Humans Perform Semi-Supervised Classification Too

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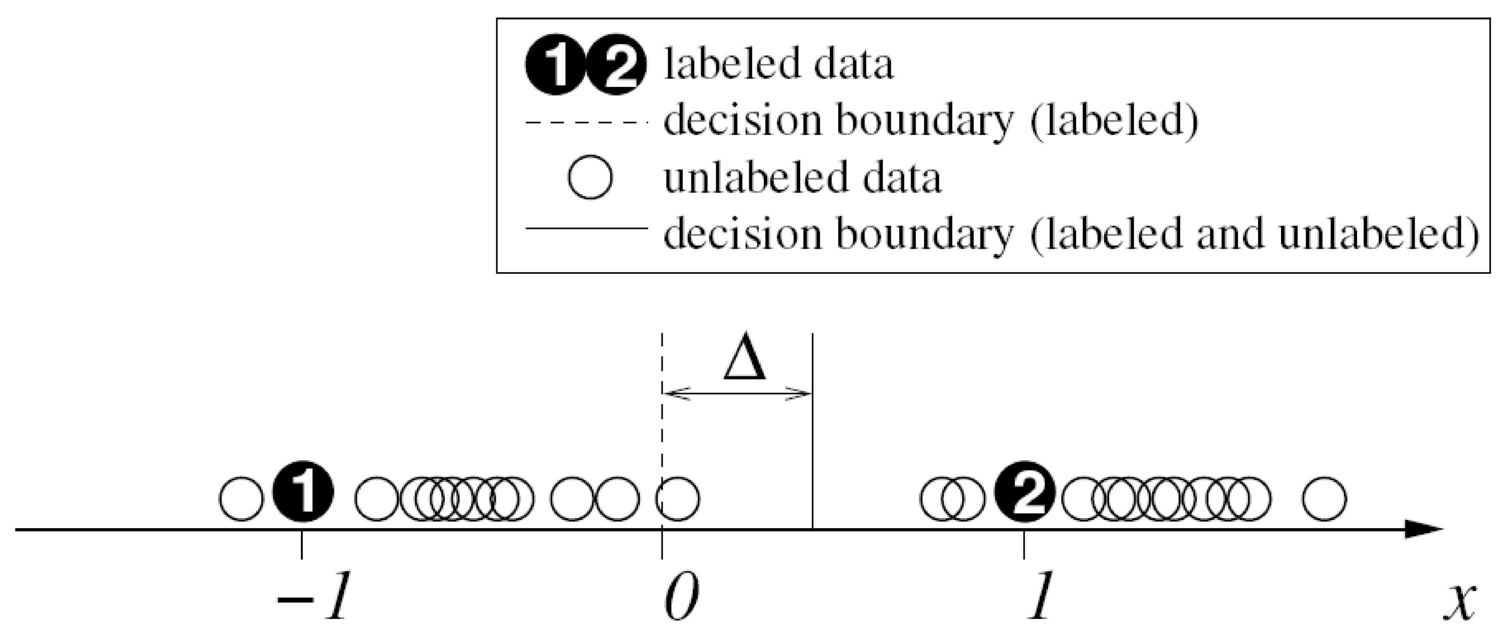
Abstract

This work explores the connections between machine learning and human learning. Under a specific setting, human behavior conforms well to a generative model (Gaussian Mixture Models) for semi-supervised learning. We seem to learn semi-supervisedly.

The semi-supervised learning task

Two-class classification. Two labeled examples. Decision boundary in the middle.



With labeled and unlabeled examples, and under the assumption that each class form a coherent group (e.g., follow a Gaussian distribution), decision boundary shifts.

Well-known in machine learning. We want to show such decision boundary shift exists in humans.

Participants and Materials

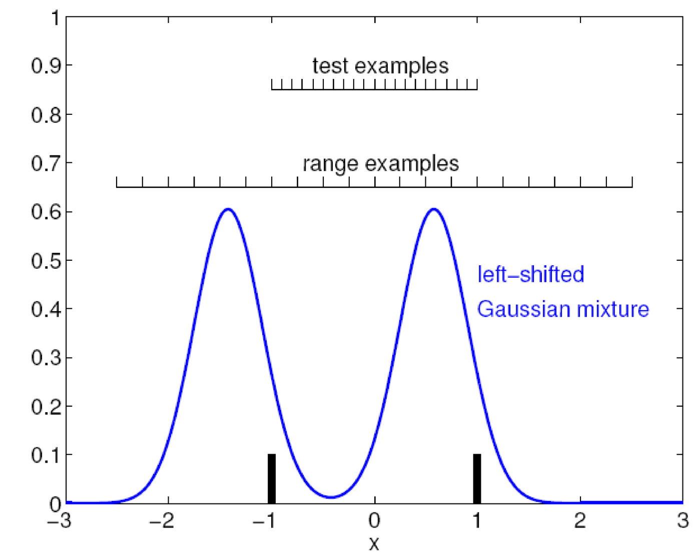
22 University of Wisconsin students. Novel visual stimuli, parameterized by a single parameter x, shown on screen one at a time. Classification by pressing B or N key. Audio feedback (affirmative sound if correct, warning sound if wrong) serves as label. No audio feedback for unlabeled examples.

