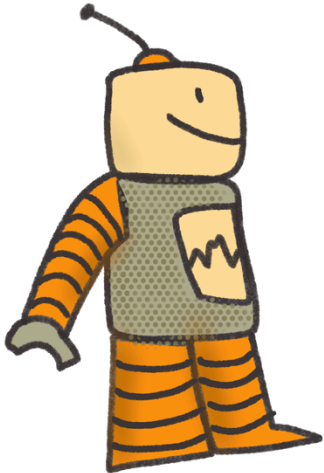


HUMAN-IN-THE-LOOP FROM THE HUMAN PERSPECTIVE

Marti Hearst

UC Berkeley

KDD Dash Workshop, Aug 24, 2020



Pairing People & Algorithms for Data Science

Two Perspectives

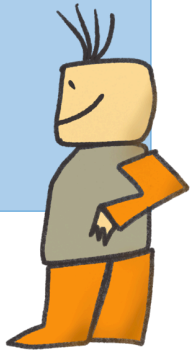
Human-in-the-Loop

- Goal: improving ML
- Perspective:
 - *Human aids machine*



Mixed-Initiative Interaction

- Goal: analysis/exploration
- Perspective:
 - *Machine aids human*



Pairing People & Algorithms for Data Science

This Workshop: Two Perspectives

Human-in-the-Loop

Active Learning Improvement (Ghai et al.,
Kanchinadam et al.)

Data Augmentation & Model Improvement
(Venkataram et al.)

GUI for Annotation (Qian et al., Das & Dutt)

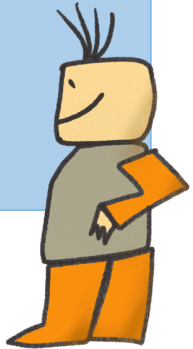


Mixed-Initiative Interaction

GUI & Algorithm for SenseMaking (Bunch et al.)

GUI & Algorithm to Explain Errors (Hanafi et al.)

GUI & Algorithm to Build Better Models (Wang et al.)



OUTLINE

Two Perspectives

Human-in-the-Loop
Two interesting examples

Mixed-Initiative
Two interesting examples
Trust issue: Data Science

Conclusions

Pairing People & Algorithms for Data Science

Two Perspectives

Human-in-the-Loop

- Goal: improving ML
- Perspective:
 - *Human aids machine*

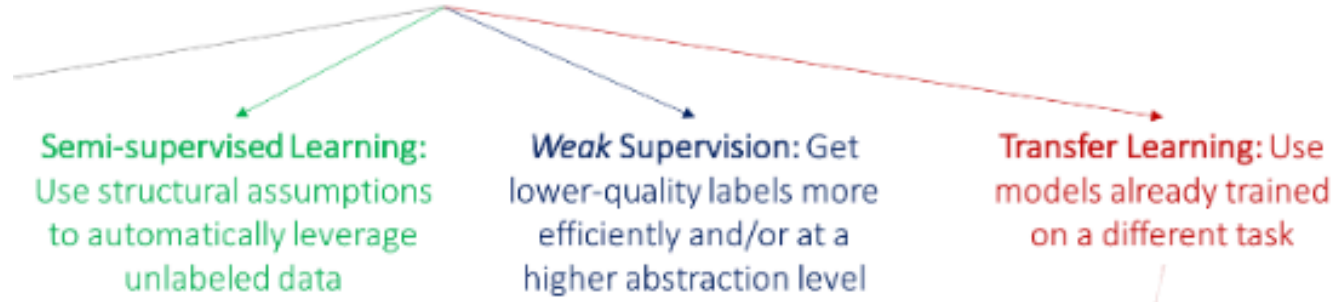


Labeling Data: Human vs. No Human

How to get more labeled training data?

Labeling Data: Human vs. No Human

How to get more labeled training data?

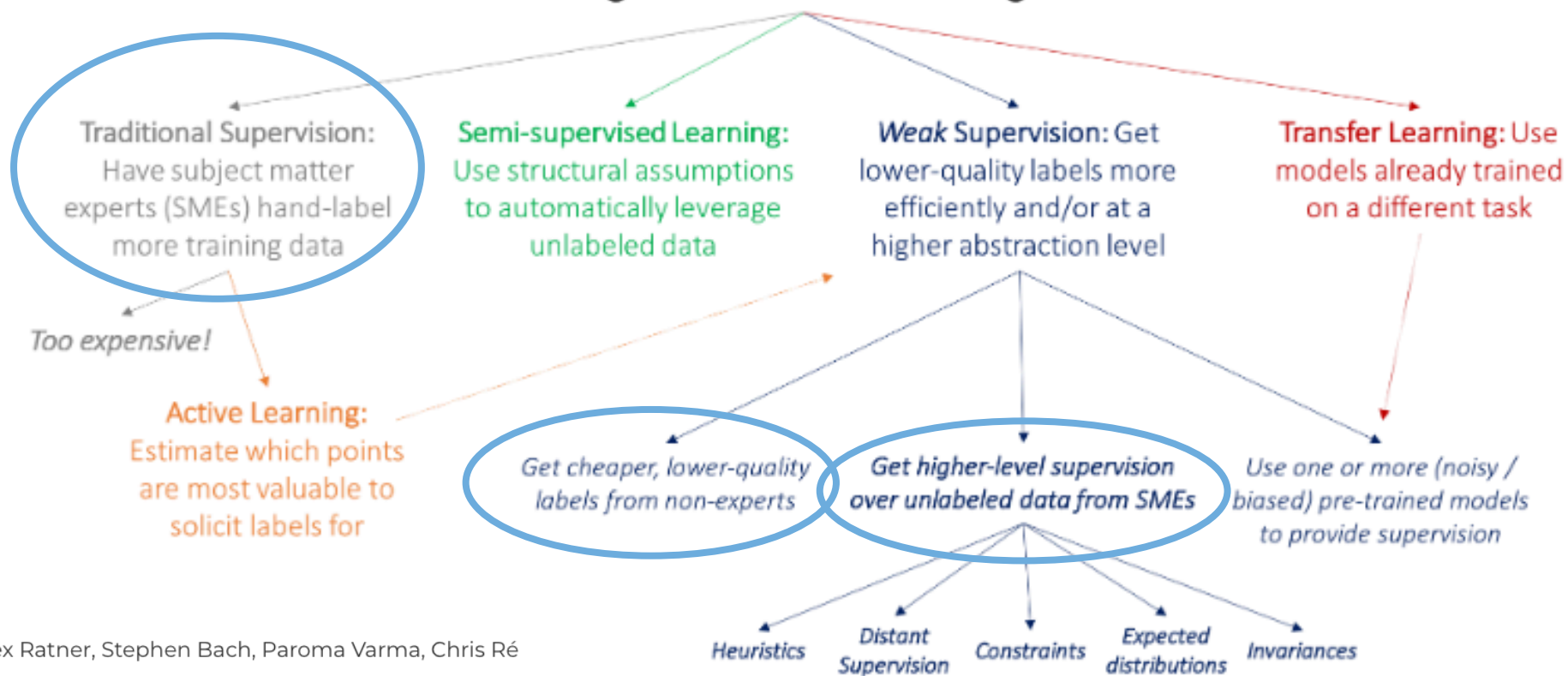


Labeling Data: Human vs. No Human



Labeling Data: Human vs. No Human

How to get more labeled training data?



