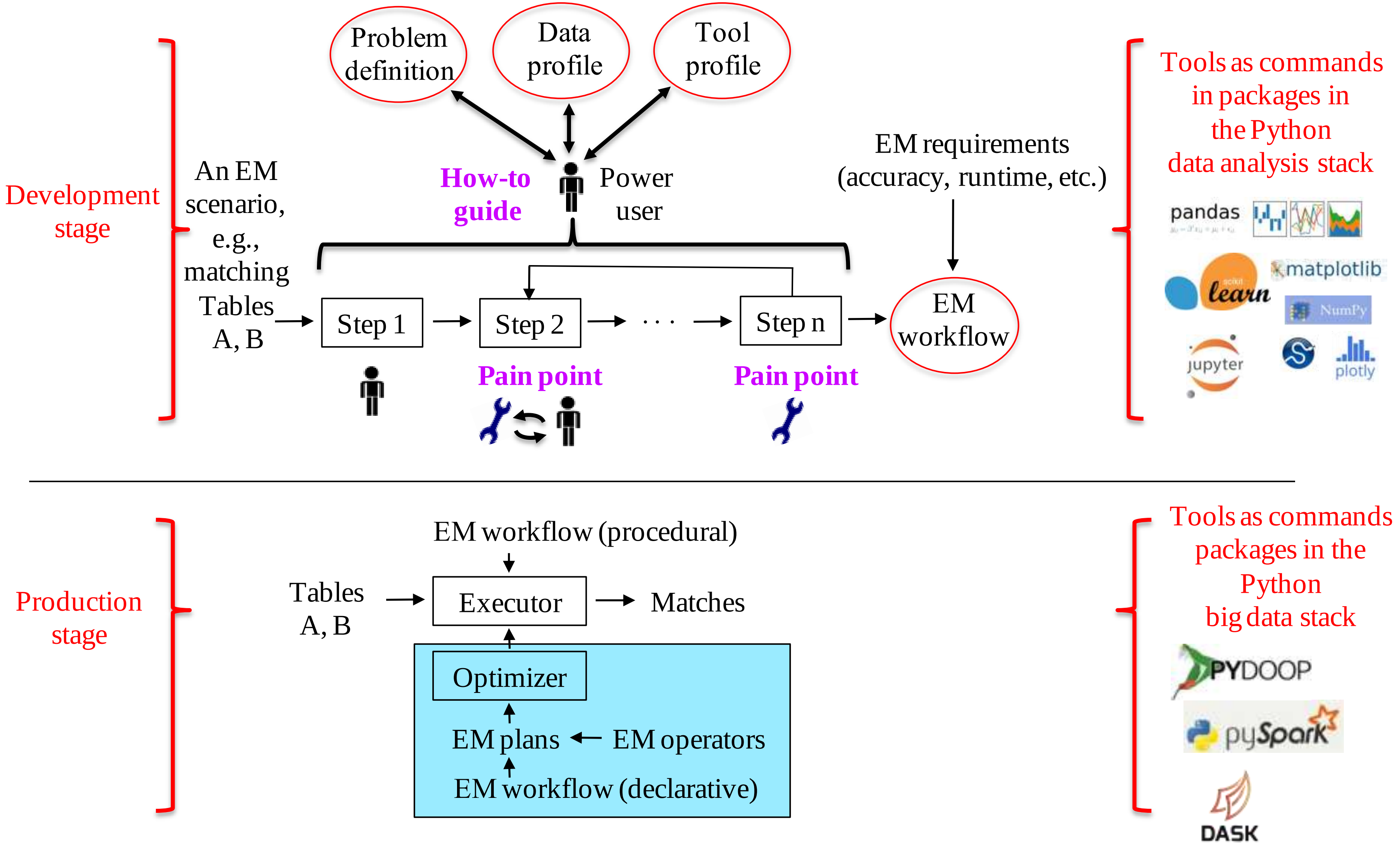
- **Tools need to exploit a wide variety of techniques**
  - Relational data processing, ML, statistics, visualization, cleaning, etc.
- **Very time consuming to implement so many techniques from scratch**
  - Best to exploit existing data science ecosystems
  - A natural starting point is PyData, ecosystem of DS tools in Python
- **We also don't want complex "monolithic" tools**
  - Difficult to build & maintain them in academia
  - Difficult to reuse
  - Difficult to combine them in unexpected ways, which users often do
- **So we build tools that are atomic and easy to combine**
- **Build them as commands in Python packages, as part of PyData**
- **Then combine them to build more complex tools**

