



# Advanced Methodologies for Predictive Learning

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# OUTLINE

- **Motivation and Background**
  - standard inductive learning
  - assumptions
- **Advanced Methodologies**
  - Transduction and semi-supervised learning
  - Universum learning
  - Multi-Task Learning
  - Learning Using Privileged Information
- **Practical Issues and Concerns**

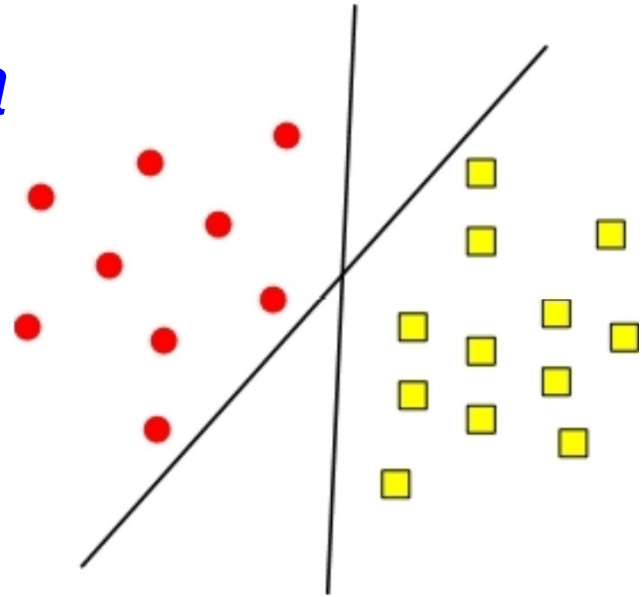
# Standard Inductive Learning - 1

**Given:** data samples ( $\sim$  *training data*)

**Estimate:** a model (function) that can

- explain this data
- predict future *test data*

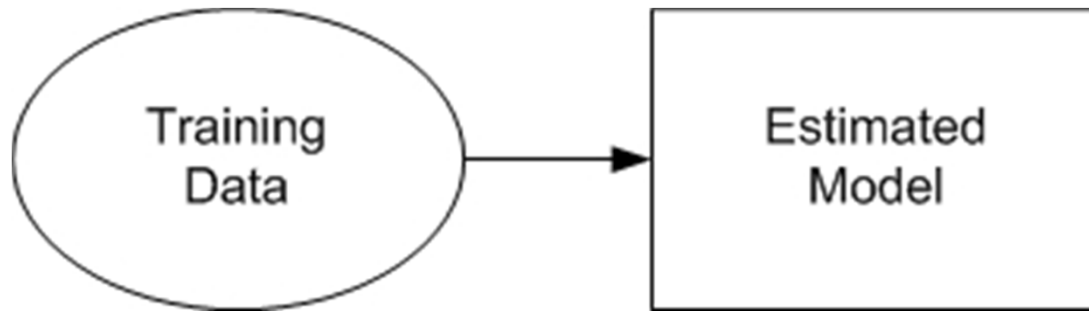
*Classification problem:*



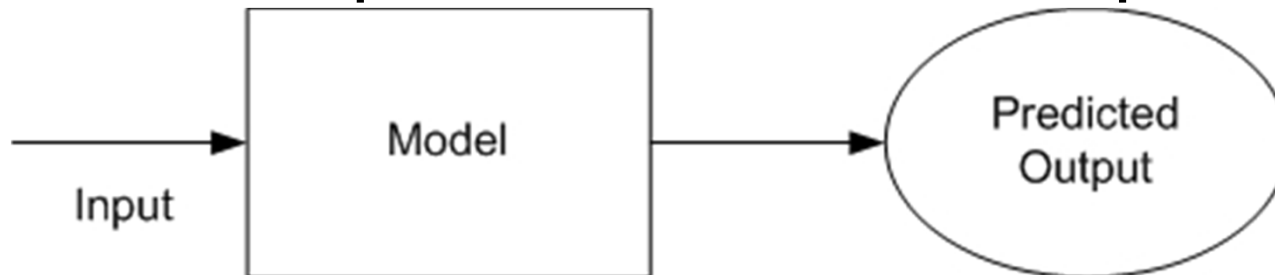
*Note:* *training data* is similar to *test data*