a few examples of our stimuli, with the parameters x

Procedure

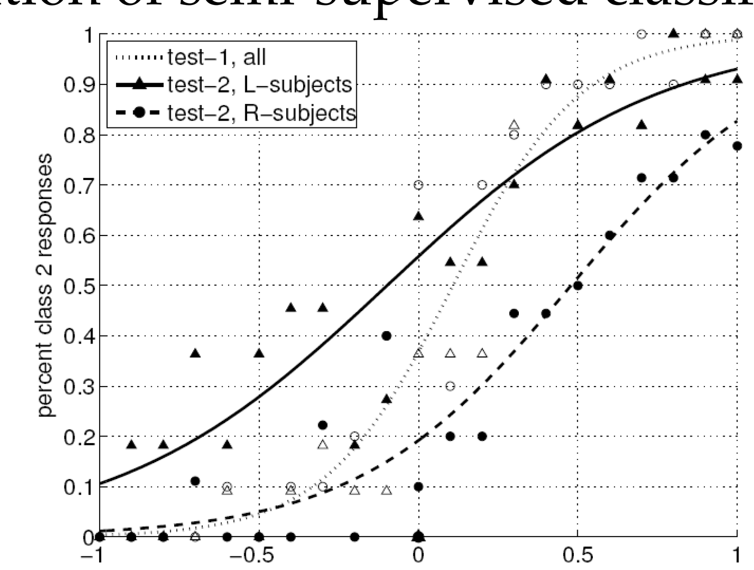
Two groups: L-subjects and R-subjects.
Each subject sees 6 blocks of stimuli.
Order within each block is randomized.
Only block 1 is labeled.

1. [labeled] 10 (x=1,y=1), 10 (x=-1,y=-1)
2. [test-1] x=-1, -0.9, …, 0.9, 1
3. [unlabeled-1] 230 sampled from two Gaussian (left or right shifted). 21 "range stimuli" evenly in [-2.5, 2.5].
4. [unlabeled-2] same as block 3
5. [unlabeled-3] same as block 3
6. [test-2] x=-1, -0.9, …, 0.9, 1



Behavioral experiment results

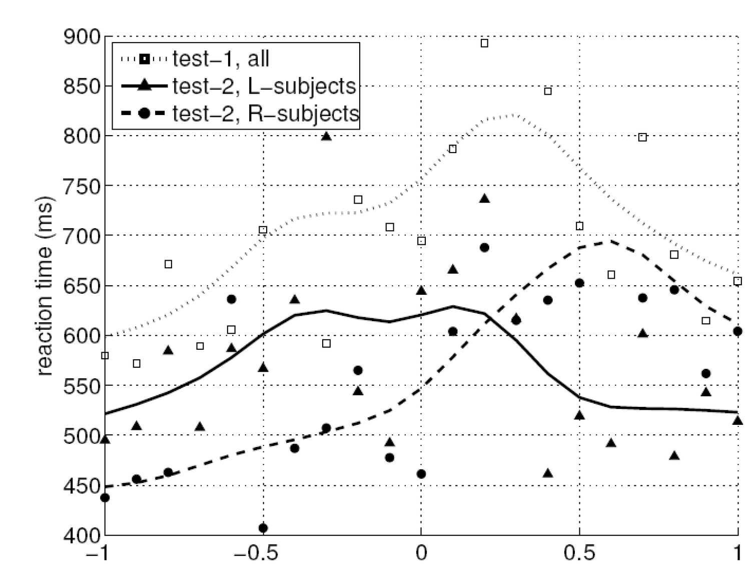
Observation 1: Unlabeled data changes the decision boundary.
[test-1] (0.11); L-subjects [test-2] (-0.1); R-subjects [test-2] (0.48)
The shift represents the effect of unlabeled data on subjects, and fits the expectation of semi-supervised classification.



(a) classification

Observation 2: Reaction time reflects decision boundary shift.

