Machine Learning in Ecosystem Informatics and Sustainability

Tom Dietterich

School of Electrical Engineering and Computer Science
Oregon State University
http://web.engr.oregonstate.edu/~tgd

tgd@eeecs.oregonstate.edu
Threats to the Biosphere

Pollution including Greenhouse Gases

Habitat Loss and Fragmentation

Over-Harvesting
Needed: Robust Optimal Policy Based on Sound Science

- Our understanding of ecosystem structure and function is poor
  - Extremely complex interactions
  - Operate at many temporal and spatial scales
  - Hard to do controlled experiments
  - Impossible to observe critical past events

- Long record of policy failures: “Ecological Surprises”
  - “Surprises are common and extreme”
A Limiting Factor: Ecological Data

- Many ecological simulation models are based on little or no data
- Historical time series only extend back 100 years
  - Oldest continuous data set at HJ Andrews Experimental Forest is 1909-present
  - Most begin in 1990s
- Location, population size, interactions for virtually all species are unobserved
Ecosystem Sciences

- Past approaches
  - Naturalists: museum collections
  - Artificial ecosystems (test tubes; barrels)
  - Isotope tagging of fluxes
- Emerging approaches
  - In-situ sensor networks
  - Radio/RFID tagging and tracking of organisms
  - Radar ornithology
  - Remote sensing
Data Pipeline

Sensor Placement

Data Collection

Feature Extraction

Data Cleaning

Model Fitting

Policy Optimization
Optimal Sensor Placement for Environmental Data Collection

- Objectives
  - detection probability
  - improving model accuracy
  - improving causal understanding
  - improving policy effectiveness

Leskovec et al, KDD2007
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Optimal Sensor Placement

Detectability
Errors / Noise
Sampling Bias
Sampling Bias: ebird.org

- Citizen science collected by amateur bird watchers
- Strong bias toward where people live
- Explicit models of sampling bias

Detectability

- Birds in Forested Landscapes protocol
  - Step 1: 2 minutes silent listening and observing
  - Step 2: Play “con-specific” mating calls and listen/observe
  - Step 3: Play “predator mobbing” tape and listen/observe

- Coupled models of detectability and occurrence can be fit simultaneously

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Species classification
Recognizing individuals
Tracking individuals

IJCAI 2009
The BugID Project: Rapid Throughput Arthropod Counting

- Arthropods are a powerful data source
  - Found in virtually all environments
    - streams, lakes, oceans, soils, birds, mammals
  - Easy to collect
  - Provide valuable information on ecosystem function
    - Consume the primary producers: bacteria, fungi, plants
    - Are consumed by more charismatic organisms: birds, mammals, fish
- Problem: Identification is time-consuming and requires scarce expertise
- Solution: Combine robotics, computer vision, and machine learning to automate classification and population counting
Data Pipeline

- **Sensor Placement**
- **Data Collection**
- **Feature Extraction**
- **Data Cleaning**
- **Model Fitting**
- **Policy Optimization**

**Optimal Sensor Placement**
- Detectability
- Errors / Noise
- Sampling Bias

**Species classification**
- Recognizing individuals
- Tracking individuals

**Sensor failures**
- Networking failures
- Recognition errors
Multi-Sensor Anomaly Detection
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Species distribution models
Behavioral models
Dynamical systems models

Coupling Multiple Problems
Species Distribution Models

- What are the environmental/biological requirements for a species?

**Given:**
- Environmental features (elevation, soil properties, weather) of a site
- Presence, presence/absence, or abundance of K species

**Find:**
- Probability that each of the K species will be found at new sites
- Extrapolation to global climate change scenarios
Plants in Victoria

- 5,605 plant species measured at >113,000 sites
- 83 environmental features
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Optima that are robust to model uncertainty

Coupling Multiple Problems
Robust Reserve Design

- **Given:**
  - Species distribution model
  - Budget

- **Find:**
  - Set of reserves to purchase that are good habitat for the species and fit within the budget
  - Robust to uncertainties in the model (and climate, etc.)
    - Optimize the machine learning to be more accurate where land is cheaper to acquire?
    - Joint optimization of model fitting and optimization?