HUMAN-IN-THE-LOOP: ROLE OF HUMANS

Goal: improve training data for ML algorithm

Traditional: People label items:

- *Category*
- *Relevance / Ranking*
- *Span*

HUMAN-IN-THE-LOOP: APPROACHES

Approaches:

- **Naïve**: Humans label lots of items
- **Active Learning**: Humans label *strategically* selected items
- **Smart UIs**: Reduce labeling effort, geared toward human actions / cognition

OUTLINE

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HUMAN-IN-THE-LOOP: ADD MORE HUMAN INITIATIVE

Recent innovations give more agency to humans:

- Ask humans to outsmart the algorithm (Nie et al.)
- Ask humans to program patterns (Raskin et al.)
- This workshop:
 - Humans give rationales for features (Ghai et al., Kanchinadam et al.)
 - Humans write queries to ferret out negative examples (Venkataram et al.)

ADVERSARIAL LABELING

Today, evaluation sets for ML get “tapped out” quickly

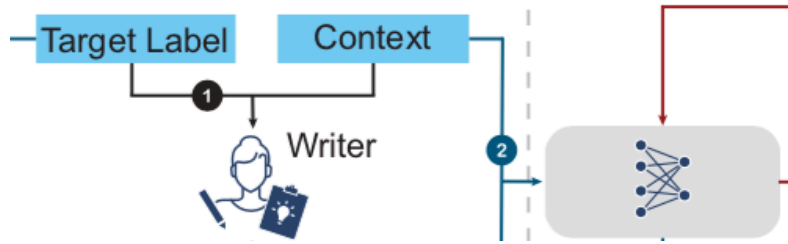
- *15 years for near-human performance on MNIST*
- *7 years for ImageNet*
- *~1 year for GLUE (combined NLP benchmark)*

Why a Problem?

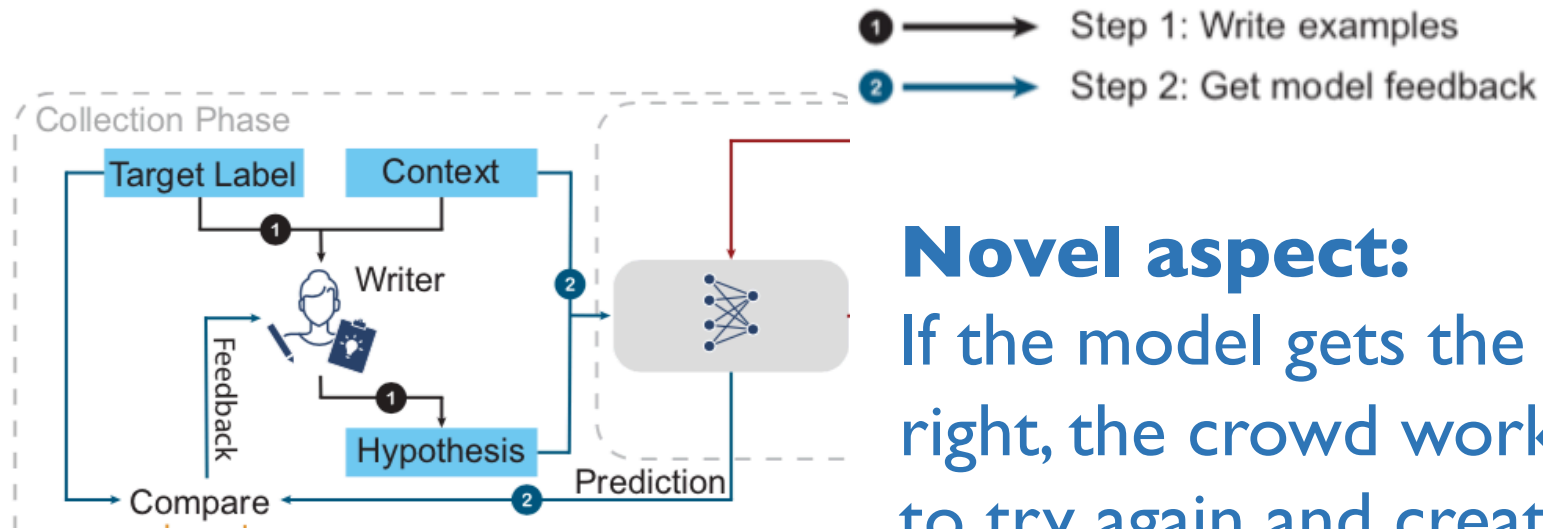
- *Algorithms learn biases and tricks*
- *Training doesn't really reflect the underlying task*
- **We need more robust training sets!**

IDEA: ASK HUMANS TO OUTSMART THE ALGORITHM

- Like adversarial learning, except
 - *Instead of an algorithm making the adversarial examples,*
 - *Humans figure out difficult examples for the model*
- A *Dynamic* Benchmark
- End result: more accurate and robust model

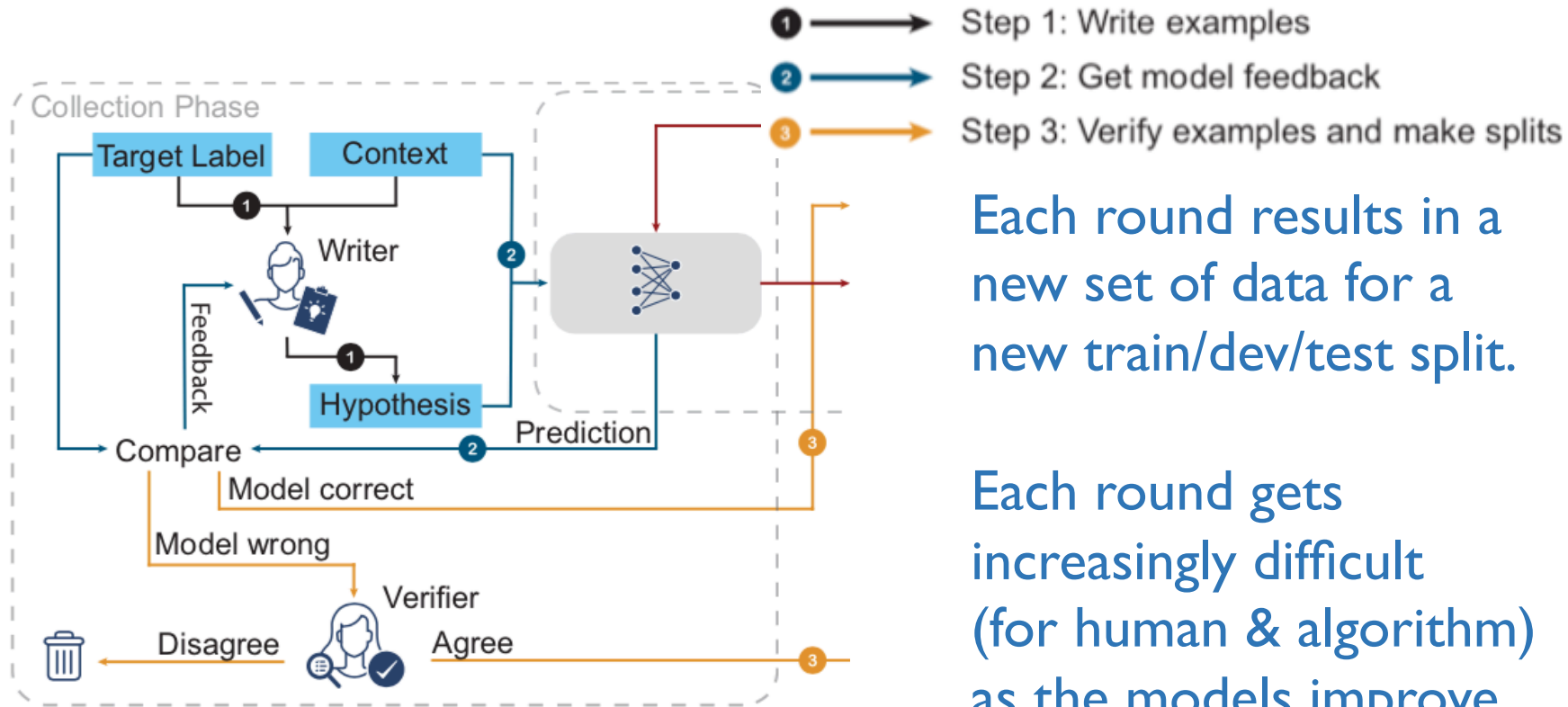


In typical crowd work, humans write examples, perhaps with constraints on novelty.



