Data Mining:
Concepts and Techniques

(3rd ed.)

Classification & Clustering: Other Topics

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Classification & Clustering: Other Topics

- Additional Topics Regarding Classification
- Clustering Categorical Data
- Summary

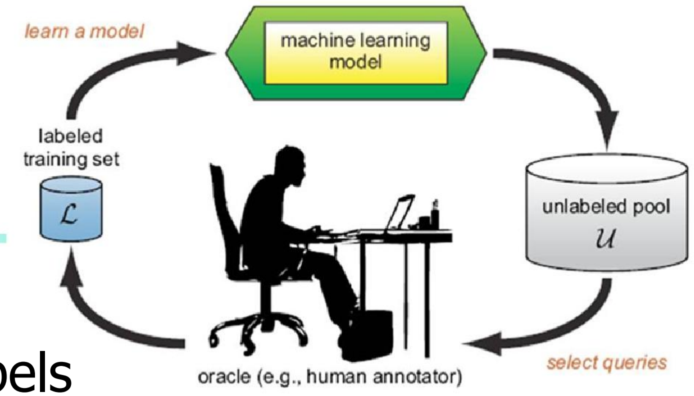
Multiclass Classification

- Classification involving more than two classes (i.e., > 2 Classes)
- Method 1. **One-vs.-all** (OVA): Learn a classifier one at a time
  - Given m classes, train m classifiers: one for each class
  - Classifier j: treat tuples in class j as *positive* & all others as *negative*
  - To classify a tuple **X**, the set of classifiers vote as an ensemble
- Method 2. **All-vs.-all** (AVA): Learn a classifier for each pair of classes
  - Given m classes, construct m(m-1)/2 binary classifiers
  - A classifier is trained using tuples of the two classes
  - To classify a tuple **X**, each classifier votes. X is assigned to the class with maximal vote
- Comparison
  - All-vs.-all tends to be superior to one-vs.-all
  - Problem: Binary classifier is sensitive to errors, and errors affect vote count

Semi-Supervised Classification

- Semi-supervised: Uses labeled and unlabeled data to build a classifier
- Self-training:
  - Build a classifier using the labeled data
  - Use it to label the unlabeled data, and those with the most confident label prediction are added to the set of labeled data
  - Repeat the above process
  - Adv: easy to understand; disadv: may reinforce errors
- Co-training: Use two or more classifiers to teach each other
  - Each learner uses a mutually independent set of features of each tuple to train a good classifier, say f_1
  - Then f_1 and f_2 are used to predict the class label for unlabeled data X
  - Teach each other: The tuple having the most confident prediction from f_1 is added to the set of labeled data for f_2, & vice versa
- Other methods, e.g., joint probability distribution of features and labels