# Standard Inductive Learning -2

**Induction** ~ function estimation from data:



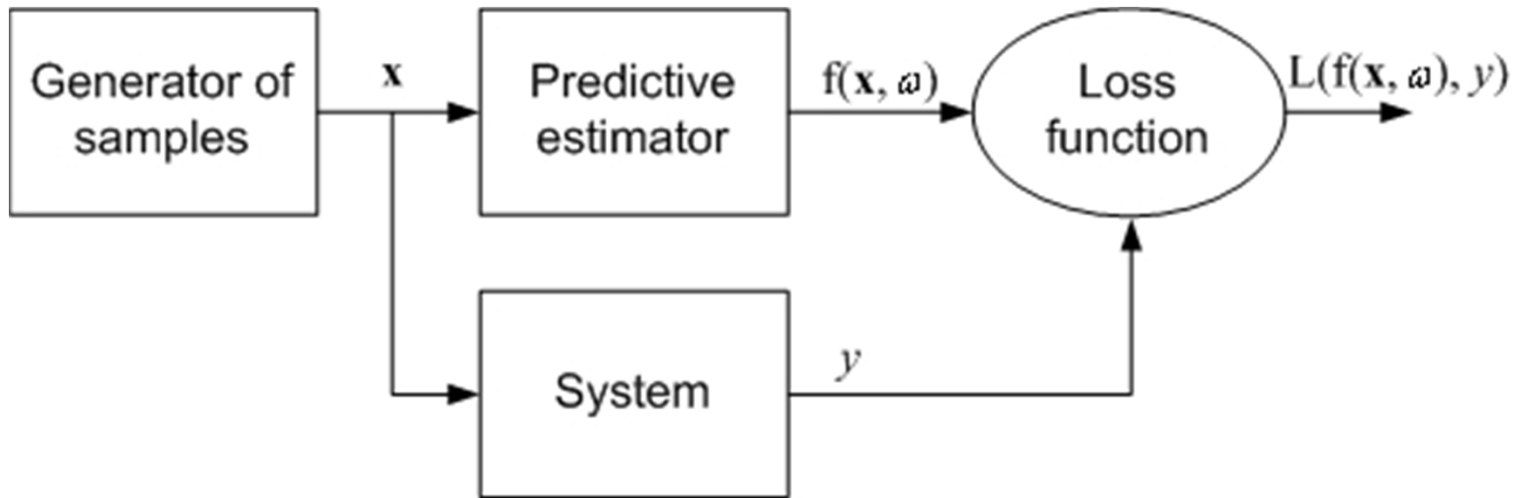
**Deduction** ~ prediction for new inputs:



*Note:* All practical methods follow this paradigm

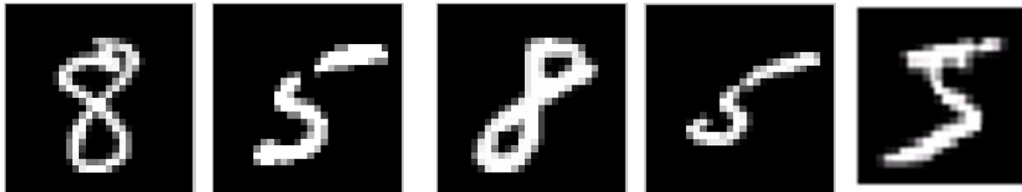
# Assumptions for Inductive Learning

- Finite training set  $(\mathbf{x}, y)$ , large test set, i.i.d. sampling
- Test inputs unknown during learning
- Training and future (test) data from the same  $P(\mathbf{x}, y)$
- Given loss function – e.g. MSE, error rate, ...
- Performance index is minimization of test error