Predicted winter distribution of tree swallows (Fink, et al., unpublished)
Outline

- BugID Project: Arthropod Counting
- Automated Data Cleaning for Wireless Sensor Network Data
Automated Rapid-Throughput Arthropod Population Counting

- **Goal:**
  - technician collects specimens in the field by various means
  - robotic device automatically manipulates, photographs, classifies, and sorts the specimens

- **Three applications:**
  - stoneflies in freshwater streams
  - soil mesofauna
  - freshwater zooplankton
Application 1: Stonefly populations in freshwater streams

- differentially sensitive to many pollutants
- live in rivers; reliable indicator of stream health
- difficult and expensive for people to classify (particularly to genus or species levels)
- hundreds of species
Application 2: Small arthropods in soil: “soil mesofauna”

Achipteria
Bdellozonium
Belba
Belbal
Catoposurus
Eniochthonius
Ptenothrix

Entomobrya
Epidamaeus
Epilohmannia
Epilohmannia
Hypochthonius
Hypogastrura
Isotoma
Liacarus
Metrioppia
Nothrus

Tomocerus
Onychiurus
Oppiella
Peltenuia
Phthiracarus
Platynothrus
Platynothrus
Siro

24 IJCAI 2009
Application 3: Freshwater Zooplankton

- Measure biodiversity in freshwater lakes
- 70 species

Images from Microscopy-UK.
Image Capture Apparatus

Stonefly Imaging

Soil Mesofauna Imaging
Robotic Extraction of Specimens
Computer Vision Challenges(1)

- Highly-articulated objects with deformation
Huge intra-class changes of appearances due to development and maturation
Computer Vision Challenges (3)

- Small between-class differences

Calinueria

Doronueria
Machine Learning

Training Examples

| Calineuria | Calineuria | Doroneuria | Doroneuria |

Learning Algorithm

New Examples

Classifier

Doroneuria
Region-Based Approaches: Convert Image to Bag of Patches

- Handles
  - Occlusion
  - Rotation, translation
  - Scale (with scale-independent patch representation)
  - Partial out-of-plane orientation
  - Articulation / Pose

- Problem:
  - How to define the patches?
  - How to represent each patch?
  - How to classify a BAG of patches?
Defining the Patches: Interest Region Detectors

- Hessian-Affine Detector
- Kadir Entropy Detector
- PCBR Detector
Representing the Patches: SIFT (Lowe, 1999)

- Morph ellipse into a circle
- Compute intensity gradient at each pixel in 16x16 region
- Rotate whole circle according to dominant intensity gradient
- Weight gradients by a gaussian distribution (indicated by circle)
- Collect into histograms within each 4x4 region (gives 16 histograms)
- Result: 128-element vector normalized to have Euclidean norm 1
Classify Bag of Patches
Method 1: Visual Dictionaries

- “look up” each patch in dictionary and count into a feature vector
- feature vector is then given to the classifier

\[ \hat{y} = 2 \]
Learn visual dictionary via clustering

- Gaussian Mixture Model (k=100) with diagonal covariance matrices (EM, initialized with K-means)
Classify Bag of Patches
Method 2: Multiple-Instance Classifier

- The classifier predicts the class of the image separately from each patch
- These vote to make the final decision

\(\hat{y}=2\)

Final prediction: \(\hat{y}=2\)
Improved Multiple-Instance Classification

- Evidence Trees: Like decision trees, but store the “evidence” in each leaf
- Given an input, output the evidence
Classify Bag of Patches
Voted Evidence Trees

- The classifier predicts the class of the image separately from each patch
- These vote to make the final decision

Final prediction: $\hat{y} = 1$
Theorem: Voting Evidence is Better than Voting Decisions

- Intuition: When voting decisions, there are two opportunities to make a mistake:
  1. Making the wrong decision at each leaf
  2. Making the wrong decision when combining the votes
- With evidence trees, the first opportunity is avoided

\[ \gamma = \text{margin of decision tree nodes} \]
\[ \pi = \text{fraction of non-noise patches} \]
Ensemble Learning

