

Lecture 4

Label Aggregation: EM-Based Methods

Questions: <https://sli.do> #48937

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Logistics: Reminders

- Review:
 - The next required reading is mathematically dense. Try to at least understand the formulation and the interpretations of the main results.
- Assignments:
 - Assignment 1 is due next Friday
 - Assignment 2 will be announced next Tuesday
- Bidding of presentations
 - Form a team and choose 3~5 topics that interest you
 - Bidding link will be up next Tuesday (and due the same day)
 - Presentation assignments will be announced next Wednesday
- Finding teammates
 - I'll enable a single break-out room after the lecture. Anyone looking for teammates can stay and talk to each other.

Logistics: Project Timeline

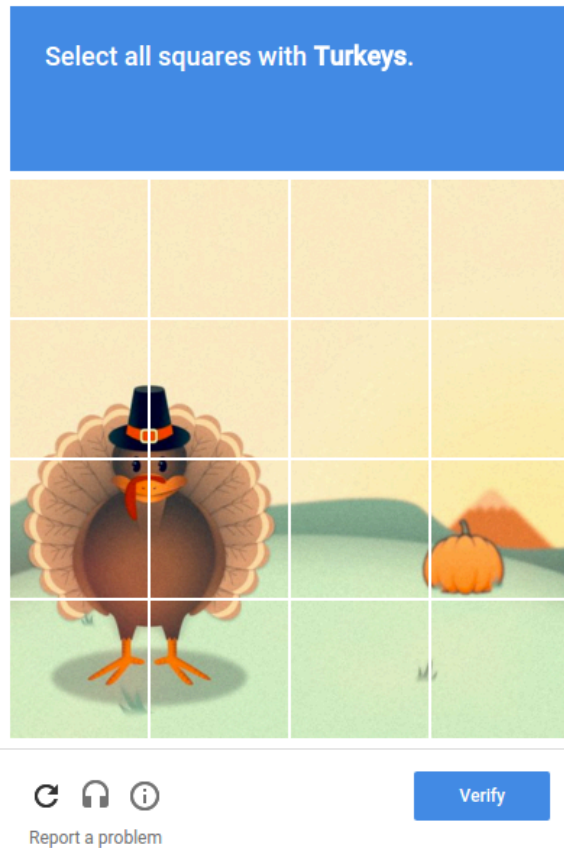
- Oct 9: Project proposal
 - Brief description of the proposed project (1~2 paragraph)
 - Citing at least one paper that's relevant to your proposal
- Oct 30: Milestone 1
 - A brief literature review and the description of your plan (one page)
 - Last chance to change the topic of the project
- Nov 20: Milestone 2
 - Summary of your current progress (up to 2 pages)
 - Last chance to convert the research project to (a more ex
- Dec 15/17: In-class project presentations
- Dec 20: Project report due

About how to choose topics:

1. I will post a list of example/past projects this weekend.
2. Looking at future topics could help.
3. I will open some time slots before the deadline so you can reserve to discuss with me about your project if you like.

A Short Recap of Last Lecture

Course Overview



Human as data sources: Label aggregation

Probabilistic reasoning to
aggregate noisy human data

Humans are “Humans”: Incentive design

Game theoretical modeling of
humans and incentive design

Practical challenges:

Real-time and complex tasks

Studies on workflow and team
designs from HCI perspective

Selected recent topics:

Ethical issues of AI/ML, learning
with strategic behavior, Human-
AI collaborations.

Label Aggregation

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

- Goal: infer true labels
- Challenges
 - Unknown worker skills
 - Different task difficulties
 - More factors to consider (some structures of tasks/workers?)

