Lecture 3
Humans as Data Sources: Label Aggregation

Questions: https://sli.do #R887

Instructor: Chien-Ju (CJ) Ho

Logistics

- Website: http://chienjuho.com/courses/cse518a
- Piazza: http://piazza.com/wustl/fall2020/cse518a

- Please follow the updates and announcements.
- You are responsible for following the announcements/discussion made on the website and Piazza.

Logistics: Assignment 1

- Amazon has been putting stronger restrictions on new accounts
  - For tax and data quality reasons
- If you have a hard time getting the account:
  - Use other crowdsourcing platforms
    - Use your own judgements on what information to share
    - Be careful about potential scamming tasks (that ask you to give personal information or ask you to write fake reviews)
  - Borrow a MTurk account from others
    - You can complete the task but do NOT submit if you are worried about violations of ToS
    - Providing screenshots of the task interface is sufficient

Logistics: Paper Reviews

- Reserve more time if you are not used to read research papers

Sep 9	Label Aggregation: EM-based Algorithms	**Required** Whose Vote Should Count More: Optimal Integration of Labels from Labelers of Unknown Expertise. Whitehill et al. NIPS 2009. **Optional** Learning from Crowds. Raykar et al. JMLR 2010. Maximum Likeihood Estimation of Observer Error-Rates Using the EM Algorithm. Dawid and Skene. Applied Statistics. 1979.	Submit Review (Due: Midnight, Sep 8)

- Review questions
  - Common questions
    - Summarize the paper in 2~3 sentences
    - List 1~3 points you like/dislike about the paper.
  - 1~2 paper-specific questions

Presentation and Leading of Discussion

- Presentation requirements
  - Group presentation (**two persons** per group)
    - 3-person groups might be okay, but you need to ask me for approval.
    - I would expect a bit more from 3-person groups
    - By default, the same group will also work on the project together
  - Give a **45-50 min** presentation based on the **required reading** and **one option reading** (2 option readings for 3-person groups) of a lecture.
    - The chosen papers are the "backbone" of the presentation. You are free to be creative and/or include materials outside of the papers
    - I'll fill in the remaining time of the lecture
  - Prepare **2 reading questions** for the required reading
  - Prepare **1~2 discussion sessions**
  - Lead the discussion for the discussion sessions

Presentation and Leading of Discussion

- Talk to me one week before your presentations
  - By default, stay after the lecture one week before your presentation
  - Or you can arrange other meeting time with me
  - You need to be ready for the following before meeting with me
    - A structure of your presentation
    - Two reading questions for the required reading
    - Topics for one or two discussion sessions

- Finding teammates
  - Stay after the lectures to chat with others (I'll keep the zoom open)
  - The "Finding Teammate" feature is enabled on Piazza

Presentation and Leading of Discussion

- Presentation topics
  - Check the course schedule for the labels **[Student Presentation #]**

Oct 13	Incentive Design: Financial Incentives **[Student Presentation #1]**

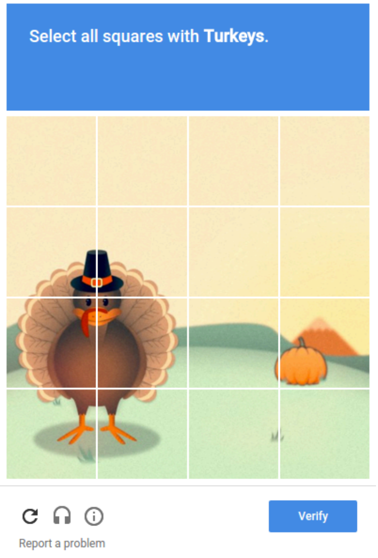
  - You will be asked to bid for lectures you are interested in presenting next Tuesday.
    - I'll try to accommodate your preferences, but no guarantees on that
    - Each group will be assigned one lecture (in charge of 45~50 minutes of the lecture)
    - I'll fill in the remaining lectures
  - The first two presentation slots will have relatively short amount of time to prepare. Please make sure you are fine with it