Novel aspect:
 If the model gets the answer right, the crowd worker has to try again and create another sentence.

In typical crowd work, humans write examples, perhaps with constraints on novelty.



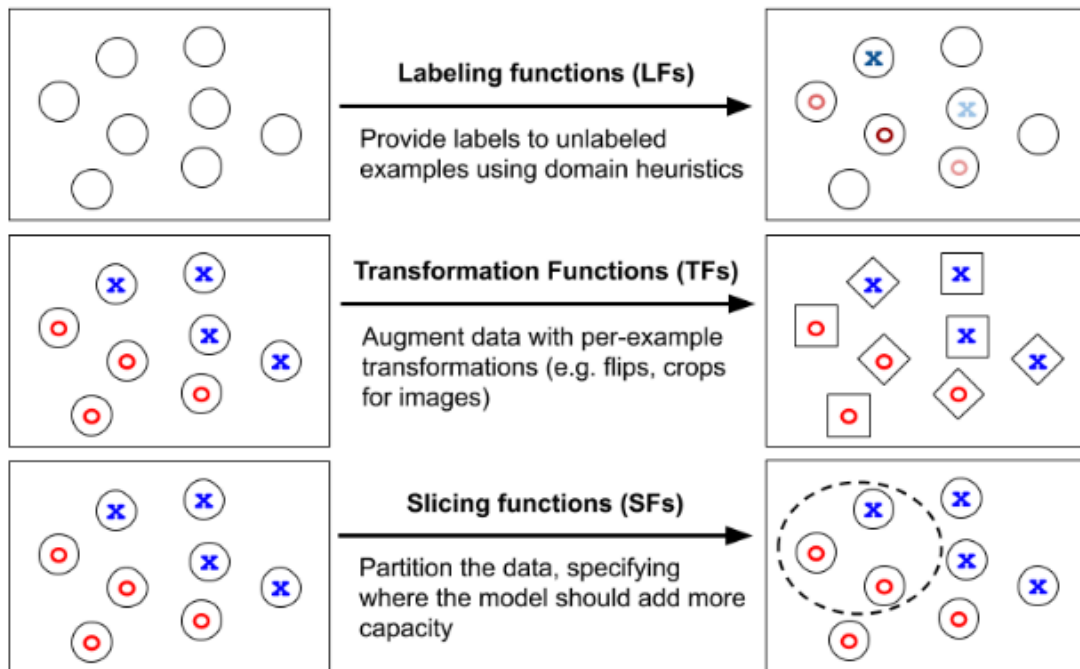
HUMANS WRITE RULES; ALGORITHMS COMBINE AND FIX INCONSISTENCIES

Programmatically building and manipulating the training data — rather than the models — improves ML performance.



snorkel

Ratner et al., VLDB 2017



SUMMARY:

HUMAN-IN-THE-LOOP TREND:

ADD MORE HUMAN INITIATIVE

OUTLINE

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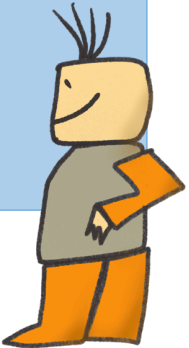
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Two Perspectives

Mixed-Initiative Interaction

- Goal: analysis/exploration
- Perspective:
 - *Machine aids human*



Mixed-initiative interaction



By Mari Ellen Allen
University of California, Berkeley
marial@cs.berkeley.edu

In the last few years, a series of well-publicized debates argued the merits of total automation of user needs (via intelligent agents) versus the importance of user control and decision making (via graphical user interfaces).¹ Perhaps a more productive way to frame this discussion is to note that there is an interesting duality between AI and human-computer interaction. In AI, we try to model the way a human thinks in order to create a computer system that leverage off a human user to aid the user in the execution of intelligent actions. In HCI, we design computer interfaces that leverage off a human user to aid the user in the execution of intelligent actions. In AI, we try to model the way a human thinks in order to create a computer system that leverage off a human user to aid the user in the execution of intelligent actions. In HCI, we design computer interfaces that leverage off a human user to aid the user in the execution of intelligent actions.

What is the boundary between these two fields? An area that is becoming known as mixed-initiative interaction might turn out to be the missing link. Mixed-initiative interaction refers to a flexible interaction strategy in which each agent (human or computer) contributes what it is best suited at. A system that helps a user explore a dataset using a statistics software package, AIDE both makes suggestions to the user and responds to user guidance about what to do next.

In this installment of "Trends and Controversies," James Allen of the University of Rochester introduces the area and creates a useful taxonomy of mixed-initiative planning systems. The second essay, by Eric Horvitz at Microsoft Research, describes the role of uncertainty in mixed-initiative interaction and describes two innovative systems, including semi-automated assistance that makes use of Bayesian reasoning. The third essay, by James F. Allen and P.R. Cohen, of the Association for Artificial Intelligence and the ACM, describes how to design a system that helps a user explore a dataset using a statistics software package, AIDE both makes suggestions to the user and responds to user guidance about what to do next.

—Mari Ellen

References

1. B. Shneiderman and P. Maes, "Direct Manipulation vs. Interface Agents," *Interactions*, Vol. 10, No. 5, 1999, pp. 42-61.
2. R. St. Amant and P.R. Cohen, "Interaction with a Mixed-Initiative System for Exploratory Data Analysis," to be published in *Knowledge-Based Systems*, Vol. 10, No. 5, 1999.

Mixed-initiative interaction

James F. Allen, University of Rochester
Mixed-initiative interaction is a key aspect of effective human-computer interaction and has great potential to affect action and thought in a wide range of human-computer systems. The term mixed-initiative interaction is sometimes used to describe human-computer interaction that is not purely human-initiated, but this is a mistake because almost all models of HCI so far are not mixed-initiative, and mixed-initiative systems need not involve a human. It is perhaps in HCI where we will see the greatest impact.

The development of mixed-initiative intelligent systems will ultimately revolutionize the world of computing even more than the recent move to GUIs, in my view. This essay describes the goals of research in mixed-initiative interaction, suggests a general framework for thinking about work in the area based on the properties of human dialogue, and then briefly describes the key principles to overcome before a mixed-initiative system can become a reality. For simplicity, I will focus on a single scenario consisting of two agents: a human and an intelligent system. Mixed-initiative

interaction can occur in many other scenarios as well, including between multiple machines (cooperating to perform tasks such as in distributed planning) or between (such as in distributed planning) or between multiple people and machines interacting to coordinate their activities (collaboration systems, for example). Most everything I say here generalizes to these other cases. In fact, many of the issues become even more crucial as the number of agents grows. In many examples, I will draw from my experience in building mixed-initiative systems over the last five years.