# Non-standard Learning Settings

- Example: Handwritten digit recognition 5 vs 8



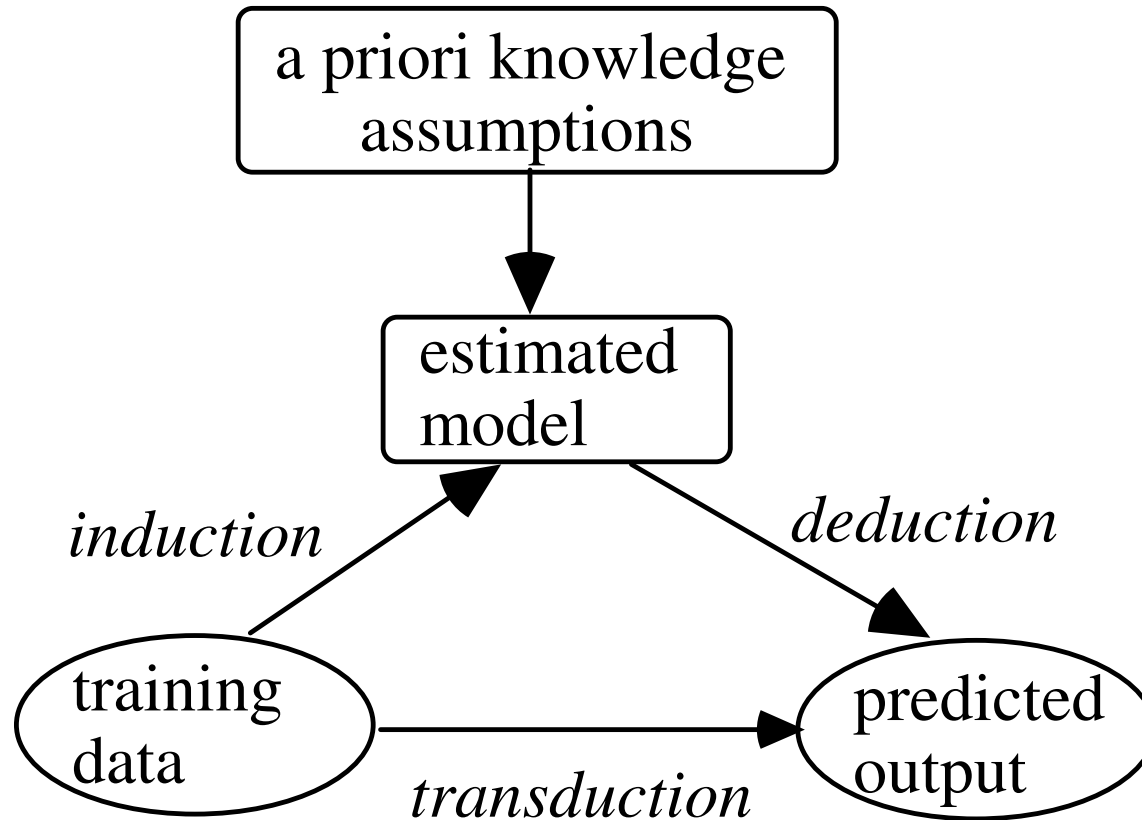
**each example** ~ 28x28 pixel image → 784-dimensional input  $\mathbf{x}$

- **Inductive learning**: estimate a model from training data
- **Transduction and SSL**:  $\mathbf{x}$ -values of test inputs also known
- **Universum learning**: additional samples ('other digits')
- **Multi-Task Learning**: training and test data is generated by  $t$  different persons. *Need to estimate  $t$  related classifiers*
- **Learning Using Privileged Information**: training data is generated by  $t$  persons. *Need to estimate a single classifier*

