CS 5306
INFO 5306:
Crowdsourcing and
Human Computation

Lecture 22
11/16/17
Haym Hirsh
Long-term goal: Integrating human and machine intelligence

Using artificial intelligence in human computation

Using human computation in artificial intelligence
“artificial artificial intelligence”: Human Computation as “Fake” AI
“AI gets a brain”
Barr, J. and Cabrera, L.F.
Queue, 4(4), 2006

• “humans still significantly outperform the most powerful computers at completing such simple tasks as identifying objects in photographs—something children can do even before they learn to speak”

• “If software developers could programmatically access and incorporate human intelligence into their applications, a whole new class of innovative businesses and applications would be possible”

• “With Amazon Mechanical Turk, people are freer to innovate because they can now imbue software with real human intelligence.”
“AI gets a brain”  
Barr, J. and Cabrera, L.F.  
Queue, 4(4), 2006

• “To the application, the transaction looks very much like any remote procedure call: The application sends the request, and the service returns the results.”

• “In reality, a network of humans fuels this “artificial artificial intelligence” by coming to the Web site, searching for and completing tasks, and receiving payment for their work.”

• “This allows software developers to easily and economically build programs that tap into a worldwide, massively parallel, Internet-scale human workforce on an incremental, as-needed basis.”
“AI gets a brain”
Barr, J. and Cabrera, L.F.
Queue, 4(4), 2006

- Amazon internal uses:
  - Data quality: “data improvement and validation processes on its product catalog”
  - Japanese text orientation
  - Image selection: “After automatic processing has chosen several candidate images, human intelligence is used to choose the best possible image to represent each street address and business”

- Others
  - Podcast transcription: castingwords.com
  - Language translation: English-to-French and French-to-English translation
  - Data gathering: “lists of “Top 3” items (restaurants, theaters, and so forth) on a city-by-city basis”
  - Image tagging
  - Web site review: “answer a series of multiple choice questions”
  - Marketing survey
  - Sound verification
  - Facial image verification
Transcription made fast & easy

3 EASY STEPS
Choose a service to begin:

💰 BUDGET $1.00/minute
📅 1 WEEK $1.50/minute
⏰ 1 DAY $2.50/minute
✈️ INTERNATIONAL $1.75/minute
<table>
<thead>
<tr>
<th>HITs containing 'transcribe'</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-10 of 97 Results</td>
</tr>
<tr>
<td>Sort by: HITs Available (most first) ▼</td>
</tr>
<tr>
<td>Show all details ▼ Hide all details</td>
</tr>
<tr>
<td>Items per Page: 10 ▼</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>HIT</th>
<th>Requester</th>
<th>HIT Expiration Date</th>
<th>Time Allotted</th>
<th>Reward</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Transcribe up to 35 Seconds of Media to Text - Earn up to $0.07 per HIT!</td>
<td>Nov 15, 2019 (51 weeks 6 days)</td>
<td>15 minutes</td>
<td>$0.05</td>
</tr>
<tr>
<td>2</td>
<td>Transcribe US Elections Data from PDF</td>
<td>Nov 29, 2017 (1 week 5 days)</td>
<td>60 minutes</td>
<td>$0.05</td>
</tr>
<tr>
<td>3</td>
<td>Transcription of code-switched Hindi-English dialog speech data</td>
<td>Dec 1, 2017 (2 weeks 1 day)</td>
<td>2 hours</td>
<td>$0.35</td>
</tr>
<tr>
<td>4</td>
<td>SmartScan - Merchant and Category</td>
<td>Nov 17, 2017 (23 hours 57 minutes)</td>
<td>10 minutes</td>
<td>$0.00</td>
</tr>
<tr>
<td>5</td>
<td>SmartScan - Amount and Currency</td>
<td>Nov 17, 2017 (23 hours 57 minutes)</td>
<td>10 minutes</td>
<td>$0.00</td>
</tr>
<tr>
<td>6</td>
<td>Review, edit, and score the transcription of up to 35 seconds of media - Earn up to $0.14 per HIT!</td>
<td>Nov 17, 2017 (23 hours 57 minutes)</td>
<td>10 minutes</td>
<td>$0.00</td>
</tr>
</tbody>
</table>
Expense reports that don't suck!