Probabilistic Approach for Label Aggregation

- High-level ideas:
 - Let \mathcal{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
 - Posterior: $\Pr(\theta|\mathcal{D})$ [More discussion in CSE515T]
 - Likelihood: $\Pr(\mathcal{D}|\theta)$ [More discussion in CSE417T]
 - Connection: $\Pr(\theta|\mathcal{D}) = \frac{\Pr(\theta)\Pr(\mathcal{D}|\theta)}{\Pr(\mathcal{D})}$

MLE approach (roughly speaking):
Find $\theta^* = \operatorname{argmax}_{\theta} \Pr[\mathcal{D}|\theta]$

Majority Voting for "Homogeneous" Workers

- Majority voting leads to maximum likelihood estimation (MLE)

MLE (roughly speaking):
Find $\theta^* = \operatorname{argmax}_{\theta} \Pr[D|\theta]$

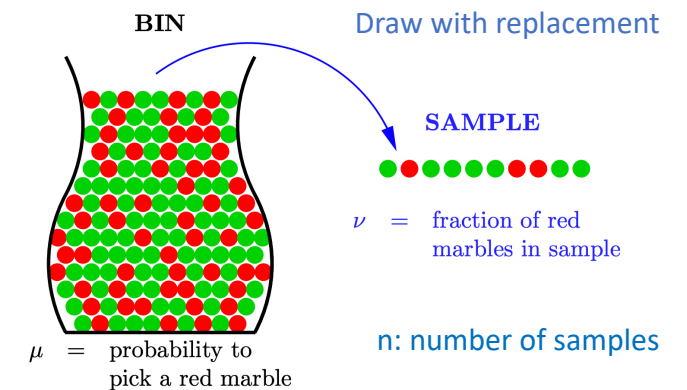
- Theoretical guarantees of majority voting

- Hoeffding's Inequality

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

- Plug it into label aggregation binary classification

$$\text{Prob of error} \leq e^{-\frac{1}{2}n(2p-1)^2}, \text{ where } p \text{ is the prob of correct label}$$



What if Workers are Heterogeneous

- Worker $i \in \{1, \dots, n\}$
 - provides label $l_i \in \{-1, +1\}$
 - assumption: each label l_i is correct with probability p_i
 - assume p_i is known

Think about why we can write it in this way?

Hint: it's due to the choice of the label presentation $\{+1, -1\}$

- Weighted majority voting Predict $\text{sign}(\sum_{i=1}^n w_i l_i)$

- Weights that lead to MLE: $w_i = \ln \frac{p_i}{1-p_i}$ for label l_i
 - You can prove this yourself following the proof of simple majority voting
- Weights that minimizes error bound: $w_i = 2p_i - 1$ for label l_i
 - (Lemma 1 in [Ho et al. ICML 2013](#))

Today's Lecture

Framework for Probabilistic Inference

- Notations:

- $D = \{d_1, \dots, d_n\}$: observations (e.g., training data, labels we got from workers)
- θ : be the set of latent parameters we care about (e.g., ML hypothesis, true labels)

- MLE approach

- $\theta^* = \operatorname{argmax}_{\theta} \Pr(D|\theta)$
 $= \operatorname{argmax}_{\theta} \prod_{i=1}^n \Pr(d_i|\theta)$ (from the common “independence” assumption)
 $= \operatorname{argmax}_{\theta} \log \prod_{i=1}^n \Pr(d_i|\theta)$
 $= \operatorname{argmax}_{\theta} \sum_{i=1}^n \log \Pr(d_i|\theta)$

In machine learning, we often replace this as a (negative) point-wise “loss function”

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- Another interpretation

- Define point-wise loss function $\ell(d, \theta)$
- Solving $\theta^* = \operatorname{argmin}_{\theta} \sum_{i=1}^n \ell(d_i, \theta)$

Solving this optimization problem is one of the “key” steps in machine learning.