# Transduction and SSL

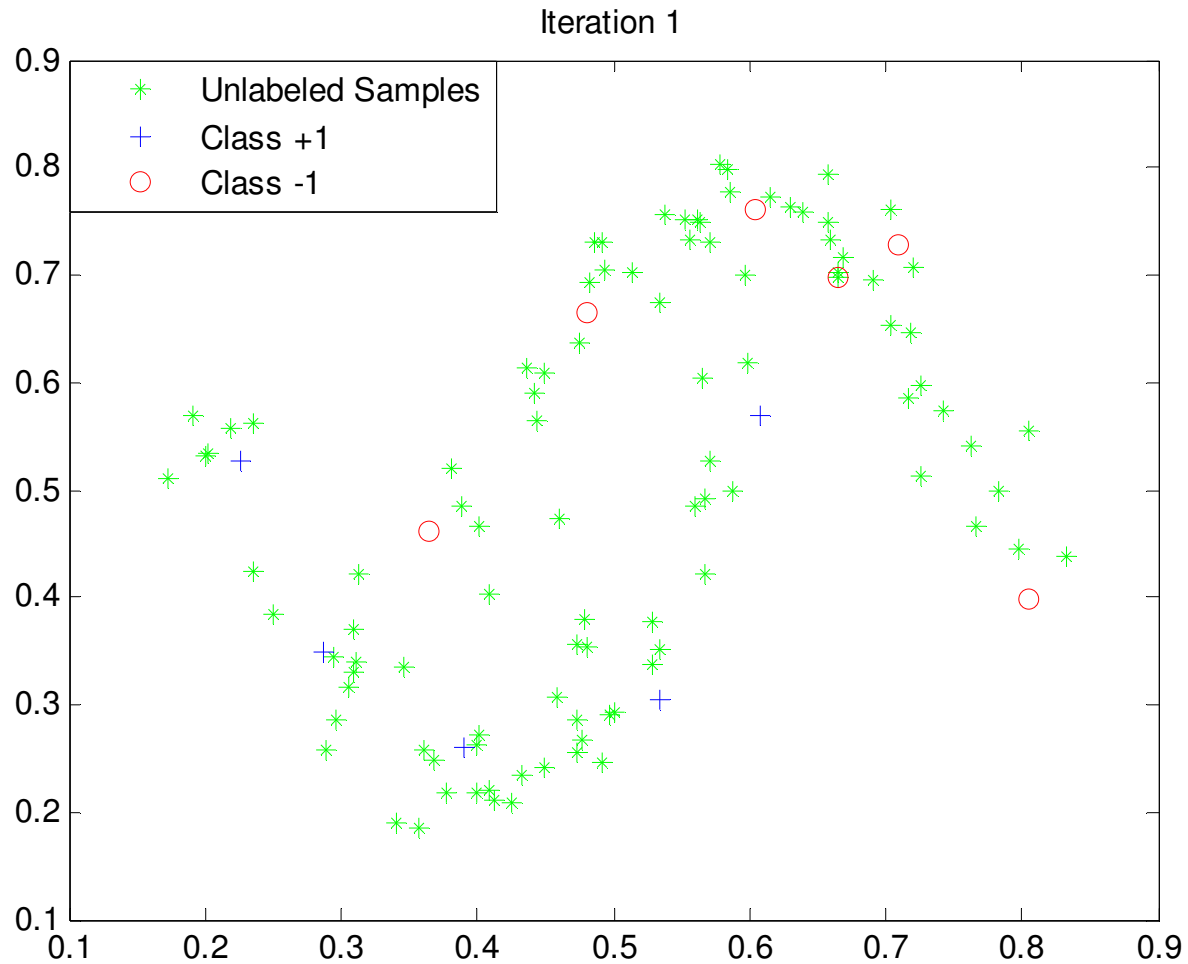
**Given:** labeled data  $L$  + unlabeled data  $U$   
(from the same distribution)