Project (done by groups)

- Will talk more about this next or next next lecture
- Reminder on the tentative timeline
  - Oct 9: Project proposal (and deciding team members)
    - Brief description of the proposed project (1~2 paragraph)
    - Citing at least one paper that’s relevant to your proposal
  - Oct 30: Milestone 1
    - A brief literature review and the description of your plan (one page)
    - Last chance to change the topic of the project
  - Nov 20: Milestone 2
    - Summary of your current progress (up to 2 pages)
    - Last chance to convert the research project to (a more extensive) literature review
  - Dec 15/17: In-class project presentations
  - Dec 20: Project report due

Lecture Today

Course Overview



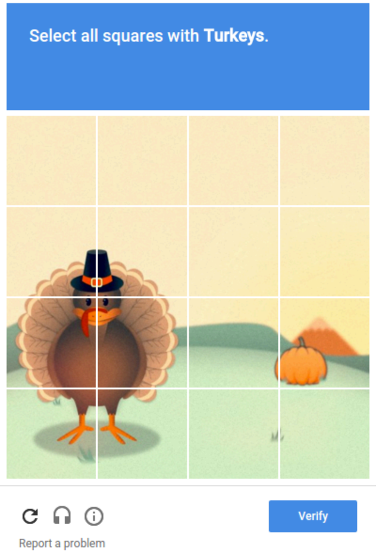
Human as data sources:
Label aggregation
Probabilistic reasoning to aggregate noisy human data

Practical challenges:
Real-time and complex tasks
Studies on workflow and team designs from HCI perspective

Humans are "Humans":
Incentive design
Game theoretical modeling of humans and incentive design

Selected recent topics:
Ethical issues of AI/ML, learning with strategic behavior, Human-AI collaborations.

Course Overview



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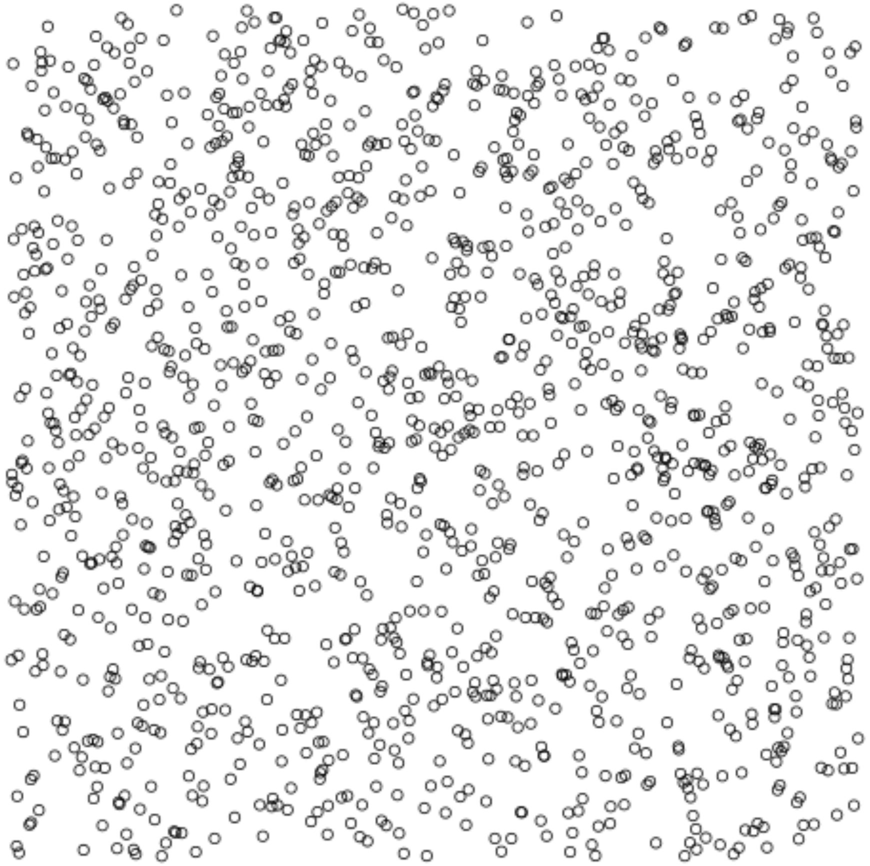
Today's Lecture