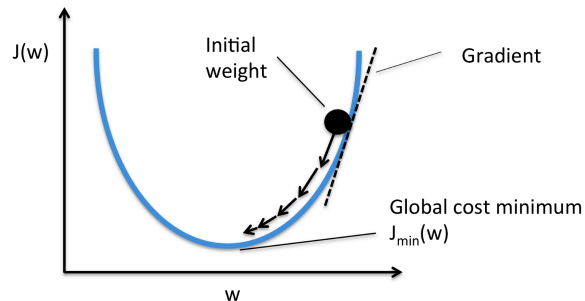
Get Back to Label Aggregation

- Steps for MLE approach
 - Define label generation model $\Pr(d_i|\theta)$ (define loss functions in ML)
 - θ contains the true labels and other latent factors in your models
 - Optimization: Find $\theta^* = \operatorname{argmax}_{\theta} \sum_{i=1}^n \log \Pr(d_i|\theta)$
 - In last lecture, there are only two possible values for θ . So we find it in a brute-force way

- Maximum likelihood estimation (MLE):
 - Predict +1 if $\Pr[L|l^* = +1] \geq \Pr[L|l^* = -1]$
 - Predict -1 otherwise
 - What if there are (infinitely) many possible values of θ ?
 - Need to perform “optimization” algorithms to find it θ^* .

Optimization

- One of the key elements in modern machine learning.
 - Therefore, most ML courses require probability, calculus, and linear algebra.
- Assume the function we want to minimize (maximize) is **convex (concave)**.
 - Gradient descent is one of the most common-used algorithm.



$$w_{t+1} = w_t - \gamma_t \nabla J(w)$$

1. Requires gradient to exist everywhere
2. Only guarantees to find local optimum

In convex functions, local optimum == global optimum

- What if the function is not convex
 - Start at a random point, do many times, report the best one.
 - (This is essentially what deep learning is doing for minimizing loss)

Expectation-Maximization (EM)

- What if gradient doesn't always exist
- Consider the function we want to minimize: $L(\theta_1, \theta_2)$
 - $\partial L / \partial \theta_1$ can be obtained (e.g., θ_1 are the unknown worker skills)
 - $\partial L / \partial \theta_2$ are hard to obtain (e.g., θ_2 are the "true" labels)
- EM: an iterative approach
 - Start with some initial estimates of θ_1, θ_2
 - Iteratively perform the following until the stop conditions are met:
 - Fix θ_1 , estimate θ_2 (e.g., find MLE)
 - Fix θ_2 , estimate θ_1
 - Stopping condition: converged, # iterations \geq pre-determined threshold, etc

Only guarantee to converge to local optimum.

Consider a simpler case: Optional Reading

Maximum Likelihood Estimation of Observer Error-Rates Using the EM Algorithm.
Dawid and Skene. Applied Statistics. 1979.

Motivating Scenario

- Multiple doctors give judgements of patients' information
 - Doctors might make mistakes (with unknown probability)
 - Given judgements from multiple doctors, how to infer patients' true information.
-
- In the context of label aggregation
 - Doctors -> workers
 - Judgements -> labels
 - They consider the setting all tasks are the same

Reminder: If Worker Skills are Known

- Worker $i \in \{1, \dots, n\}$
 - provides label $l_i \in \{-1, +1\}$
 - assumption: each label l_i is correct with probability p_i
 - **assume we know** p_i

Think about why we can write it in this way?

Hint: it's due to the choice of the label presentation $\{+1, -1\}$

- Weighted majority voting

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

- Weights that lead to MLE: $w_i = \ln \frac{p_i}{1-p_i}$ for label l_i
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What if Workers' Skills are Unknown

- Short Discussion: What can we do?
 - Think about the EM idea we just discussed

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

EM: an iterative approach

Start with some initial estimates of θ_1, θ_2

Iteratively perform the following until the stop conditions are met:

Fix θ_1 , estimate θ_2 (e.g., find MLE)

Fix θ_2 , estimate θ_1

Stopping condition: converged, # iterations \geq pre-determined threshold, etc

What if Workers' Skills are Unknown

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Task 2	+1	+1	-1	+1	-1
Task 3	+1	-1	+1	-1	+1
Task 4	-1	-1	+1	+1	+1

High-Level Description of EM

Algorithm 1 The basic EM framework of Dawid and Skene (1979).