The goals of mixed-initiative interaction

Mixed-initiative interaction is a multi-tant aspect of effective multi-agent systems to solve problems or perform minimal human-computer interaction, such tasks could include: assigned to interact with a user, emergency relief mission, how to use new equipment, refers to a flexible interaction where each agent can contribute what it does best. Further, in general cases, but opportunities to be negotiated between them as the problem is solved. At any one time, one agent might have the initiative—controlling the interaction—while the other works to assist it. At other times, the roles are reversed, and other times again the agents might be working independently, assisting each other only when specifically asked. The agents dynamically adapt their interaction style to best address the problem at hand.

Mixed-initiative interaction lets agents work most effectively as a team—that's the secret is to let the agents who currently know best how to proceed coordinate the other agents. Involving a human in the

1999

James F. Allen
Curry Guinn
Eric Horvitz

Uncertainty, action, and initiative in pursuit of mixed-initiative computing

Eric Horvitz, Microsoft Research
Recent debate has highlighted differing views on the most promising opportunities for user-interface innovation. One group of investigators has expressed optimism about the potential for refining intelligent representations and inferential machinery should focus on developing more powerful representations and inferential machinery for sensing a user's activity and taking automated actions.¹⁻⁴ Other researchers have voiced concerns that efforts focused on automation might be better expended on tools and metaphors that either expanded the ability of users to directly manipulate and inspect objects and information.⁵⁻⁸ Rather than advocating one approach over the other, we propose an integration of direct manipulation and automated services could be a promising path forward. This path is characterized by deeper, more collaborative, between users and particular, there are rich opportunities for intervening direct computation and interfaces.



James F. Allen is a professor of computer science at the University of Rochester. His research interests include natural language understanding, discourse, knowledge representation, common sense reasoning, and planning. He was one of the first winners of the Presidential Young Investigator Award, and is a Fellow of the American Association of Artificial Intelligence. Contact him at the Univ. of Rochester, Computer Science Dept., Rochester, NY 14627, james@iit.rochester.edu; http://www.cs.rochester.edu/~jfa/.



Curry L. Guinn is a research engineer at the Research Triangle Institute's Center for Digital Systems Engineering and an adjunct assistant professor at Duke University's Department of Computer Science. His research interests include human-computer collaboration, multimedia tools for education, text abstraction, argumentation theory, expert systems, and semantic networks. He earned a BS in computer science and philosophy from Virginia Polytechnic Institute, and an MS and PhD in computer science from the Research Triangle Inst., 3040 Cornwallis Rd., Research Triangle Park, NC 27709-2194. http://www.cs.duke.edu/~sig.



Eric Horvitz is a senior researcher and manager of the Adaptive Systems and Interaction Group at Microsoft Research. His research interests center on probabilistic and applications of reasoning, learning, and action under uncertainty. He received a PhD and MD from Stanford University. He serves on the board of the Association for Artificial Intelligence and the Association for the Advancement of Artificial Intelligence, and is the ACM Charles Kimball Award Researcher, Redmond, WA 98052; horvitz@microsoft.com.

the goals and needs of users. Thus, methods for reasoning under uncertainty play a critical role in mixed-initiative interaction.

Supporting joint activity under uncertainty

People appear to be well adapted to mixed-initiative problem solving. In daily life, we continue to engage one another in efforts to achieve goals through a sharing of beliefs, needs, and context. A common arena for exploring mixed-initiative interaction is conversation, centering on a collaborative interaction to achieve the goal of communicating needs and information. However, interaction to encompass a wide variety of interactions that rely on a collaborative interweaving of contributions by participants, some of which might include conversational interaction.

Psychologists and computer scientists have referred to efficient collaborations converging on shared goals as *joint activity*.⁹⁻¹¹ Joint activity captures the behavior displayed in fast-paced, well-coordinated activity to solve a mutual goal. Examples of joint activity include the collaborative behaviors seen in conversation, dancing, and the familiar

struggle of moving a large piece of furniture through cramped hallways. Participants in joint activity seek convergence on a shared set of beliefs about the setting, activity, and goals, and the nature and timing of individual contributions. Uncertainty about goals and needs are resolved through a drive toward a mutual understanding or common ground in a process referred to by psychologists as *grounding*.^{9,10,12} Joint activity embodies an especially fluid and efficient form of mixed-initiative interaction. The pursuit of metaphors, insights, and reasoning machinery for supporting joint activity presents the most difficult challenges—and the greatest opportunity—for research on mixed-initiative interaction.

Beliefs, actions, and initiative

Mixed-initiative systems must consider a set of key decisions in their efforts to provide, how to best contribute to solving a problem, when to pass control of problem solving back to users for refinement or guidance, and when to query a user for additional information in pursuit of minimizing uncertainty about a task. Systems that provide automated services rely on the ability to make good guesses

MIXED-INITIATIVE DEFINITION

“A **flexible interaction strategy**, where each agent can contribute to the task what it does best.”

- James Allen

MIXED-INITIATIVE DEFINITION

“Methods that explicitly support an efficient, natural **interweaving** of contributions **by users and automated services** aimed at converging on solutions to problems.”

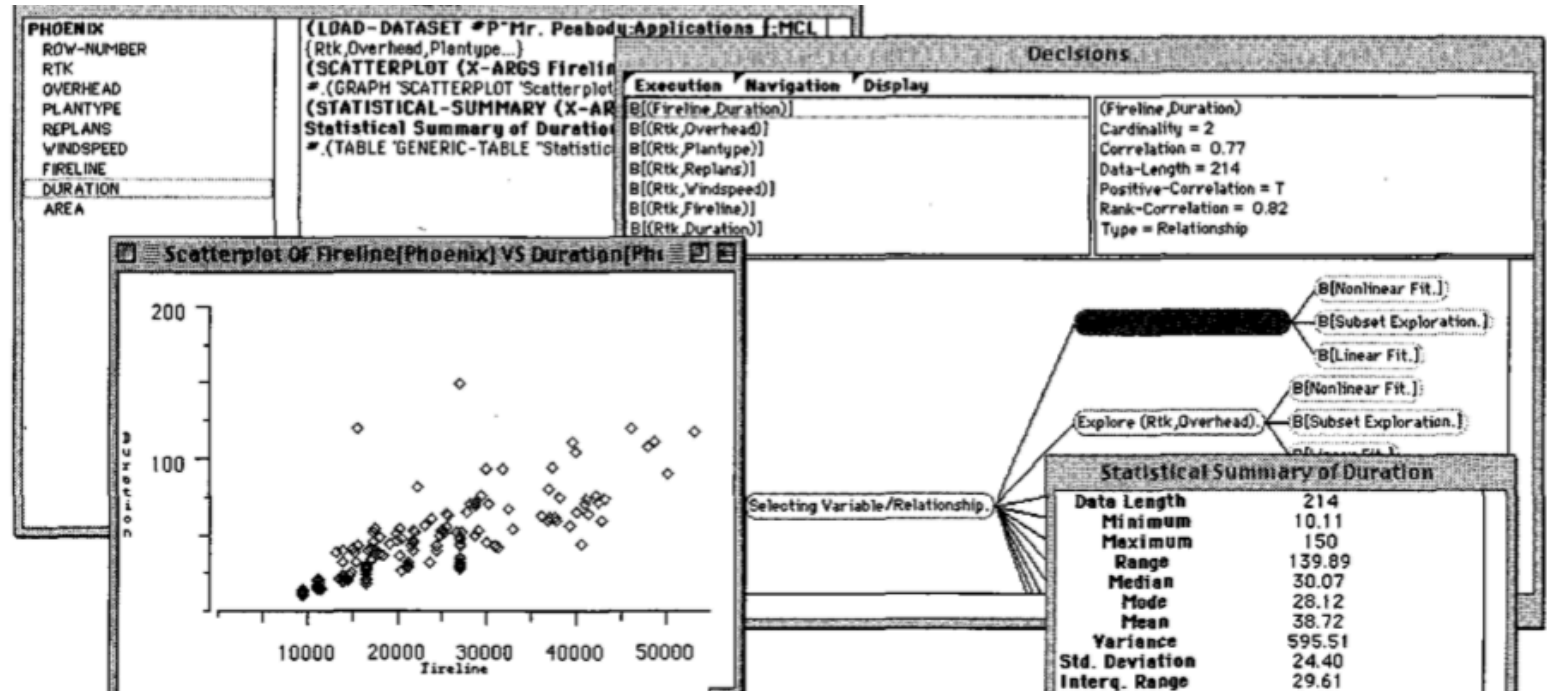
- Eric Horvitz

MIXED-INITIATIVE INTERACTION: AIDE 1997

An assistant for data exploration based on AI planning:

- **An assistant is at least partly autonomous**
 - *Makes decisions on how to carry out user guidance*
- **An assistant responds to guidance as it works**
 - *Its reasoning process must be available to the user to modify*

Mixed-Initiative Interaction: AIDE 1997



MIXED-INITIATIVE EXAMPLES



PixelTone Multimedia Editing (Adar et al.)



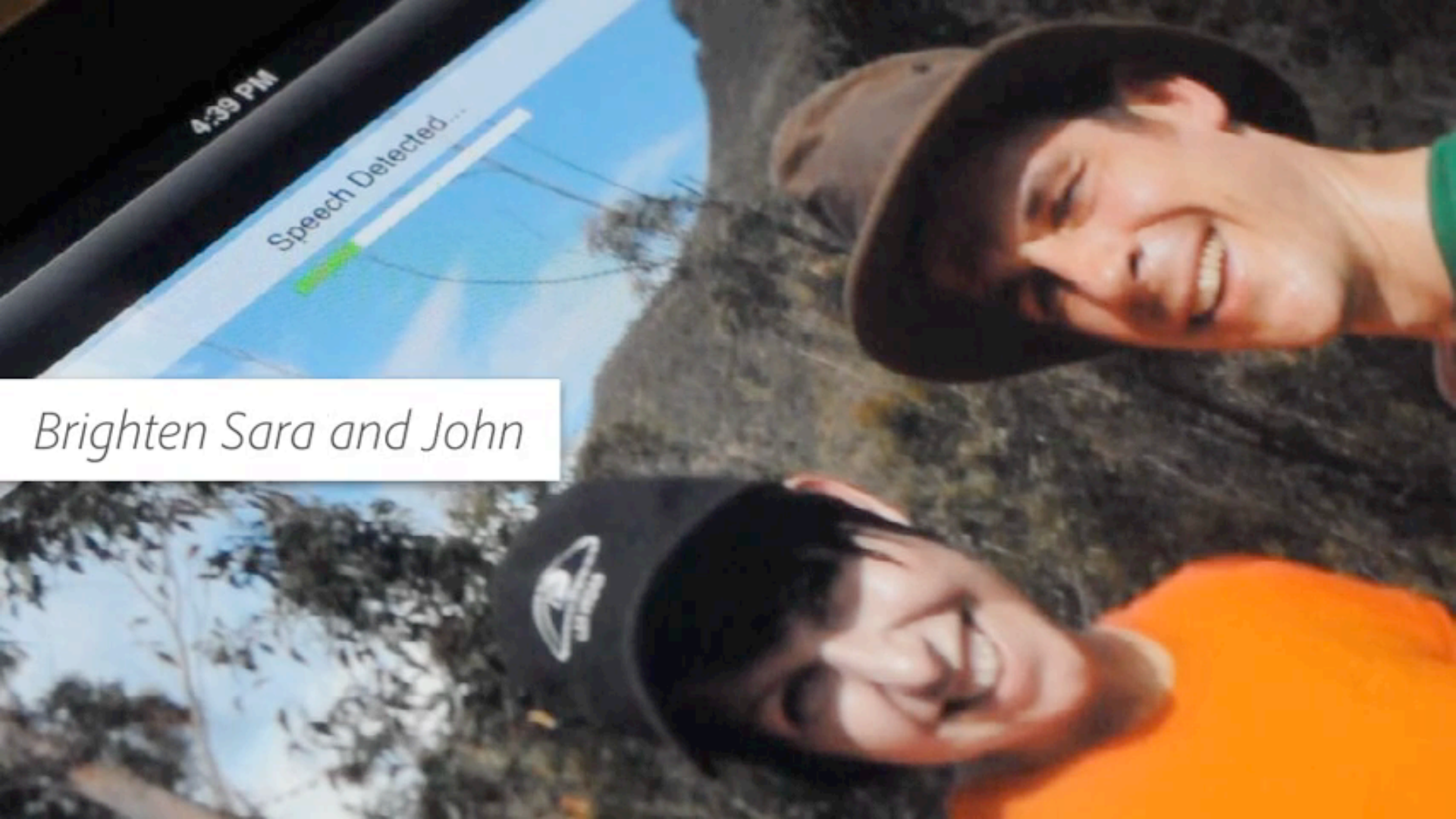
Collaborative Search (Pickens et al.)

This workshop:

- *GUI & Algorithm for SenseMaking (Bunch et al.)*
- *GUI & Algorithm to Explain Errors (Hanafi et al.)*
- *GUI & Algorithm to Build Better Models (Wang et al.)*

Mixed-I Example: Multimedia Editing





4:39 PM

Speech Detected ...

Brighten Sara and John

PixelTone In Depth

“A flexible interaction strategy, where each agent can contribute to the task what it does best.”

“Methods that explicitly support an efficient, natural interweaving of contributions by users and automated services aimed at converging on solutions to problems.”

An assistant is at least partly autonomous

- Makes decisions on how to carry out user guidance

An assistant responds to guidance as it works

- Its reasoning process must be available to the user to modify

PixelTone In Depth

“A flexible interaction strategy, where each agent can contribute to the task what it does best.”

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An assistant is at least partly autonomous
Makes decisions on how to carry out user guidance
An assistant responds to guidance as it works
Its reasoning process must be available to the user to modify

Human: high level design choices
Agent: executes low level details

“increase the contrast on the lower part”
system knows lower part is ocean

“make it heavenly”

PixelTone In Depth

“A flexible interaction strategy, where each agent can contribute to the task what it does best.”

“Methods that explicitly support an efficient, natural interweaving of contributions by users and automated services aimed at converging on solutions to problems.”

An assistant is at least partly autonomous

- Makes decisions on how to carry out user guidance

An assistant responds to guidance as it works

- Its reasoning process must be available to the user to modify

Sliders allow user to adjust results of an agent’s action

Gestures by human (“blur in this direction”) augment command.

However, system does not ask for feedback.

PixelTone In Depth

“A flexible interaction strategy, where each agent can contribute to the task what it does best.”

“Methods that explicitly support an efficient, natural interweaving of contributions by users and automated services aimed at converging on solutions to problems.”