- Probability background on label aggregation
  - (Weighted) Majority Voting
  - Maximum likelihood estimation
  - Concentration bounds

Remember this task?

- How many circles are in the image



These are the “labels” from you

173	863	1500
300	950	1500
340	1000	2400
500	1150	2500
500	1150	4000
600	1200	5000
700	1467	23456

Mean: 2440.43
Median: 1150
Answer: 721

- How to aggregate the answers?
  - Depend on how the labels are generated.

A Naïve Model of Label Generation

- People have unbiased estimates of the true answer

user guess = **true answer** + **Gaussian noise**

Observations | Latent values we want to know | Zero-Mean Noises

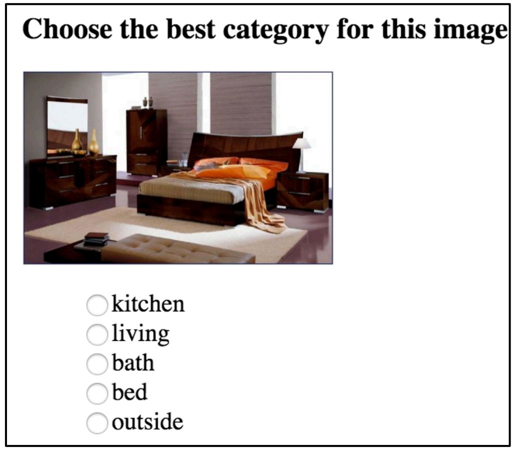
- If this model approximates the reality well, we can decide on **aggregation**
  - **Mean** of user guesses is an **unbiased** estimator for **true answer**

This Lecture Focuses on Binary Classification

- Binary classification

N.B.
- Guessing the Dots: **regression** problem
- Aggregation in general space is hard/non-trivial (e.g., aggregating multiple transcriptions)

- Most techniques/results can be extended to multi-label case, but the presentation could be more complicated.



Warm-Up Discussion

{1,0} or {+1, -1} are two common choices of binary labels
We'll use {+1,-1} for its mathematical convenience

- Case 1: What's your prediction of the true label of task 1? Why?

	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5
Task 1	+1	-1	+1	+1	-1

- Case 2: What's your prediction of the true label of task 2? Why?
  - What assumptions have you implicitly made in your arguments?

	True label	Worker 6	Worker 7	Worker 8	Worker 9
Task 2		+1	-1	+1	-1
Task 3	+1	+1	-1	+1	-1
Task 4	+1	-1	+1	-1	+1
Task 5	-1	-1	+1	+1	+1

Majority Voting (MV)

Q1: ***Why*** MV might be a good idea?

Q2: Can we obtain ***theoretical guarantees*** for majority voting?

Understanding this simple scenario helps us develop aggregation methods for more complicated scenarios.

Probabilistic Approach

- Foundations of modern machine learning
  - You should develop a strong background in probability/statistics if interested in doing research in AI/ML.

- High-level ideas:
  - Let D be the set of observations (e.g., training dataset, the set of labels we got from workers)
  - Let θ be the set of latent parameters we care about (e.g., ML hypothesis, true labels)

  - Two important concepts
    - Likelihood: $\Pr(D|\theta)$ [More discussion in CSE417T]
    - Posterior: $\Pr(\theta|D)$ [More discussion in CSE515T]

    - Connection: $\Pr(\theta|D) = \frac{\Pr(\theta)\Pr(D|\theta)}{\Pr(D)}$

Maximum likelihood estimation:
Find $\theta^* = argmax_\theta \Pr(D|\theta)$

$\Pr(\theta)$: Prior
(Additional assumption)

Why Majority Voting:
Majority Voting Gives the Maximum-Likelihood Estimation

- Consider a task with true label $l^* \in \{-1, +1\}$
- We collect labels $L = \{l_1, l_2, \dots, l_n\}$ from n workers for this task.