Input: Sets of worker-generated labels for each instance

Initialize each instance's label based on a simple majority vote

repeat

for all Workers w **do**

 Calculate w 's quality parameter(s), treating each instance's current label as ground truth

end for

for all Instances i **do**

 Calculate the most likely label for i , treating each worker's approximated quality parameter(s) as ground truth

end for

until Label assignments have converged

Output: The current label assignments for each instance

Required Reading

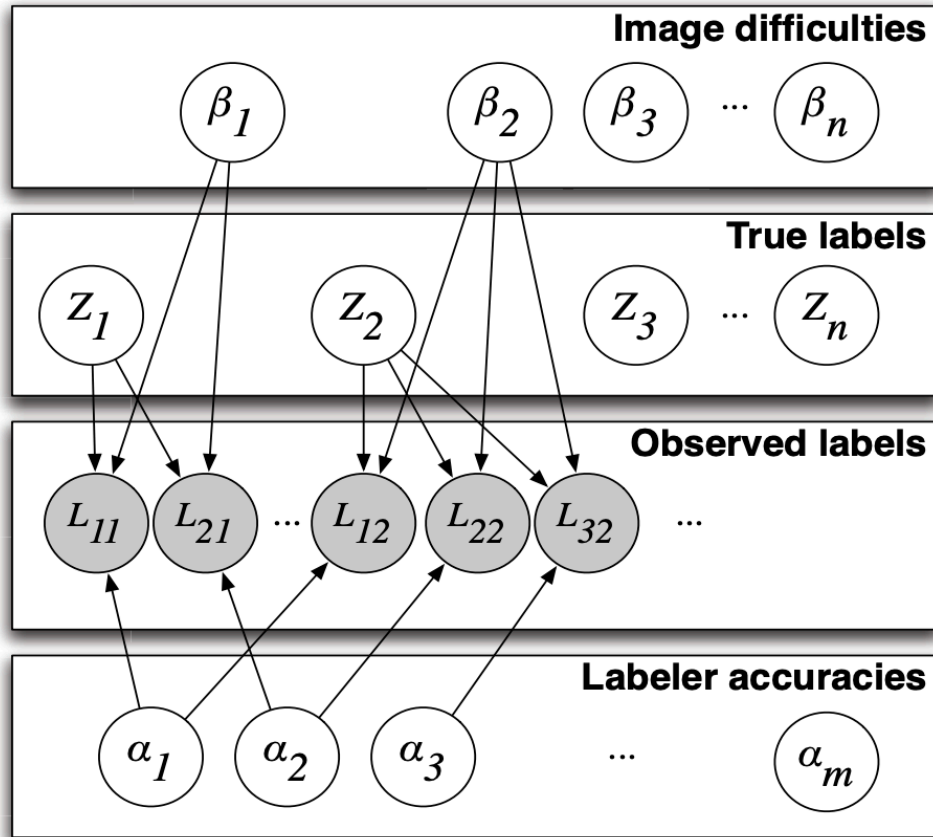
Whose Vote Should Count More: Optimal Integration of Labels from Labelers of Unknown Expertise. Whitehill et al. NIPS 2009.

Reminder on the Framework

- Steps for MLE approach
 - Define label generation model $\Pr(d_i|\theta)$
 - θ contains the true labels and other latent factors in your models
 - Optimization: Find $\theta^* = \operatorname{argmax}_{\theta} \sum_{i=1}^n \log \Pr(d_i|\theta)$
 - In last lecture, there are only two possible values for θ . So we brute-force find it.