Current PyData Tools

Step of the How-to Guide (A)	Use Existing Packages (B)	Write Our Own Code (C)	Develop Tools for Pain Points (D)	Number of Commands (E)
Read/Write Data	pandas			6
Down Sample			Down sampler	1
Data Exploration	pandas pandas-profiling pandas-table OpenRefine			2
Blocking	Dask joblib	Multiple blockers py_stringmatching py_stringsimjoin	Blocking debugger	21
Sampling	pandas			1
Labeling	PyQt5		GUI labeler	2
Creating Feature Vectors	joblib	py_stringmatching	Automatic feature creation Manual feature creation	12
Matching	scikit-learn PyTorch XGBoost		Matching debuggers Deep learning-based matcher	20
Computing Accuracy	pandas			4
Adding Rules			Rule specification and execution	9
Managing Metadata			Catalog management	22

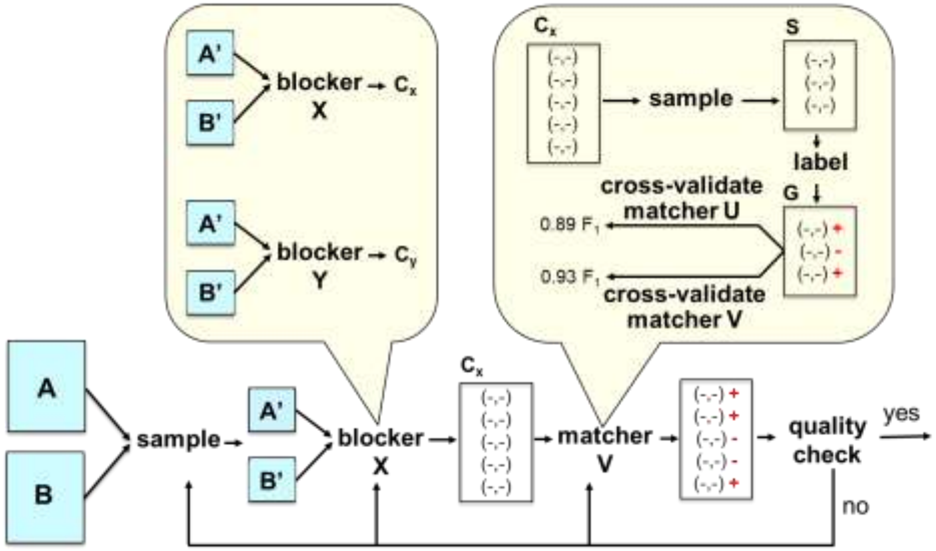
Main Packages: py_stringmatching, py_stringsimjoin, py_entitymatching, py_labeler, DeepMatcher

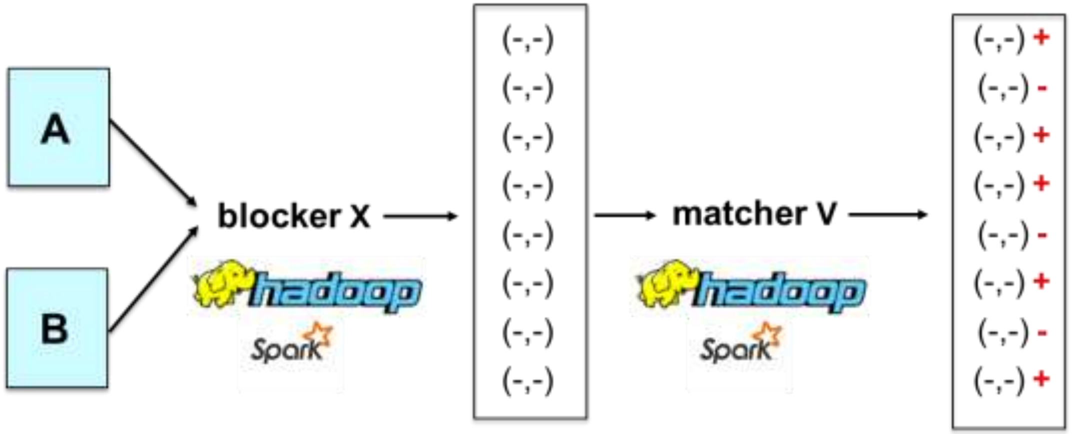
Our First System Architecture



Our Second Observation

- **Tools in PyData ecosystem can be used mostly on-prem**
- **When doing EM, users often want to move among three exec environments**
  - On-prem, cloud, mobile