- l^* is the latent variable and L is our observation.

Likelihood: $\Pr[D|\theta]$
D: Observations
θ: latent variables

- Maximum likelihood estimation (MLE):
  - Predict +1 if $\boxed{\Pr[\, L|l^* = +1]} \geq \Pr[\, L|l^* = -1]$
  - Predict -1 otherwise

MLE approach (roughly speaking):
Find $\theta^* = argmax_\theta \Pr[D|\theta]$

It requires models/assumptions to calculate

How should we model the label generation process?

A Simple Model for Case 1

	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5
Task 1	+1	-1	+1	+1	-1

Maximum likelihood estimation (MLE):
Predict +1 if $\Pr[\, L | l^* = +1] \geq \Pr[\, L | l^* = -1]$
Predict -1 otherwise

- Assumption:
  - Each worker has the same ability of giving correct labels
  - Each worker gives label in a probabilistic manner
- Model
  - Each worker gives the correct label independently ***with probability*** ***p > 0.5***
- Given no additional information, this is close to the best you can model

Derivation of MLE ⇔ MV

Maximum likelihood estimation (MLE):

Predict +1 if $\Pr[\,L|l^* = +1] \geq \Pr[\,L|l^* = -1]$

Predict -1 otherwise

- Key assumption: independent worker labels

Derivation of MLE ⇔ MV

Maximum likelihood estimation (MLE):

Predict +1 if $\Pr[\, L|l^* = +1] \geq \Pr[\, L|l^* = -1]$

Predict -1 otherwise

- Key assumption: independent worker labels
  - Let (n_+, n_-) be the number of (+1, -1) labels in L
  - $\Pr[\, L|l^* = +1] = p^{n_+}(1-p)^{n_-}$
  - $\Pr[\, L|l^* = -1] = p^{n_-}(1-p)^{n_+}$

Derivation of MLE ⇔ MV

Maximum likelihood estimation (MLE):

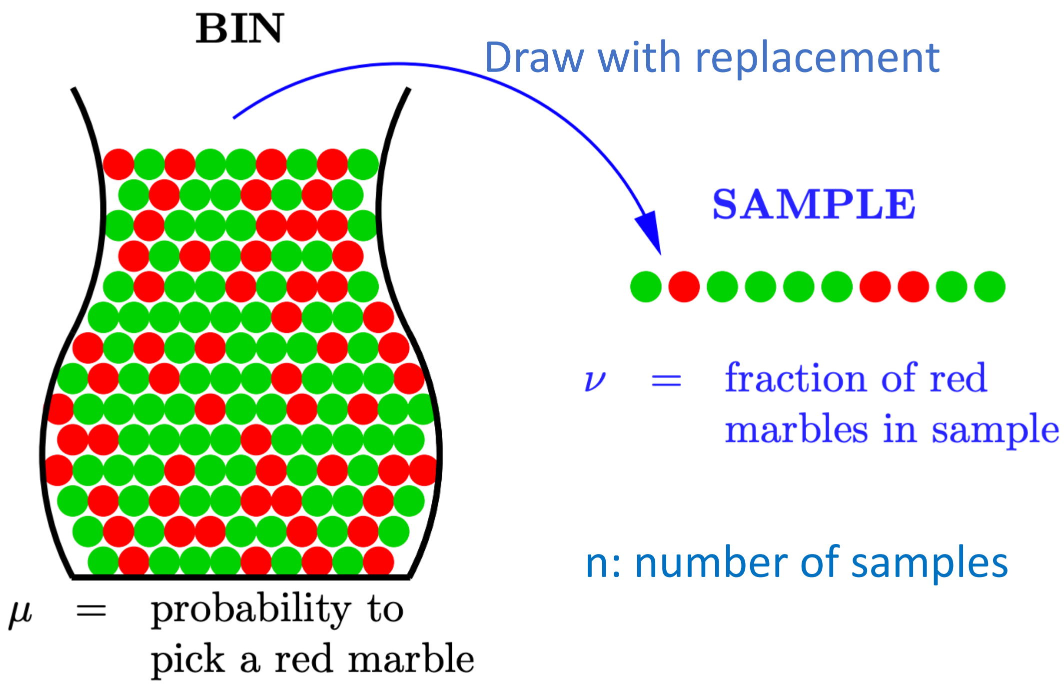
Predict +1 if $\Pr[\, L | l^* = +1] \geq \Pr[\, L | l^* = -1]$