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



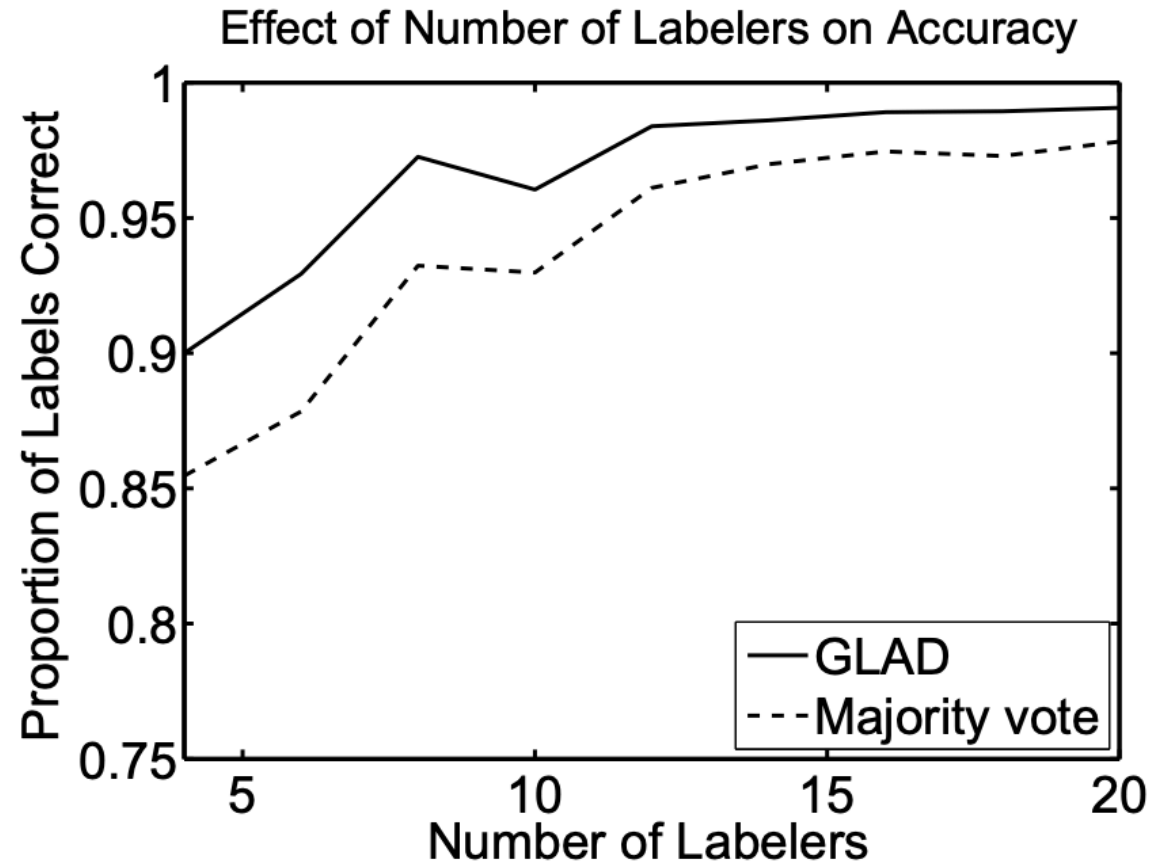
$$p(L_{ij} = Z_j | \alpha_i, \beta_j) = \frac{1}{1 + e^{-\alpha_i \beta_j}}$$

What do these parameters really mean?

Using EM to find the MLE

- E-Step:
 - Fix current estimate α and β , calculate the distribution of true labels
- M-Step
 - Fix current estimate of true labels, finding α and β that maximize likelihood
 - Using gradient descent

Simulation/Experiments



Discussion

- What are your general thoughts about the paper.
- When do you think majority voting would actually be a preferred method than GLAD or other more sophisticated method?
- What other aspects of label generation do you think can/should also be modeled (the application doesn't need to be restricted to image labeling)?