- **Idea:** Learn multiple evidence trees and have them vote
- **Question:** How to construct multiple diverse trees?
  - **Bootstrapping:** train each tree on a different bootstrap sample
    - Majority vote
  - **Boosting:** train each tree based on a sample containing 50% points misclassified by the previous trees and 50% points correctly classified by previous trees
    - Focuses subsequent trees on the misclassified points
    - Weighted vote
  - **Random Forests:** at each node, randomly sample a subset of features and choose the best split from among them
    - Majority vote
Final Classifier: Stacked Random Forests

1. Each patch is processed by a *random forest* of evidence trees
2. Evidence is summed and normalized to produce $C$
3. $C$ is classified by a second-level *boosted decision tree ensemble*
Experimental Study
9 Taxa of Stoneflies

Cal
Dor
Hes

Iso
Mos
Pte

Swe
Yor
Zap
STONEFLY9 Dataset

- 3826 images
- 773 specimens
- 9 classes
- Error estimation by 3-fold cross-validation
  - all images of a specimen belong to the same fold
Comparison of Methods

![Error Rate Graph](image)

- Visual Dictionary
- Stacked Evidence Trees

Error Rate
Issues with Visual Dictionaries

- Unsupervised
  - Several efforts to construct discriminative dictionaries (Moosman et al., 2006)

- Lose information
  - 128-element SIFT contains 1024 bits, a bag of 256 SIFTs contains 256K bits
  - Keyword histogram from 2700-element dictionary contains ~2700 bits
Next Steps

- Stoneflies
  - Detecting and Rejecting “Distractors”
  - Extending coverage to Ephemeroptera (mayflies) and Trichoptera (caddis flies)
  - EMAP study
- Soil Mesofauna
- Freshwater Zooplankton
- Moths
- Shellfish Larvae
Outline

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Upper Lookout Met. Station

thermometers at 1.5, 2.5, 3.5, and 4.5m
Approach:
Learn a Very Accurate Model of Normal Behavior

\[ P(\text{current observation} \mid \text{previous observations}) \]

- If predicted probability is too low, then declare an anomaly
Single Sensor Bayesian Network Model

\[ S_{t-1} \rightarrow B_{t-1} \rightarrow T_{t-1} \rightarrow O_{t-1} \rightarrow S_t \rightarrow \Delta_{t-1} \rightarrow T_t \rightarrow O_t \rightarrow \Delta_t \]

**S**: Sensor State (Very Good, Good, Bad, Very Bad)

**ToD**: Time of Day (the quarter-hour)

**DoY**: Day of Year (365 day year)

**B**: Baseline Temperature

\( \Delta \): Deviation from Baseline

**T**: Predicted Temperature

**O**: Observed Temperature

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For more details, please refer to the page number 52.
Assessment

- Assessment:
  - near 100% recall for anomalies
  - 5.3% false positive rate
  - would allow expert to ignore 94% of data = 15x speedup in manual cleaning time
Multiple Sensors

- Discover correlation structure among multiple sensors
- Exploit this to make more accurate inferences
Example: SensorScope
(EPFL, Switzerland)
Multi-Sensor Anomaly Detection
Multiple Sensor Evaluation

❖ Protocol:
  ■ Insert artificial anomalies
  ■ Measure how well we can detect them

❖ Results:
  ■ Robust to large amounts of noise
  ■ Insensitive to magnitude of noise except at very low levels
Institute for Computational Sustainability

- Cornell, Oregon State, Bowdoin, Howard U.
  - PI: Carla Gomes
  - co-PIs: Tom Dietterich, David Shmoys
- Goal: Identify and solve novel computational problems in ecological science, policy, and renewable energy
Summary

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to model uncertainty

Coupling Multiple Problems
For More Information…

- Graduate program in Ecosystem Informatics: [http://ecoinformatics.oregonstate.edu/](http://ecoinformatics.oregonstate.edu/)
- Summer Institute in Ecosystem Informatics: [http://eco-informatics.engr.oregonstate.edu/](http://eco-informatics.engr.oregonstate.edu/)
Acknowledgements

- **Grant Support:** US National Science Foundation

- **BugID:**
  - Postdocs: G. Martínez-Muñoz
  - Faculty: R. Paasch, A. Moldenke, D. A. Lytle, E. Mortensen, L. G. Shapiro, S. Todorovic, T. G. Dietterich

- **Data Cleaning:** Ethan Dereszynski
Questions?