**Estimate:** predictive model



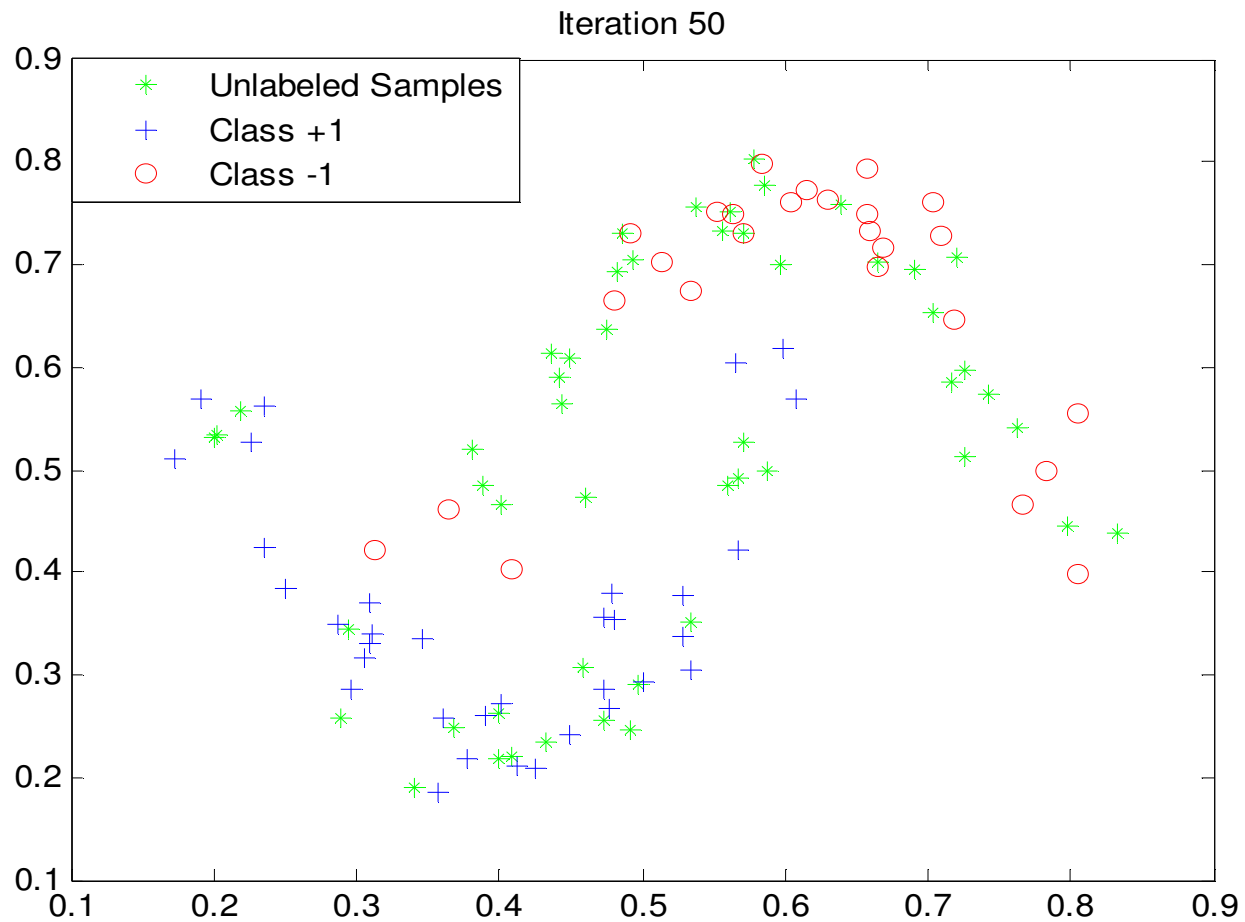
# Self-Learning Algorithm for SSL (1)