So We Build into All Three Execution Environments

PyData

- py_stringmatching
- py_stringsimjoin
- py_entitymatching
- deepmatcher

AWS

- RuleExecutor
- CloudLabeler
- CloudProfiler
- ActiveLearner

- MobileLabeler
- Cymphony

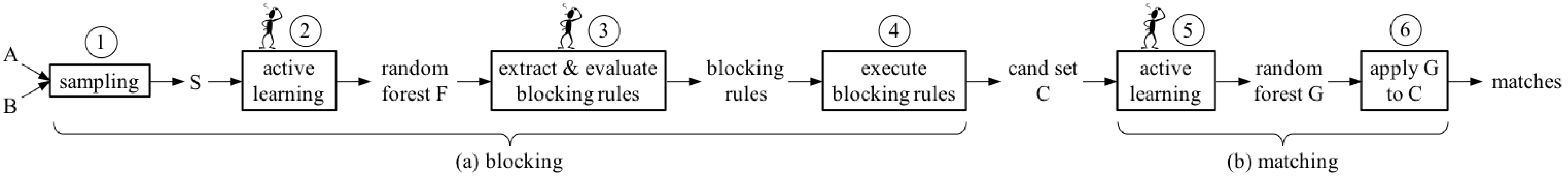
Combine Tools to Create Easy-to-Use EM Systems

PyData

- py_stringmatching
- py_stringsimjoin
- py_entitymatching
- deepmatcher

AWS

- RuleExecutor
- CloudLabeler
- CloudProfiler
- ActiveLearner
- **CloudMatcher**



Real-World Deployment of CloudMatcher

Problem Owner	Problem Type	Table A	Table B	Precision (in %)	Recall (in %)	Cost			Time		
						Questions	Crowd	Compute	User/Crowd	Machine	Total
American Family Insurance	Phoenix customers	300	300	96.4	99.03	160	-	$2.33	9m	5m	14m
	Commercial insurance policy holders	1,049	17,572	96.15	97.22	321	-	$2.33	18m	25m	43m
	Commercial farm/ranch policy members	109,974	4,922,505	99.5	95	780	-	$13.96	50m	4h 58m	5h 48m
	Vehicles	18,938	72,898	66.02 – 80.02	81.65 – 93.15	851	-	$7.00	2h	46m	2h 46m
	Drivers	790	634	99.86	94.89	250	-	$2.33	10m	8m	18m
Johnson Controls International	Addresses	90,673	231,081	93.22 – 95.72	76.93 – 81.01	1200	$72	-	36h 48m	38m	37h 26m
	Vendors	50,295	50,292	29.95 – 38.04	91.89 – 98.10	1160	$69.60	-	30h 31m	58m	31h 29m
	Vendors (no Brazil)	28,152	28,149	95.44 – 97.75	88.82 – 92.41	1200	$72	-	22h 19m	22m	22h 41m
UW Health	Doctors & staff	1,786	1,786	99.66	98.18	1200	-	$4.66	50m	15m	1h 5m
Informatica	Persons	48,119	48,119	100 – 100	98.42 – 100	462	-	$7.00	36m	1h 35m	2h 11m
Marshfield Clinic	Drugs	446,048	440,048	99.14 – 99.63	98.45 – 99.14	1162	-	-	1h 10m	8h 40m	9h 50m
Non-profit Org	Elected officials	9,751	706,878	93.75 – 96.32	95.50 – 97.76	960	$57.60	-	23h 14m	23m	23h 37m
Domain Science	UMetrics economics	2,616	21,530	94.5 – 96.5	98.12 – 99.21	680	$61.20	-	23h 12m	12m	23h 24m