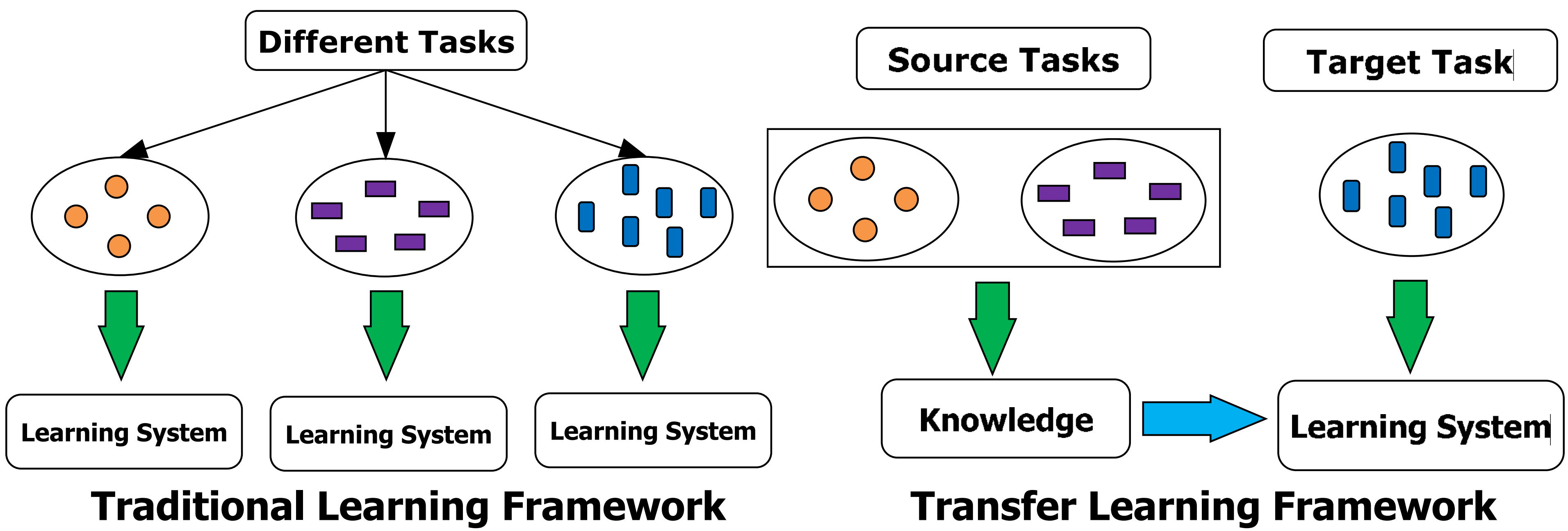
Active Learning



- Class labels are expensive to obtain
- Active learner: query human (oracle) for labels
- Pool-based approach: Uses a pool of unlabeled data
  - L: a small subset of D is labeled, U: a pool of unlabeled data in D
  - Use a query function to carefully select one or more tuples from U and request labels from an oracle (a human annotator)
  - The newly labeled samples are added to L, and learn a model
  - Goal: Achieve high accuracy using as few labeled data as possible
- Evaluated using *learning curves*: Accuracy as a function of the number of instances queried (# of tuples to be queried should be small)
- Research issue: How to choose the data tuples to be queried?
  - Uncertainty sampling: choose the least certain ones
  - Reduce *version space*, the subset of hypotheses consistent w. the training data
  - Reduce expected entropy over U: Find the greatest reduction in the total number of incorrect predictions

Transfer Learning: Conceptual Framework

- Transfer learning: Extract knowledge from one or more source tasks and apply the knowledge to a target task
- Traditional learning: Build a new classifier for each new task
- Transfer learning: Build new classifier by applying existing knowledge learned from source tasks



Transfer Learning: Methods and Applications

- Applications: Especially useful when data is outdated or distribution changes, e.g., Web document classification, e-mail spam filtering
- *Instance-based transfer learning*: Reweight some of the data from source tasks and use it to learn the target task
- TrAdaBoost (Transfer AdaBoost)
  - Assume source and target data each described by the same set of attributes (features) & class labels, but rather diff. distributions
  - Require only labeling a small amount of target data
  - Use source data in training: When a source tuple is misclassified, reduce the weight of such tupels so that they will have less effect on the subsequent classifier
- Research issues
  - Negative transfer: When it performs worse than no transfer at all
  - Heterogeneous transfer learning: Transfer knowledge from different feature space or multiple source domains
  - Large-scale transfer learning

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ROCK: Clustering Categorical Data

- ROCK: RObust Clustering using linKs
  - S. Guha, R. Rastogi & K. Shim, ICDE'99
- Major ideas
  - Use links to measure similarity/proximity
  - Not distance-based
- Algorithm: sampling-based clustering
  - Draw random sample
  - Cluster with links
  - Label data in disk
- Experiments
  - Congressional voting, mushroom data