**Given:** labeled data L and unlabeled U:  $U \gg L$



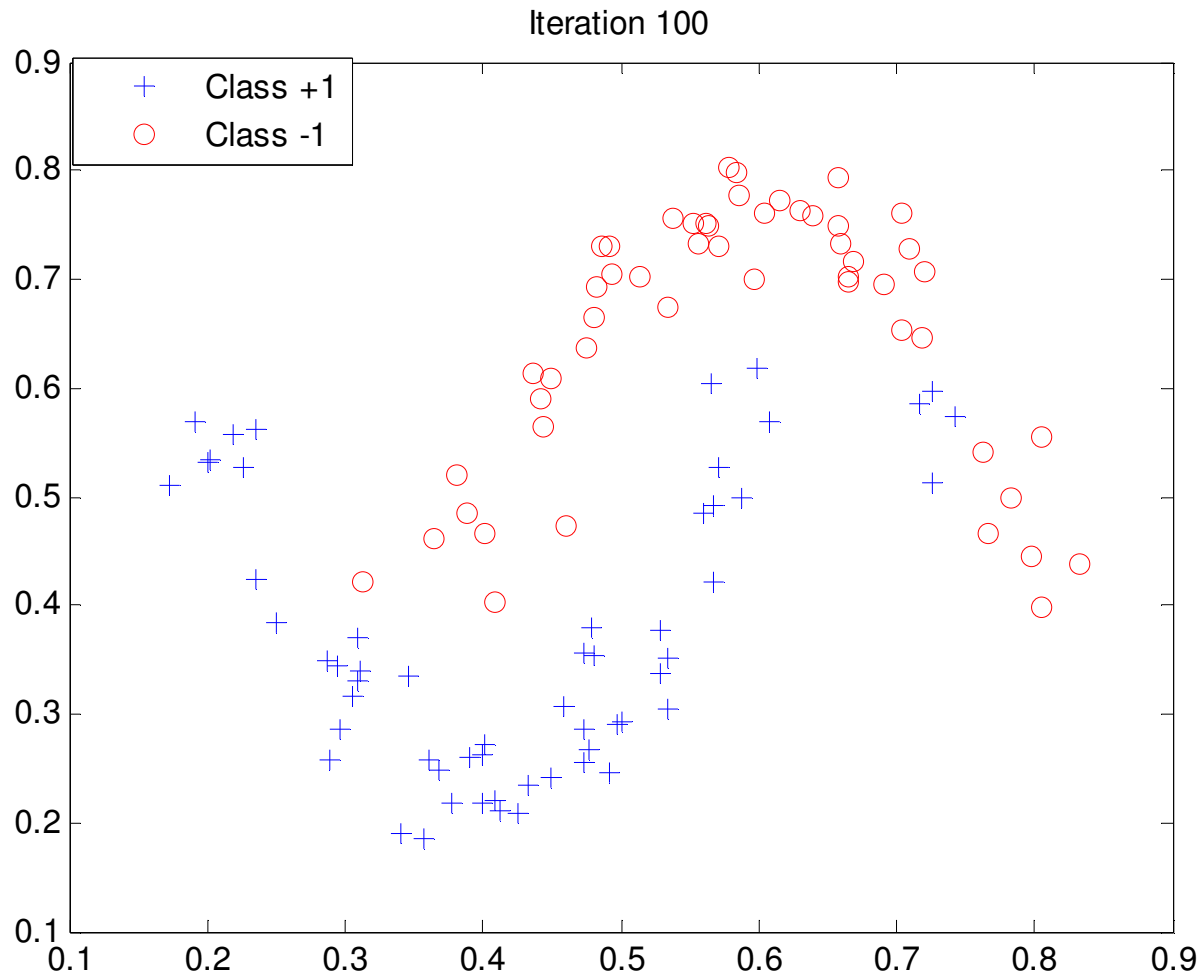
# Self-Learning Algorithm for SSL (2)

**Classification of test data:** after 50 iterations



# Self-Learning Algorithm for SSL (3)

**Classification of test data:** after 100 iterations



# Many applications for transduction

- **Text categorization:** classify word documents into a number of predetermined categories
- **Email classification:** Spam vs non-spam
- **Web page classification**
- **Image database classification**
- All these applications:
  - **high-dimensional data**
  - **small labeled training set** (human-labeled)
  - **large unlabeled test set**