From receipt scanning to reimbursement, Expensify automates every step of the expense reporting process.

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Preferred Partner Solution of CPA.com, an AICPA Company
Merchant Name Guidelines

Follow these instructions for entering the correct merchant on a receipt.

1. In most cases, enter the merchant name exactly as it is written on the receipt.
   - Any punctuation in the merchant name must be included exactly as it is on the receipt.
   - Some receipts may have a legal name, bank name, or atm name at the top of the receipt. The actual
Hey all! It's been a while--last I chatted was over on mturkgrind.com. My more recent posts there were how I got an official job, and that job does things that might've transitioned well to MTurk (discussions starting here and in subsequent posts).

Well, great news--now that stuff is on Turk! If you need proof I work here, my name's Keagan and I'm on this page. Here's the HIT group we have up at the moment.

That said, I wanted to come here because I saw some pretty bad reviews on turkopticon and assume the difficulties we're having rolling this out are translating to those reviews, which then tend to propagate like wildfire. We're actually at the beginning of rolling out, and I really don't want this to be a permanent impression, so I'm here to serve as a bit of a liaison because I know how important it is to workers to have quality hits, and I know how important it is to Expensify to be a quality requester.

So--for those that have worked on these, how can we help? For those who haven't but are just looking now, how can we make these HITs better (e.g., instructions more clear, etc.)?

Essentially--how can I make everything as awesome as possible so this is a great HIT group that we can maintain an awesome pool of high-quality HIT workers to enjoy?

For now, one little disclaimer I want to pass along: we're still rolling this out and it's definitely not mainstream at this time, so please give us a hot minute (a week or so I'd say) to iron out the main issues working on it, I promise!
Labeling Data

AI = Machine Learning
Machine Learning = Human-Labeled Data
Human-Labeled Data = Human Computation
Labeling Data

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Labeling Data

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AI = Human Computation
(just get me more data)
Labeling Data

• Main application areas:
  • Computer vision
  • Natural language processing
Labeling Data: Images

  - 800 people, 30,000 craters, 4 days

- **2004:** ESP Game
  - 100,000 images with tags

  - Videos, current top score 2369825 (max per item is 85)

  - >250,000 galaxies
Labeling Data: Images


• 2010: >14,000,000 images with Wordnet tags

Labeling Data: Natural Language

• **1989**: Penn Treebank


Labeling Data: Natural Language


Human Computation in Machine Learning

• Clustering:
Machine Learning with Humans “In the Loop”

• Iterate between learning and human labeling

• Game does machine learning behind the scene, guiding the game

• Iterate between learning and feature elicitation
Computer Vision/Robotics with Human Computation

• Game with two players, one is human controller other “robot”, learn from how they interact

• Robot reinforcement learning with humans providing the feedback signal with clicks

• Use crowd for dialog authoring, dialog editing, and nonverbal behavior authoring

• Get samples of natural language commands using AMT, get judgments of robot success using AMT
  • "Understanding Natural Language Commands for Robotic Navigation and Mobile Manipulation“, Tellex, S. et al, AAAI 2011
Long-term goal: Integrating human and machine intelligence

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Using human computation in artificial intelligence
In arguing that expert systems, if they are to satisfy the legitimate needs of their users, must include dialogue capabilities as sophisticated as those proposed in current Natural Language Research. In particular, they must allow the user to direct the flow of the dialogue and must take into account the user's goals and expectations such as analyzing the user's statements and in providing appropriate responses. Our studies are corroborated by analysis of transcripts of a "naturally occurring" expert system, a radio talk show in which callers ask an expert for financial advice. We present data demonstrating that user-expert dialogue has been viewed as a negotiation process, and we describe the exchanges that compose the dialogue in terms of the "collations, goals, negotiations, and moves of the participants."

To date, user participation in the reasoning processes of expert systems has been largely limited to asking expert reasoning or asking limited information. The user may ask why the system reached its conclusion how it arrived at its answer. Research into extending the abilities of expert systems [1,2,3] has so far failed to recognize the need to permit the full range of interaction possible when humans engage in the normal giving and getting of advice.