- The harder the stimuli, the longer the reaction time
- Peaks shift to follow new decision boundary



(b) reaction time

The machine learning model

We can explain the human experiment using a Gaussian Mixture Model (GMM) with 2 components:

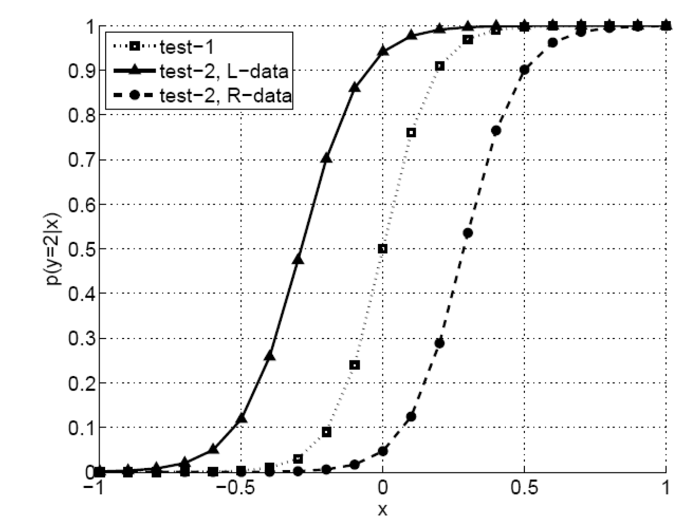
$$w_1 N(\mu_1, \sigma_1^2) + w_2 N(\mu_2, \sigma_2^2) \quad , w_1 + w_2 = 1, w_i \geq 0$$

$$\text{Prior } w_k \sim \text{Uniform}[0,1], \mu_k \sim \text{N}(0, \infty), \sigma_k^2 \sim \text{Inv}-\chi^2(\nu, s^2), k = 1, 2$$

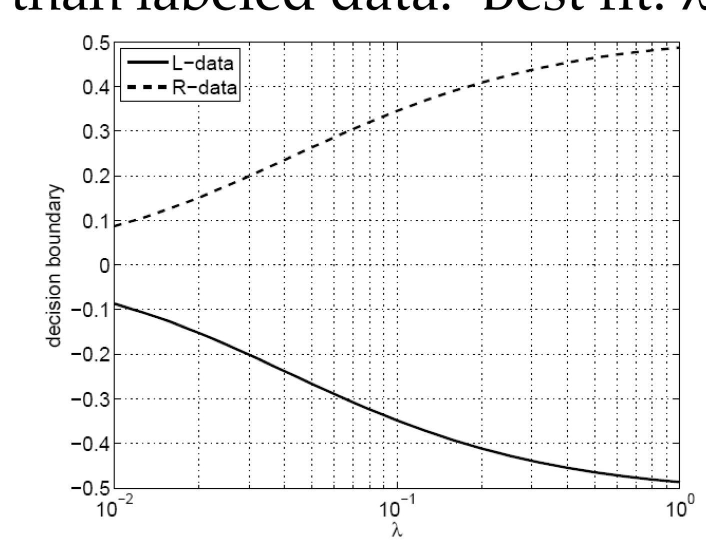
We fit the GMM with EM on blocks 1,2 vs. blocks 1−6. The EM algorithm maximizes the following objective, where λ≤1 is a weight on unlabeled examples:

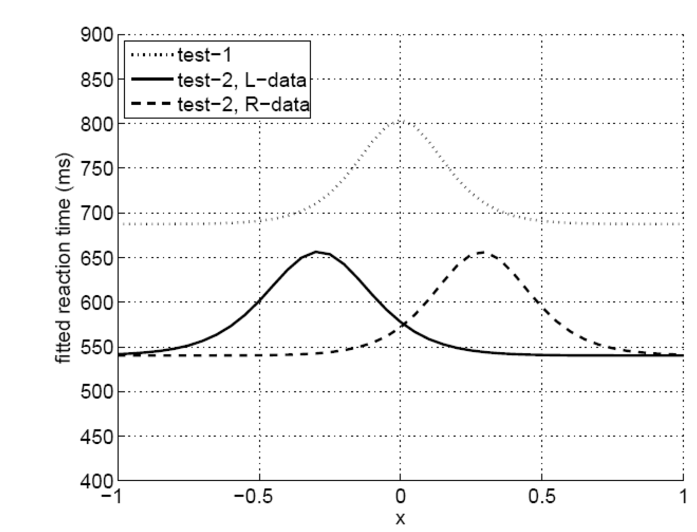
$$\log p(\theta) + \sum_{i=1}^{l} \log p(x_i, y_i|\theta) + \lambda \sum_{i=l+1}^{n} \log p(x_i|\theta)$$

Observation 3: GMMs predict the decision boundary shift.



Observation 4: Unlabeled example weight λ controls the amount of decision boundary shift. Unlabeled data seems to worth less than labeled data. Best fit: λ=0.06.





Observation 5: GMMs also explain reaction time t=aH(x)+b, where H(x) is the entropy of class prediction for x.

Conclusions

- Humans and machines both perform semi-supervised learning.
- Flatness of classification curves on [test-2] not well explained.
- Other forms of semi-supervised machine learning (e.g., manifold regularization, S3VMs, co-training) in humans should be explored.
- Further study may lead to new learning algorithms.

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