An assistant is at least partly autonomous

Makes decisions on how to carry out user guidance

An assistant responds to guidance as it works

Its reasoning process must be available to the user to modify

Automatically adjusts contrast
Allows dynamic creation of new concepts and terminology

“this is a shirt”

“change the color of the shirt”

“this is John”

“brighten Sara and John”

Mixed-I Example: Collaborative Search

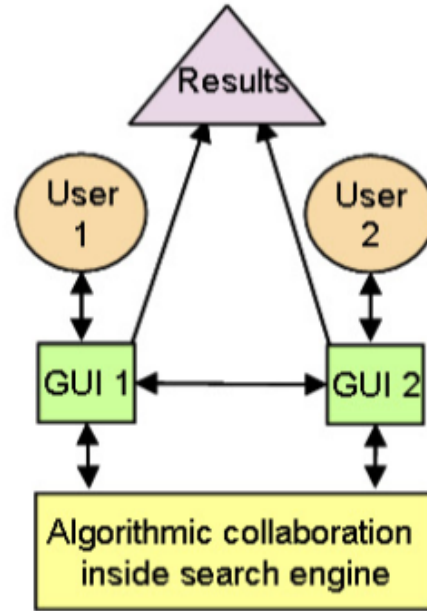


Pickens et al., SIGIR 2008

Goal: allow people to work at their own pace, but be influenced in real time by their collaborators' work.

“Influence should be synchronized, but workflow should not.”

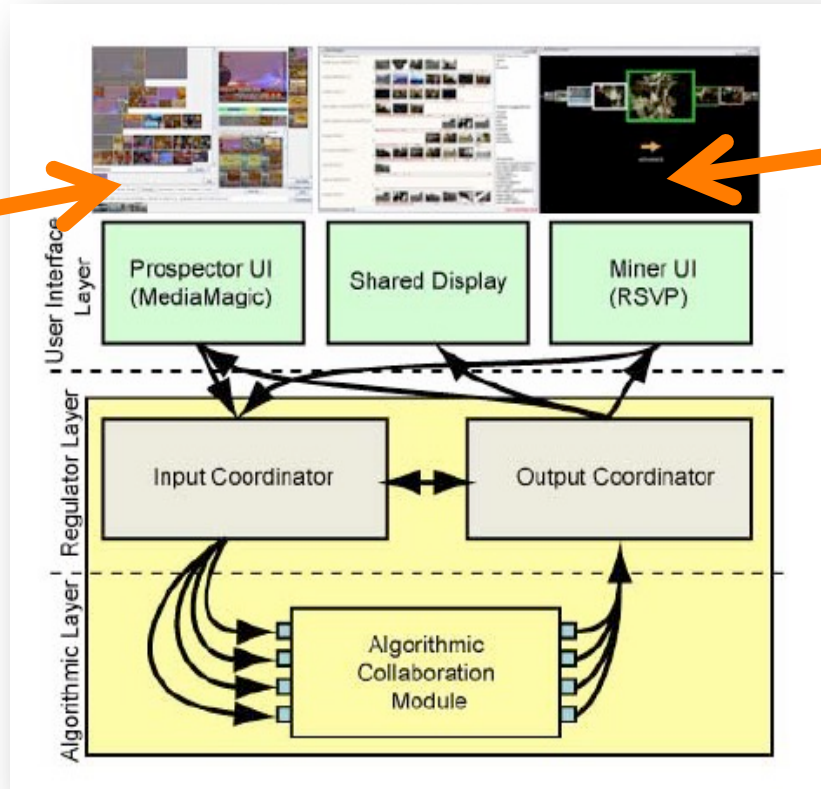
Mixed-I Example: Collaborative Search



Three UIs for Three Roles

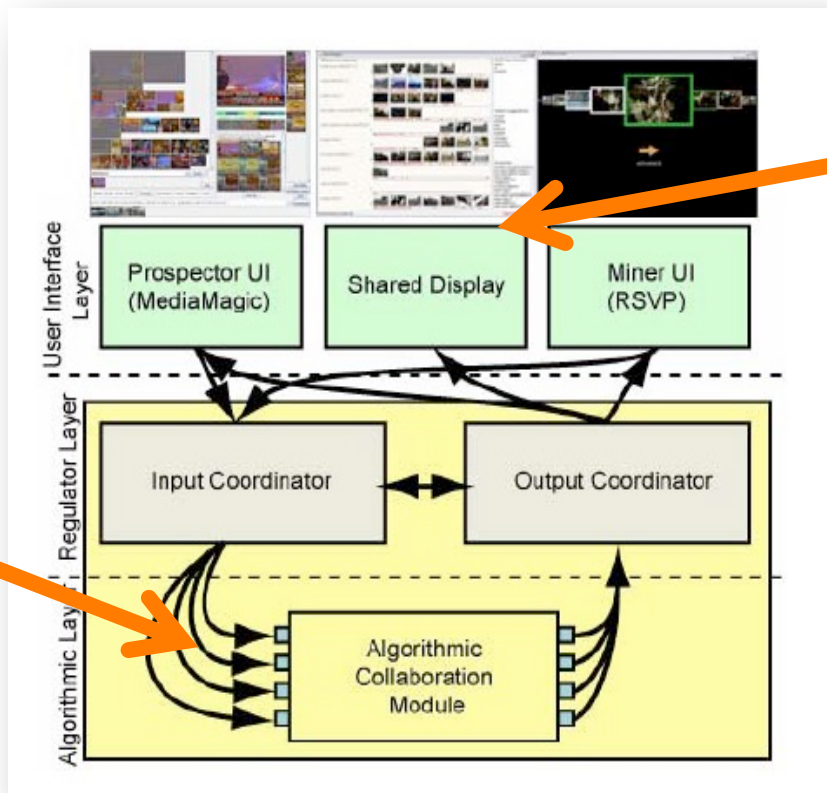
Prospector:
opens new fields
for exploration
(breadth)

Miner: explores
rich veins of
information
(breadth)

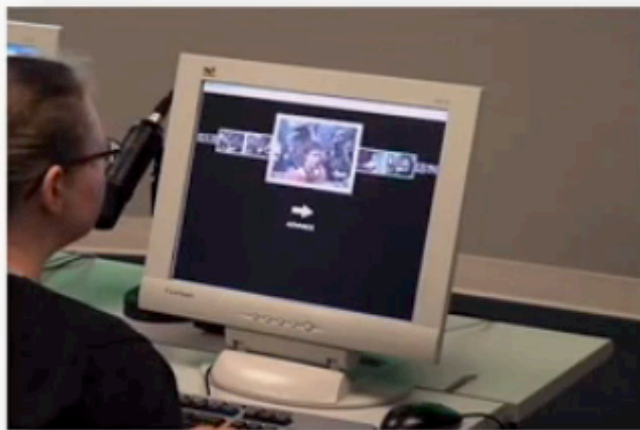
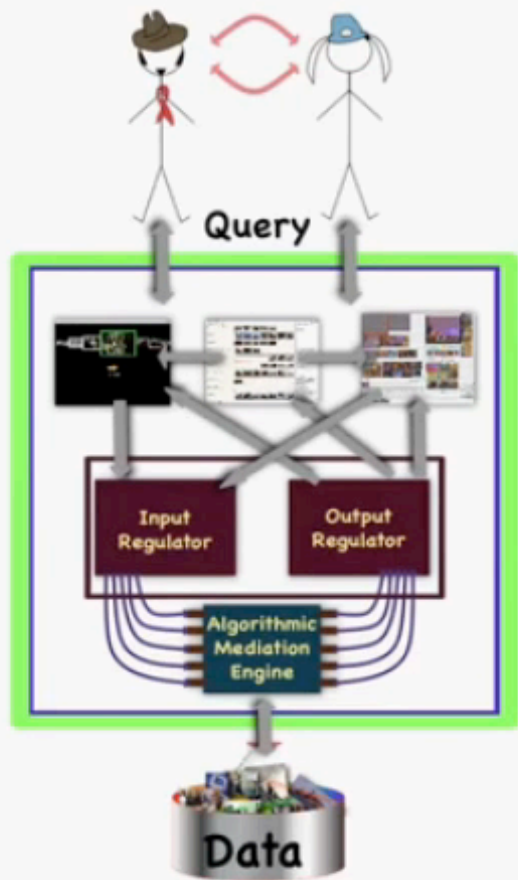