In order to delineate patterns of user-expert interaction in the reasoning process, we taped one call, February 1-5, 1981, of the radio talk show "Harry Sears: Speaking of Your Money" on station WCAE in Philadelphia. In this program listeners call in and introduce themselves and ask for financial advice, which the expert then attempts to provide. The most frequent interaction is a "naturally occurring" dialogue between a human user and a human expert. While the protocols we observed should obviously not be seen as the ideal forms, all expert systems should aspire to. Inasmuch as the nature of these naturally occurring expert systems, especially the unstructured element involved, and despite its domain specificity and the type of user toward which it is aimed, we believe that the major requirements of truly flexible and cooperative expert systems can be determined, in a principled way, from an analysis of the relationship between human user and human expert response.

Input and human expert response.

From the radio show we collected twelve and one-half hours of user-expert interaction, involving 152 callers. An examination of these protocols reveals a regular pattern of interaction, which we describe as negotiations, the process whereby people arrive at a solution by means of a discussion. More than a caller simply states a problem and passively listens to the expert's response. Rather, the caller actively participates in the formulation and resolution of the problem. Caller and expert must often negotiate to determine the statement of a problem the expert can solve and the statement of a solution the expert can support and the caller accept—and, ideally, understand. They may also negotiate a common understanding of terminology, a common set of world or domain beliefs, or an acceptable justification for the solution.

Given this view of the interaction between user and expert as a negotiation process, we can characterize the particulars of such verbal exchange in terms of the participants' activities, roles, and strategies. In order to achieve a response appropriate to the user's participation, the expert must first recognize the user's motivation(s), goal(s) and strategies) through an examination of his role in the content of the discourse history and the user model, and then, based on such analysis and his own goals, determine his own goals, his own strategies) and so on.

When the user decides to participate s/he has some motive for doing so and some goal s/he hopes to achieve. Motivation answers the question "Why does the user participate?" and goal answers "What does the user hopes to achieve through participation?" The user then adopts some strategy by which s/he attempts to achieve the goal(s) s/he has set; s/he then answers the question "How does the user attempt to achieve the goal?" This activity is realized linguistically in an utterance, the user's move. For example, a user may be motivated by his/her awareness of an expert's answer: the user may have thought of and rejected an answer because s/he believes it violates some specific constraint s/he wants set. Thus, goal is then to gain assurance that the expert's response meets that constraint. s/he might try to achieve this goal.
“Mixed-Initiative Interaction”


• ...
“Human-Robot Interaction”


• ...
Shahaf, D. and Horvitz, E., 2010
In Proceedings National Conference on Artificial Intelligence.
Shahaf, D. and Horvitz, E., 2010
In *Proceedings National Conference on Artificial Intelligence*. 

![Diagram showing translation options]

(a) Human Translation English -> French
(b) Human Translation English -> Italian
(c) Machine Translation English -> French
(c) Human Correction French
Shahaf, D. and Horvitz, E., 2010
In *Proceedings National Conference on Artificial Intelligence*.
Shahaf, D. and Horvitz, E., 2010
In Proceedings National Conference on Artificial Intelligence.

Claim 3.2. A greedy strategy for selecting agents is a constant-factor approximation to the coalition problem ($k$ is constant).
Claim 3.2. A greedy strategy for selecting agents is a constant-factor approximation to the coalition problem ($k$ is constant).

The number of possible coalitions considered in GTM plan generation is exponential in $n$. Thus, a natural way to reduce the search space is to restrict the maximal size of a coalition to $k$, thus reducing the number of coalitions to $O(n^k)$. Such a restriction is reasonable for language translation as most tasks do not require more than a few participants.
Shahaf, D. and Horvitz, E., 2010
In *Proceedings National Conference on Artificial Intelligence*. 

Using AI and Machine Learning for Human/Generalized Computation
Shahaf, D. and Horvitz, E., 2010
In Proceedings National Conference on Artificial Intelligence.

Using Human Computation for AI
Shahaf, D. and Horvitz, E., 2010
In *Proceedings National Conference on Artificial Intelligence*.

Question: Where are the markets?