Predict -1 otherwise

- Key assumption: independent worker labels
  - Let (n_+, n_-) be the number of (+1, -1) labels in L
  - $\Pr[\, L | l^* = +1] = p^{n_+}(1-p)^{n_-}$
  - $\Pr[\, L | l^* = -1] = p^{n_-}(1-p)^{n_+}$
- MLE rule is equivalent to
  - Predict +1 if $\ln \frac{p^{n_+}(1-p)^{n_-}}{p^{n_-}(1-p)^{n_+}} \geq 0$
  - Predict +1 if $(n_+ - n_-)(\ln p - \ln(1-p)) \geq 0$
  - Predict +1 if $n_+ \geq n_-$
  - This is majority voting

What theoretical guarantee can MV achieve?

- Consider a thought experiment



What can we say about μ from ν?

Law of large numbers

- When $n \to \infty, \nu \to \mu$

Hoeffding's Inequality

- $\Pr[|\mu - \nu| > \epsilon] \leq 2e^{-2\epsilon^2 n}$ for any $\epsilon > 0$

Interpretations

$$\Pr[|\mu - \nu| > \epsilon] \leq 2e^{-2\epsilon^2 n}$$

Define $\delta = \Pr[|\mu - \nu| > \epsilon]$: Probably of “bad events”

- Fix $\epsilon, \delta = O(e^{-n})$; Fix $n, \delta = O\left(e^{-\epsilon^2}\right)$; Fix $\delta, \epsilon = O(\sqrt{\frac{1}{n}})$
- n=1000
  - $\mu - 0.05 \leq \nu \leq \mu + 0.05$ with 99% chance
  - $\mu - 0.10 \leq \nu \leq \mu - 0.10$ with 99.9999996% chance

- ν is approximately close to μ with high probability
- ν as an estimate of μ is **p**robably **a**pproximately **c**orrect (P.A.C.)

PAC learning is proposed by Leslie Valiant, who wins the Turing award in 2010.

More general form of Hoeffding's inequality

- Let $X_1, \ldots, X_n$ be independent random variables
  - X_i is bounded in the range $[a_i, b_i]$

- Let $\bar{X} = \frac{1}{n}(X_1 + \cdots + X_n)$

- (One-sided) Hoeffding's inequality

$$\Pr[\mathbb{E}[\bar{X}] - \bar{X} \geq \epsilon] \leq \exp\left(-\frac{2n^2\epsilon^2}{\sum_{i=1}^{n}(b_i - a_i)^2}\right)$$

We get our previous bound by setting $b_i = 1$ and $a_i = 0$

Connection to Our Problem

$$\Pr[\mathbb{E}[\bar{X}] - \bar{X} \geq \epsilon] \leq \exp\left(-\frac{2n^2\epsilon^2}{\sum_{i=1}^{n}(b_i - a_i)^2}\right)$$

- Without loss of generality, assume $l^* = +1$
- X_i is the random variable of the label provided by worker i