Similarity Measure in ROCK

- Traditional measures for categorical data may not work well, e.g., Jaccard coefficient
- Example: Two groups (clusters) of transactions
  - C_1. <a, b, c, d, e>: {a, b, c}, {a, b, d}, {a, b, e}, {a, c, d}, {a, c, e}, {a, d, e}, {b, c, d}, {b, c, e}, {b, d, e}, {c, d, e}
  - C_2. <a, b, f, g>: {a, b, f}, {a, b, g}, {a, f, g}, {b, f, g}
- Jaccard co-efficient may lead to wrong clustering result
  - C_1: 0.2 ({a, b, c}, {b, d, e}} to 0.5 ({a, b, c}, {a, b, d})
  - C_1 & C_2: could be as high as 0.5 ({a, b, c}, {a, b, f})
- Jaccard co-efficient-based similarity function:

$$Sim(T_1, T_2) = \frac{|T_1 \cap T_2|}{|T_1 \cup T_2|}$$

  - Ex. Let T_1 = {a, b, c}, T_2 = {c, d, e}

$$Sim(T_1, T_2) = \frac{|\{c\}|}{|\{a, b, c, d, e\}|} = \frac{1}{5} = 0.2$$

Link Measure in ROCK

- Clusters
  - C_1:<a, b, c, d, e>: {a, b, c}, {a, b, d}, {a, b, e}, {a, c, d}, {a, c, e}, {a, d, e}, {b, c, d}, {b, c, e}, {b, d, e}, {c, d, e}
  - C_2: <a, b, f, g>: {a, b, f}, {a, b, g}, {a, f, g}, {b, f, g}
- Neighbors
  - Two transactions are neighbors if $sim(T_1,T_2) > threshold$ (here is to 0.5)
  - Let T_1 = {a, b, c}, T_2 = {c, d, e}, T_3 = {a, b, f}
    - T_1 connected to: {a,b,d}, {a,b,e}, {a,c,d}, {a,c,e}, {b,c,d}, {b,c,e}, {a,b,f}, {a,b,g}
    - T_2 connected to: {a,c,d}, {a,c,e}, {a,d,e}, {b,c,e}, {b,d,e}, {b,c,d}
    - T_3 connected to: {a,b,c}, {a,b,d}, {a,b,e}, {a,b,g}, {a,f,g}, {b,f,g}
- Link Similarity
  - Link similarity between two transactions is the # of common neighbors
  - link(T_1, T_2) *= 4, since they have 4 common neighbors*
    - {a, c, d}, {a, c, e}, {b, c, d}, {b, c, e}
  - link(T_1, T_3) *= 3, since they have 3 common neighbors*
    - {a, b, d}, {a, b, e}, {a, b, g}

Mushroom Data Set

- http://archive.ics.uci.edu/ml/datasets/Mushroom

- Number of Instances: 8124
- Number of Attributes: 22 (all nominally valued) including cap shape, cap color, odor, etc.
- Missing Attribute Values: 2480 of them (denoted by "?")
- Class Distribution:
  - edible: 4208 (51.8%)
  - poisonous: 3916 (48.2%)
  - total: 8124 instances

Clustering result for mushroom data

Traditional Hierarchical Algorithm					
Cluster No	No of Edible	No of Poisonous	Cluster No	No of Edible	No of Poisonous
1	666	478	11	120	144
2	283	318	12	128	140
3	201	188	13	144	163
4	164	227	14	198	163
5	194	125	15	131	211
6	207	150	16	201	156
7	233	238	17	151	140
8	181	139	18	190	122
9	135	78	19	175	150
10	172	217	20	168	206

ROCK					
Cluster No	No of Edible	No of Poisonous	Cluster No	No of Edible	No of Poisonous
1	96	0	12	48	0
2	0	256	13	0	288
3	704	0	14	192	0
4	96	0	15	32	72
5	768	0	16	0	1728
6	0	192	17	288	0
7	1728	0	18	0	8
8	0	32	19	192	0
9	0	1296	20	16	0
10	0	8	21	0	36
11	48	0			

ROCK threshold is 0.8

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Summary

- Other Classification methods
  - Multiclass classification
  - Semi-supervised classification
  - Active learning
  - Transfer learning
- Clustering Categorical Data