### Modeling Experts and Novices in Citizen Science Data

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Species Distribution Modeling important for:

- Understanding specieshabitat relationships
- Conservation and reserve design
- Predicting effects of climate / land use change



Predicted distribution of tree swallows across North America (from D. Fink)

Many research questions require data to be collected at broad spatial and temporal scales

Citizen science: scientific research in which volunteers from the community participate as field assistants [Cohn 2008]

Pros:

- Inexpensive
- Can collect data over large spatial areas and long time periods

<u>Cons</u>

• Reliability of data







- One of the largest citizen science programs
- Online checklist database developed by Cornell Lab of Ornithology and National Audubon Society
- Birders submit checklists of birds observed (> 1.5 million checklists in Jan 2010)





Can we use eBird data for accurate SDM?

• Main issue: birders have different levels of expertise



- How reliable is the data?
  - Data reviewed through a verification process
  - But biases still exist



#### Labeled Training Set







[Mackenzie et al. 2006]



Assumptions on OD model

- Site closure assumption: species occupancy status stays the same over the site visits
- No false detections: can't detect a bird if it doesn't occupy the site



Occupancy-Detection-Expertise (ODE) model



ODE model details

- Allow for false detections. Results in four sets of parameters:
  - True detection and false detection parameters for experts
  - True detection and false detection parameters for novices
- Introduces an identifiability problem
  - Add constraint during training
- Train using Expectation-Maximization

- 1. Want to predict occupancy  $(Z_i)$  but ground truth not available. Instead, predicting observation  $(Y_{it})$ 
  - eBird data from NY, breeding season (2006-2008)
  - Expertise nodes observed in training data, unobserved in test data
  - Evaluating spatial data is challenging: use checkerboarding
  - Compare with Logistic Regression and OD model







#### Average AUC on four hard-to-detect bird species



- 2. Predict Expertise (E<sub>j</sub>) of birder given checklist history
  - Site occupancy  $(Z_i)$  is unobserved in both training and testing
  - Two-fold cross-validation on birders
  - Repeat 20 times and report average AUC
  - Compare against Logistic Regression





#### Average AUC on four hard-to-detect bird species





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# 3. Discovering differences between experts and novices



Average Difference in True Detection Probability



#### Future work

- Discover sources of novice bias
- Improve accuracy of species distribution models by adjusting for this novice bias
- Incorporate tree-models in occupancy and detection components
- Semi-supervised version of ODE model

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