Three UIs for Three Roles

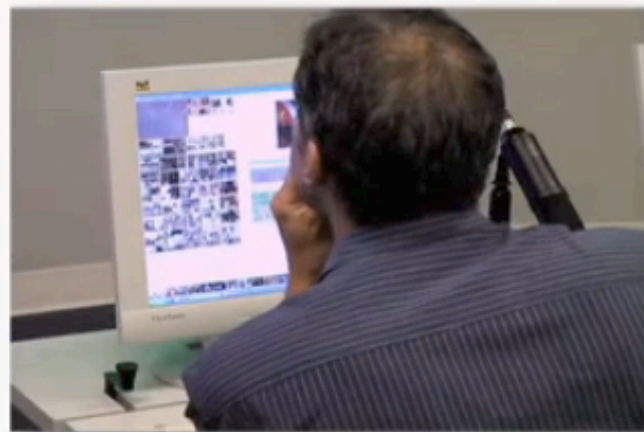
Algorithm:
combines work of
Prospector and
Miner;
makes query
suggestions and
re-ranks results.



Shared Display:
continually-updated
status:
relevant documents,
past queries,
system-suggested
search terms.



Miner – Prospector
Search



Search Collaboration In Depth

“A flexible interaction strategy, where each agent can contribute to the task what it does best.”

“Methods that explicitly support an efficient, natural interweaving of contributions by users and automated services aimed at converging on solutions to problems.”

An assistant is at least partly autonomous

- Makes decisions on how to carry out user guidance

An assistant responds to guidance as it works

- Its reasoning process must be available to the user to modify

In this case, the humans have two different tasks, and the algorithm has the mediator task.

Search Collaboration In Depth

“A flexible interaction strategy, where each agent can contribute to the task what it does best.”

“Methods that explicitly support an efficient, natural interweaving of contributions by users and automated services aimed at converging on solutions to problems.”

An assistant is at least partly autonomous

- Makes decisions on how to carry out user guidance

An assistant responds to guidance as it works

- Its reasoning process must be available to the user to modify

Interweaving is the focus of this design.

Search Collaboration In Depth

“A flexible interaction strategy, where each agent can contribute to the task what it does best.”

“Methods that explicitly support an efficient, natural interweaving of contributions by users and automated services aimed at converging on solutions to problems.”

An assistant is at least partly autonomous

Makes decisions on how to carry out user guidance

An assistant responds to guidance as it works

Its reasoning process must be available to the user to modify

The assistant is autonomous, but its guidance is a black box.

Results: MI Collaborative Search



Pickens et al., SIGIR 2008

Performed dramatically better on average than merging the results of two searchers, when relevant results are sparse.

Subjective responses not reported.

OUTLINE

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Human-in-the-Loop
Two interesting examples

Mixed-Initiative
Two interesting examples
Trust issue: Data Science

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Pairing People & Algorithms for Data Science

The Role of Trust

Human-in-the-Loop

- Goal: improving ML
- Perspective:
 - *Human aids machine*

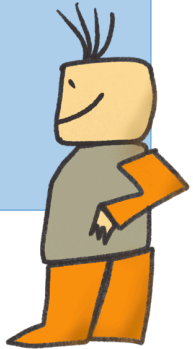
• **Trust:**
low importance



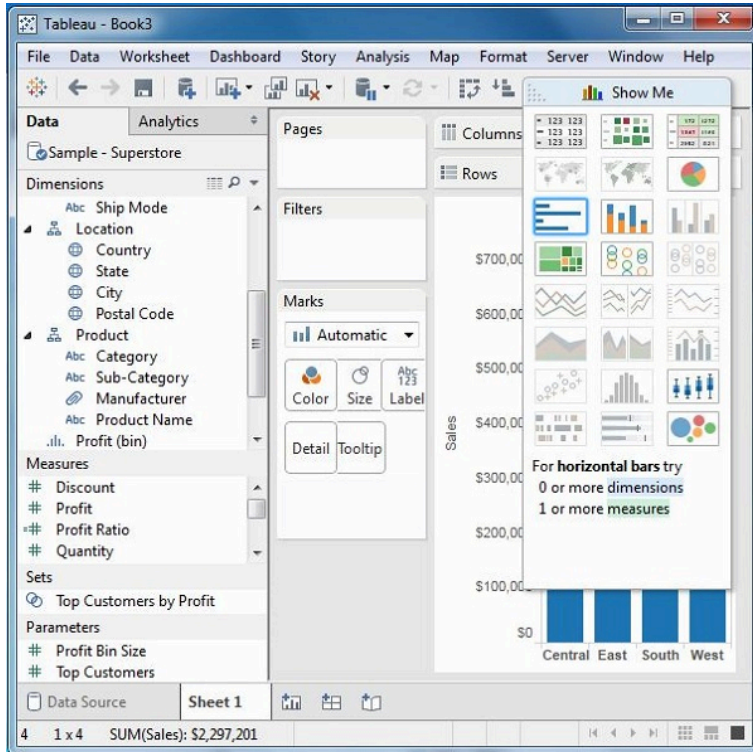
Mixed-Initiative Interaction

- Goal: analysis/exploration
- Perspective:
 - *Machine aids human*

• **Trust:**
high importance



What Kind of Automation Is Acceptable?

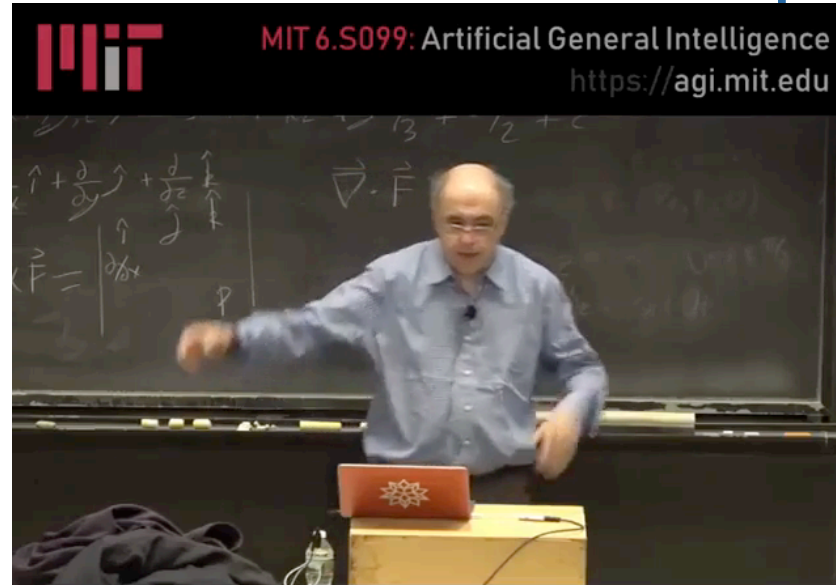


Tableau's "Show Me"

- Clearly Understandable Behavior
- Visible Effects
- Reproducible
- Reversible
- Allows Human to Specify Design,
System to Execute Details

However: **not** mixed-initiative

The Hard Part of Automation: Stephen Wolfram

A photograph of Stephen Wolfram in a lecture hall. He is standing in front of a chalkboard filled with mathematical equations, including vector calculus and partial derivatives. He is wearing a light blue button-down shirt and is gesturing with his right hand. In front of him is a wooden podium with a red laptop on it. The MIT logo is visible in the top left corner of the image, and the text "MIT 6.S099: Artificial General Intelligence" and "https://agi.mit.edu" is in the top right.