- $\bar{X} = \frac{1}{n}(X_1 + \cdots + X_n)$: $\mathbb{E}[\bar{X}] = 2p - 1 > 0$
- Majority voting => Predict $sign(\bar{X})$

- Probability of making a wrong prediction

$$\begin{aligned}\Pr[\bar{X} \leq 0] &= \Pr\left[\mathbb{E}[\bar{X}] - \bar{X} \geq \mathbb{E}[\bar{X}]\right] \\ &\leq \exp\left(-\frac{1}{2}n\,(\mathbb{E}[\bar{X}])^2\right) \\ &= \exp\left(-\frac{1}{2}n\,(2p-1)^2\right)\end{aligned}$$

Looks like we solved the problem?

only if we assume all workers are the same….

	True label	Worker 6	Worker 7	Worker 8	Worker 9
Task 2		+1	-1	+1	-1
Task 3	+1	+1	-1	+1	-1
Task 4	+1	-1	+1	-1	+1
Task 5	-1	-1	+1	+1	+1

What happens if workers are different

- Assume we obtain n labels from n workers.
- Worker $i \in \{1, \ldots, n\}$
  - provides label $l_i \in \{-1, +1\}$
  - assumption: each label is correct with probability p_i
  - assume we know p_i

- How should we aggregate?
  - Weighted majority voting?

Predict $sign(\sum_{i=1}^{n} w_i l_i)$

Weighted Majority Voting

- Weighted majority voting

  Predict $sign(\sum_{i=1}^{n} w_i l_i)$

- Turns out weighted majority voting leads to MLE
  - With weight $\mathrm{w_i} = \ln \frac{p_i}{1-p_i}$ for label l_i

- The weights to minimize the Hoeffding error are different
  - To minimize Hoeffding error, set weights $w_i = 2p_i - 1$ for label l_i
  - (Lemma 1 in Ho et al. ICML 2013)

For the next two lectures

	True label	Worker 6	Worker 7	Worker 8	Worker 9
Task 2	[redacted]	+1	-1	+1	-1
Task 3	[redacted]	+1	-1	+1	-1
Task 4	[redacted]	-1	+1	-1	+1
Task 5	[redacted]	-1	+1	+1	+1

- Unknown worker skills
- Different task difficulties
- More factors to consider (some structures of tasks/workers?)
- …

Typical label aggregation approach

- Propose a model to describe the label generation process
- True labels are the “latent variables” of the process
- Using inference algorithms (e.g., EM) to learn the latent variables

Label Aggregation: EM-based Algorithms	**Required** Whose Vote Should Count More: Optimal Integration of Labels from Labelers of Unknown Expertise. Whitehill et al. NIPS 2009. **Optional** Learning from Crowds. Raykar et al. JMLR 2010. Maximum Likeihood Estimation of Observer Error-Rates Using the EM Algorithm. Dawid and Skene. Applied Statistics. 1979.
Label Aggregation: Matrix-based Methods	**Required** Who Moderates the Moderators? Crowdsourcing Abuse Detection in User-Generated Content. Ghosh, Kale, and McAfee. EC 2011. - If you want to refresh your memory on matrix algebra, Matrix Cookbook is a good resource. Section 5 contains the matrix decomposition part. **Optional** Budget-Optimal Crowdsourcing using Low-rank Matrix Approximations. Karger, Oh, and Shah. Allerton 2011. Spectral Methods Meet EM: A Provably Optimal Algorithm for Crowdsourcing. Zhang et al. JMLR 2016.

Write down likelihood/posterior function
Using EM algorithms to find the parameters that maximize likelihood/posterior

Write labels as a matrix (worker by task)
Using low rank matrix approximation

Discussion

- Do you think the models we made so far make sense? Why? Can you think of scenarios in which MV performs poorly? What do you think are the reasonable approaches to address them?

- Can you think of other important aspects (at least in some applications) that should be modeled?

- Take this time to find your potential teammates!