# Universum Learning

**Given:** labeled data  $L$  + unlabeled data  $U$   
(known *NOT to belong* to either class)

**Estimate:** predictive model

- **Universum samples:** reflect a priori knowledge about application domain
- **For digit recognition problem 5 vs 8:**
  - other digits 0, 1, 2, 3, 4, 6, 7, 9
  - handwritten letters
  - averaging of randomly selected 5 and 8
- **Aka Learning through Contradiction**

# Random Averaging for digits 5 and 8

- Two randomly selected examples



- Universum sample (via Random Averaging):



# Cultural Interpretation of the Universe

- Absurd examples, jokes, some art forms:

Dadaism – M. Duchamp



# Multi-Task Learning

- **Application: Handwritten digit recognition**

Labeled training data provided by  $t$  persons ( $t > 1$ )

**Goal:** to estimate  $t$  related classifiers (for each person)

- **Application: Medical diagnosis**

Labeled training data provided by  $t$  groups of patients ( $t > 1$ ), say men and women ( $t = 2$ )

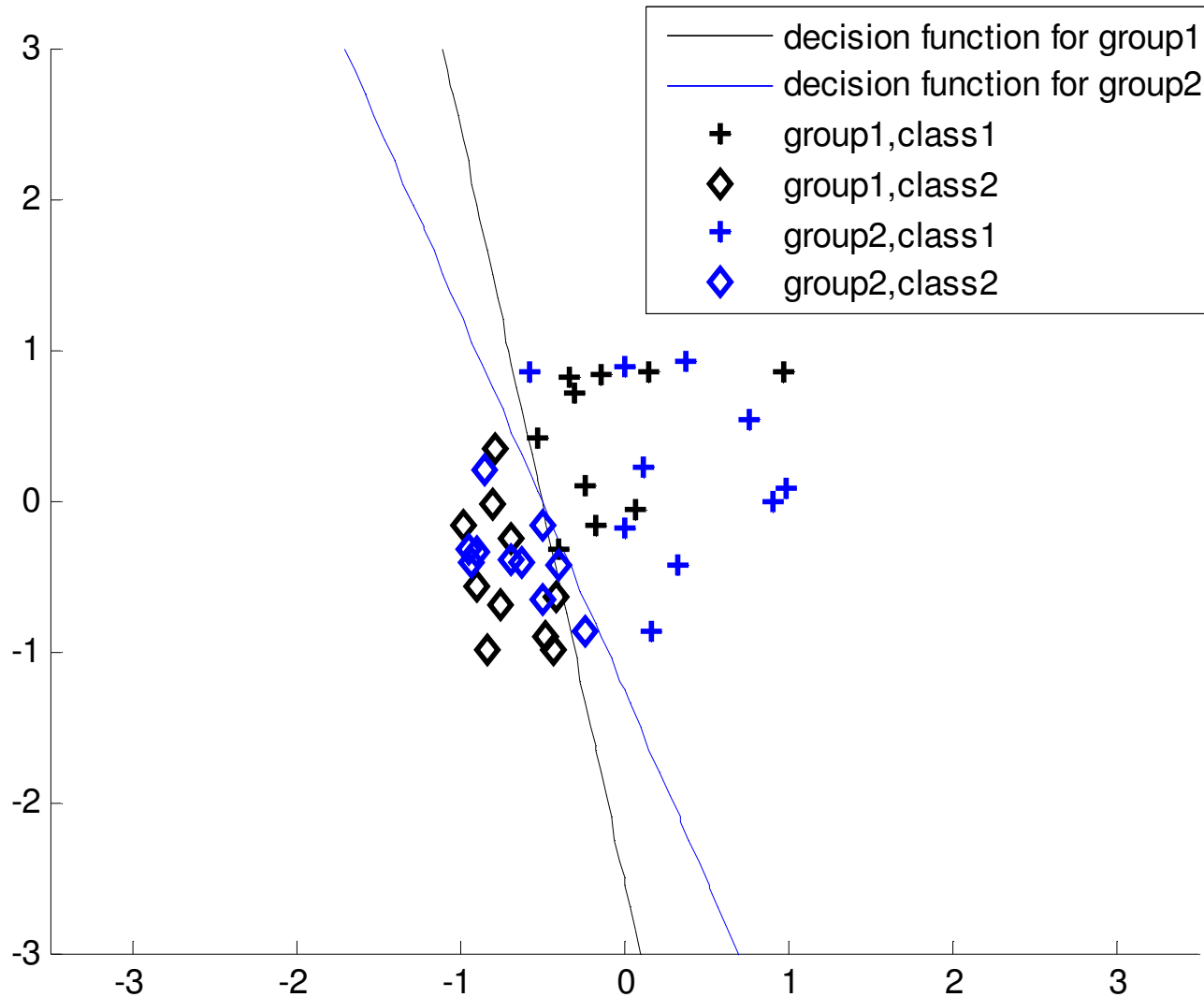
**Goal:** to estimate  $t$  classifiers specialized for each group of patients ~ MTL