- Outperformed three commercial systems

Discussion & Lessons Learned

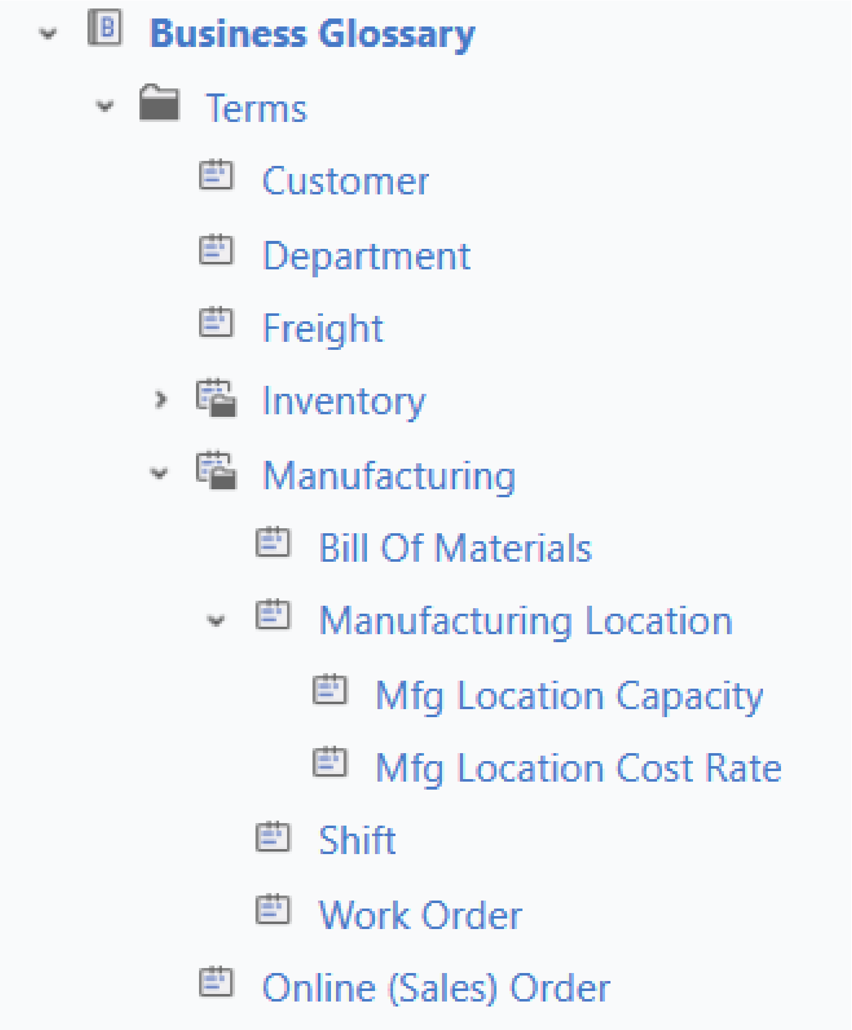
- **Building systems then using them to do research**
  - a great way to make impacts
- **It is possible to build such systems in academia with a small team**
  - we have never had a full-time programmer, just a few graduate students
  - system has many small independent tools, each student works on a tool
- **Do not overlook “boring trivial problems” for the “horses”**
  - often turn out to be very technically challenging
- **Our system-building template is very promising**
  - validated by what we have seen at Informatica

Discussion & Lessons Learned

- **For the entity matching community**
  - **need a lot more data sets**
    - that are diverse, otherwise hard to know if a technique is robust
    - that are big (10-50M tuples), many things break at scale
    - that have different levels of noise, as noisy data can really impact accuracy & runtime
    - **really need gold for these data sets, but hard to create**
  - **benchmarks and competitions must focus on a lot more pain points**
    - so far mostly focus on the matching step
    - need to consider more pain points
      - blocking, data cleaning in a pre-processing step, debugging, labeling, etc.

Discussion & Lessons Learned

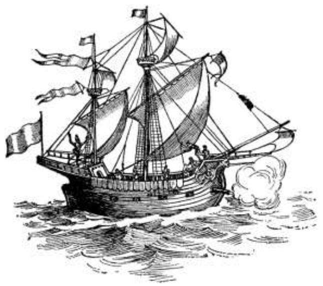
- **For the ontology matching community**
  - would be great if can help with two major problems faced by thousands of companies & domain scientists
  - schema matching for data lakes
    - given a data lake (say having 100K tables), find all column pairs that match
  - business glossary matching for data lakes
    - given a set of business terms and a data lake, find all pairs <term, column> that match
    - "Mfg Location Capacity" matches column "MLCap"
    - "House's Listed Price" matches column "HPrice"
- **These are not ontology matching, but very closely related**
  - major problems in industry & domain sciences



Discussion & Lessons Learned

- **Can apply the Magellan template to these two problems**
  - identify the end-to-end process that a real user follows to solve them
  - identify pain points, develop tools & guidance
- **There are numerous pain points**
  - cleaning column names
    - “MPCap” => Manufacturing Location Capacity
    - “HPrice” => House Price
  - finding synonyms in the lake
    - Manufacturing = Factory, Location = Area, A/C = Cooling
  - scaling up blocking
    - need to scale for lakes of up to 10M columns
- **But first must create data sets with gold**
  - **a critical but difficult problem**
  - how to create gold for a data lake with 100,000 columns? **Solving this makes big impacts**

Conclusions



- **Magellan seeks to build a general platform for entity matching**
  - generalized later to other semantic matching tasks

- **Departing radically from existing work**
  - observes that the EM process is often very complex, driven by user, can't be automated, so focus on improving the productivity of user
    - identify the complex EM process
    - identify pain points, develop tool/guidance
    - build tools into three data science ecosystems

- **Provide a promising R&D template for other semantic matching problems**
  - schema/ontology matching, business glossary matching, etc.

Reference Papers

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