MIT 6.S099: Artificial General Intelligence
<https://agi.mit.edu>

"What will AI allow us to automate? We'll be able to automate everything that we can describe. The problem is: it's not clear what we can describe."

- Stephen Wolfram

FUTZING AND MOSEYING

Interviews with Professional Data Analysts on Exploration Practices

Sara Alspaugh, Nava Zokaei, Andrea Liu, Cindy Lin, Marti Hearst
UC Berkeley

VAST 2018



Supported by the UC Berkeley AMP Lab and a Gift from Tableau Research

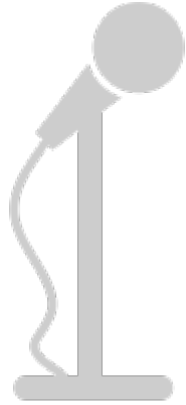
MOTIVATING QUESTION:

Do professional analysts do **exploratory data analysis**?

If so, why? If not, why not?

If so, what kinds of automated tools do they desire?

Recruiting and Interviewing



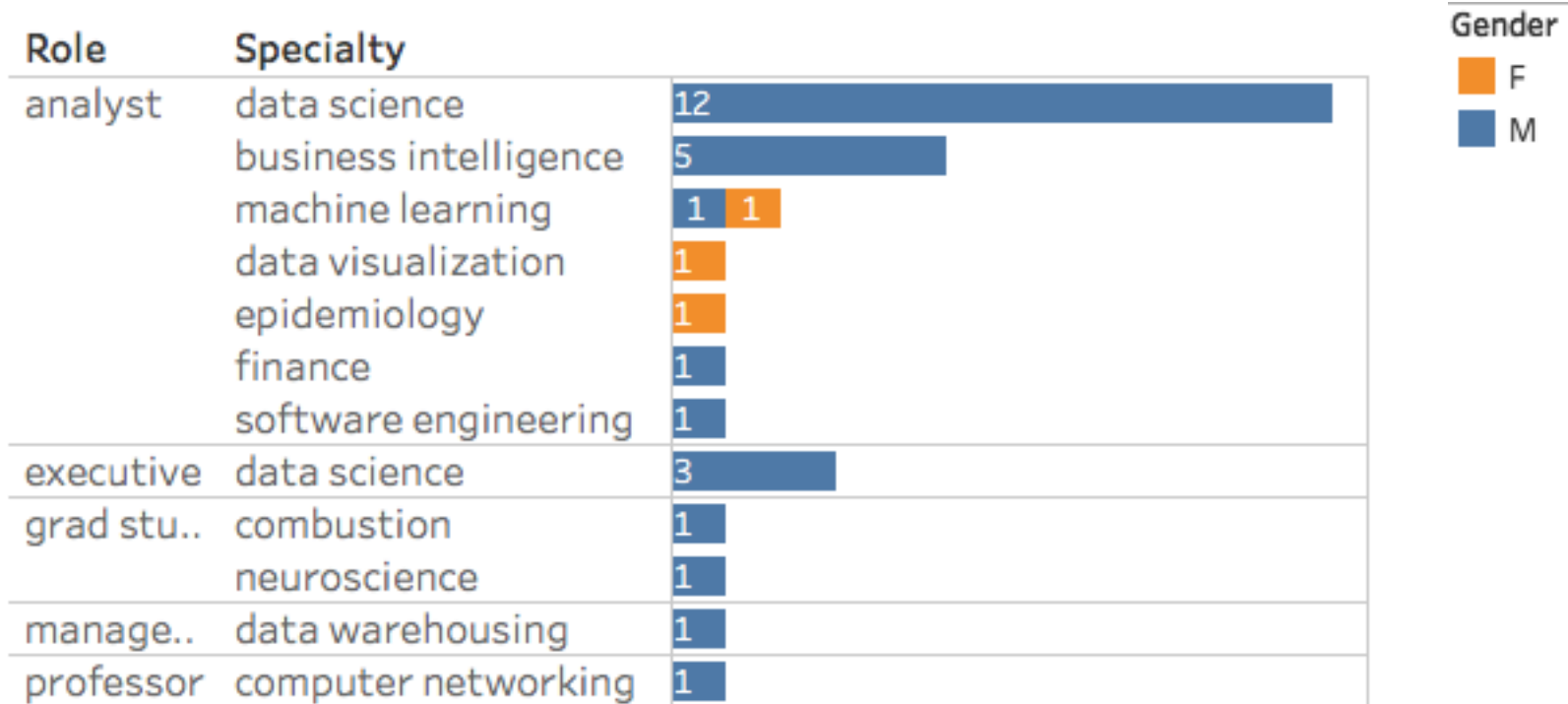
Reached out to professional network

“Professionals who analyze data” daily

Indicated that focus was EDA

30 respondents; 90 minutes on avg

Demographics



MAIN FINDINGS

Exploratory activities pervade the entire analysis process

For some analysts

Analysts want a compromise between coding and direct manipulation

Notebooks with interactive visualizations are promising

Skepticism toward automated analysis tools

Homegrown Automation

19

Described tools they had built themselves for repetitive tasks
(including wrapping common visualization commands)

3

Wrote code to profile all columns of a data set

1

Wrote their own visualization library

Homegrown Automation

(continued)

12

Copy-paste reuse: many scripts with minor variations, hard to manage

6

Barrier to home-grown automation: difficulty of generalizing solutions so others could use them.

Many other frustrations

Computer Automation?

5

Expressed interest in automated wrangling tools

3

Pointed out that manual wrangling yields valuable insight

7

Suggested tools for automatically profiling data

9

Expressed skepticism

“the parts that are easy are easy; the hard parts are difficult to automate”

Computer Automation?

(continued)

3

Expressed interest in automated suggestions of interesting relationships

12

Thought that for recommenders to be useful, they must navigate between being a black box and making the user do tedious work.

Summary: Automated DS Tools Not Trusted (yet)

THIS WORKSHOP: WANG ET AL.

- IBM's AutoAI:
 - *Automated support for DS model building*
- Controlled between-participants study
 - *AutoDS participants faster, more accurate, more models*
 - *Participants in manual condition had higher trust and confidence*

WHY IS TRUST LOW?

Automated data science methods. Do they meet:

- Clearly Understandable Behavior
- Visible Effects
- Reproducible
- Reversible
- Allow Human to Specify Design, System to Execute Details

Dialogue for Building Trust



James Allen 1999 essay:

Hoped to use AI planning; this failed

Serious mismatch; humans solve problems differently

Automated planners:

- Full specification & context
- Evaluate quantitatively
- Low communication

Human problem solving:

- Incrementally learn; refine & modify goals
- Evaluate subjectively
- High communication

Dialogue for Building Trust



James Allen 1999 essay:

Mixed-initiative collaboration planning **between humans:**

Much effort spent in maintaining understanding

Action	Amount (%)
Evaluating and comparing options	25
Suggesting courses of action	23
Clarifying and establishing state	13.5
Clarifying or confirming the communication	13.5
Discussing problem-solving strategy	10
Summarizing courses of action	8
Identifying problems and alternatives	7

Dialogue for Building Trust



James Allen 1999 essay:

Mixed-initiative collaboration planning **between humans:**

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Identifying problems and alternatives	7

We need smarter AI

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HUMAN-IN-THE-LOOP FROM THE HUMAN PERSPECTIVE

Marti Hearst / UC Berkeley / KDD Dash Workshop 2020

HITL advances give humans more agency

To improve Mixed-Initiative:

- UI design guidelines: visibility, reversibility, reproducibility, etc.
- Enriching the interactivity of the process to model human dialogue
- More advanced AI