- **Practical issues**

- how to model task-relatedness?

- with small samples, it may be better to ignore the group (task) label

# Multi-Task Learning: Simple Example



# Learning Using Privileged Info (LUPI)

**Given:** training data  $(\mathbf{x}, \mathbf{x}^*, y)$

where  $\mathbf{x}^*$  is privileged info *only for training data*

**Estimate:** predictive model  $y = f(\mathbf{x})$

**Common in many applications:**

- **Medical diagnosis:** privileged info  $\sim$  results of expensive tests, patient history *after* initial diagnosis, genetic data etc.
- **Time series prediction:** privileged info  $\sim$  future values of the training time series

# LUPI and SVM+

## **SVM+ is a new learning technology for LUPI**

- **Improved prediction accuracy** (proven both theoretically and empirically)
- **Similar to learning with a human teacher:** ‘privileged info’ ~ feedback from an experienced teacher (can be very beneficial)
- **SVM+ is perhaps the most promising new method for ‘difficult’ problems**
- **Computationally complex:** no public domain software currently available

# Practical Concerns

- Availability of public-domain software
  - **YES** transduction, SSL, Universum, MTL
  - **NO** for SVM+ (LUPI)
- Methodological:  
new technologies require *understanding* of predictive methodology + application domain
- Model selection/ parameter tuning
  - very hard (typically 3-5 parameters)
- Practical advantages of these new methodologies *cannot be guaranteed*

# References and Resources

- Vapnik, V. *Estimation of Dependencies Based on Empirical Data. Empirical Inference Science: Afterword of 2006*, Springer, 2006
- Cherkassky, V. and F. Mulier, *Learning from Data*, second edition, Wiley, 2007
- Cherkassky, V. and Y. Ma, *Introduction to Predictive learning*, Springer, 2011 (to appear)

## Public-domain SVM software

- Main web page link <http://www.kernel-machines.org>
- LIBSVM software library <http://www.csie.ntu.edu.tw/~cjlin/libsvm/>
- SVM-Light software library <http://svmlight.joachims.org/>
- Non-standard SVM-based methodologies: Universum, SVM+, MTL [http://www.ece.umn.edu/users/cherkass/predictive\\_learning/](http://www.ece.umn.edu/users/cherkass/predictive_learning/)

# Short Course on Predictive Modeling

- Offered at ECE Dept, U of M
- Half-a-day course on June 1, 2011  
See course description at  
<http://www.ece.umn.edu/ECETECHTUNEUP.html>
- Course Contents:
  - Predictive data modeling methodology
  - Support Vector Machines (SVM)
  - Practical issues and application studies
  - Advanced SVM-based technologies