When Majority-Voting Might Be Preferred

- Not enough data: Occam's Razor
- Fairness considerations: When the outcome impacts people
 - Can we give different weights to voters in Presidential Elections?
- When the label is subjective
 - Aggregating preferences is a hard question
 - Arrow's impossibility theorem

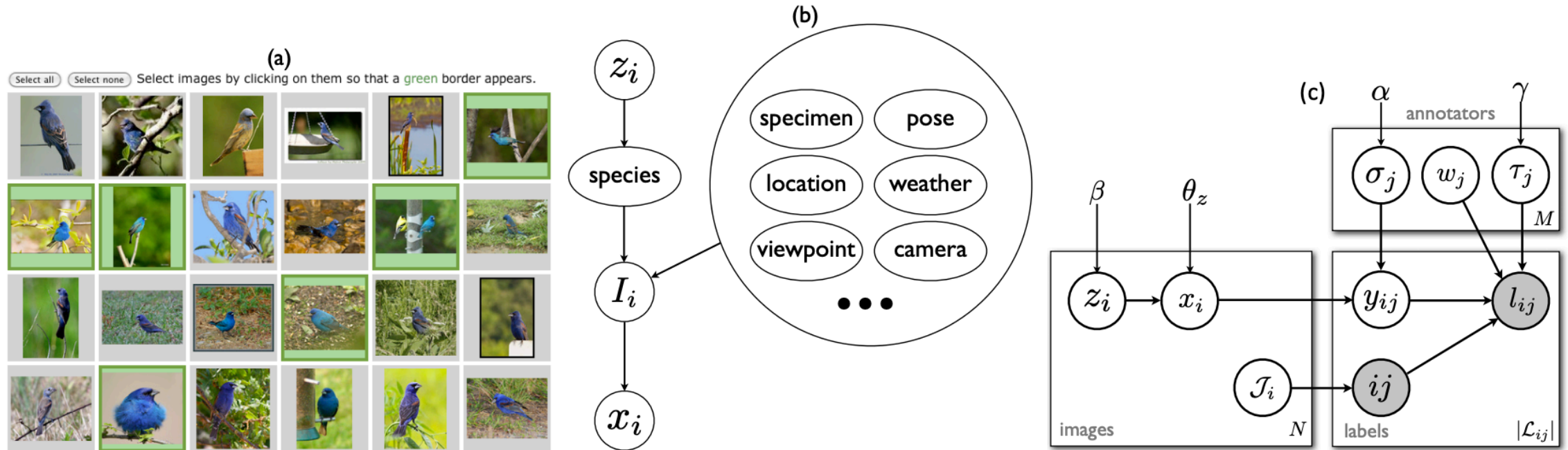
What Other Aspects to Model

- Confusion matrix
 - Instead of using a single probability for modeling worker skills for tasks

		Ground Truth		
		Label 1	Label 2	Label 3
Worker Label	Label 1	0.8	0.1	0.1
	Label 2	0.1	0.9	0
	Label 3	0.1	0.2	0.7

What Other Aspects to Model

- The Multidimensional Wisdom of Crowds. Welinder et al. NIPS 2010



What Other Aspects to Model

- Temporal Information
 - Workers get more experienced over time
 - [some recent relevant research topic: machine teaching]
 - Workers get tired over time
 - Most approaches are pretty ad-hoc

General Framework for Label Aggregation

- Most of the papers in label aggregation follow this general idea.
- Steps:
 - Model label generation $\Pr(d_i|\theta)$
 - Optimization: Find $\theta^* = \operatorname{argmax}_{\theta} \sum_{i=1}^n \log \Pr(d_i|\theta)$ [or other objective]
- With reasonable models, it works well in practice.
- However, no theoretical guarantees in general.

Next Lecture

- Read papers that give theoretical guarantees
 - Be prepared for the more math-heavy reading
 - Try to at least understand the formulation/models and the interpretations of the main results