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Nov. 6th, 2006

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- 3 What is multitask Learning
- 4 Why multitask learning makes sense
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Current Machine Learning

Typical Classification Setting

- Given some labeled data, use some learning algorithm (kNN, SVM, Naïve Bayes Classifier, decision tree) to build a model.
- widely used for face recognition, object detection, text categorization
- But most learning methods fail when number of training examples are rare!!
- Each task is single-purposed.
- Can we achieve better if we have multiple related tasks?

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- Very few examples per task (person)
- Is it possible to achieve better result by borrowing strength from each other?

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Multiple Related Tasks

- Speech recognition for different speakers
- Character recognition for different writers
- Control a robot arm for different object grasping tasks
- Driving in different landscapes
- Text categorization of different corpus
- Natural Language Processing
- Computer Vision
- Concept Drift
- Collaborative Filtering
- Multi-class classification problem
- Spam filtering

- Multitask Learning: Given multiple related tasks, learn all tasks simultaneously.
- counterpart: single-task learning

- Similar concept: transfer learning(A.K.A inductive bias transfer, learning to learn, life-long learning)
- Transfer learning is incremental-oriented while multitask learning is batch-oriented.
- Transfer learning is more general than multitask learning (within-domain transfer, cross-domain transfer, lateral transfer, vertical transfer).
- Multitask Learning requires the same feature representation for all the tasks.

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Multitask Learning vs. Transfer Learning

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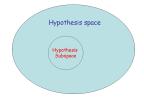
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Why multitask learning is better?

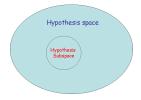
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- 3 Employ the data in all tasks, thus actually increasing the number of data

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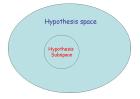
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Multitask Learning Approaches

- **1** MTL by sharing distance metric
- MTL by sharing common feature set
- MTL by sharing internal representation
- MTL by sharing priors
- MTL by sharing manifold in predictor space

A Toy Example

- Tasks: To recognize letter a written by three different people:
 Alice, Bob, and Caleb
- Each image provides three features:
 - O: whether there's a circle in the image
 - ∼: whether there's a tail
 - θ : whether the circle is cut into two parts.
- a decision function is adopted:

$$f(x) \begin{cases} > 0 & is \quad \mathbf{a} \\ < 0 & not \quad \mathbf{a} \end{cases}$$

MTL by sharing distance metric

- A distance metric is defined over all tasks.
- Objective goal: the data of the same class are close while those of different classes are far away.
- Map the original input space to another space and define a proper distance metric.
- For the toy example, we can define a distance as

$$dist(x, x') = ||g(x) - g(x')||_2$$

where $g(x) = w_1 O + w_2 \sim +w_3 O$

- Typical distance metric learning methods can be used.
- A classifier which employs the distance directly (kNN, kernel classifiers) is used.

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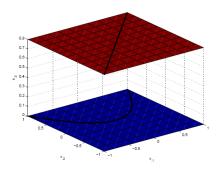
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MTL by sharing common feature set



- Optical character recognition of different people. Focusing on some common feature sets; avoid selecting too many specific features.
- Methods:
 - boosting methods to do greedy search
 - different forms of norm
 - assign an indicator variable for each feature

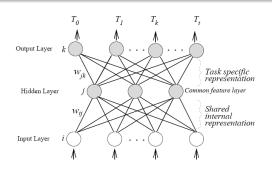
MTL by sharing internal representation

Sharing the internal features after mapping.

Alice:
$$f(x) = w_{A1}(0.80 + 0.9 \sim) + w_{A2}(0.400 - 0.5\theta)$$

Bob:
$$f(x) = w_{B1}(0.80 + 0.9 \sim) + w_{B2}(0.400 - 0.5\theta)$$

Caleb:
$$f(x) = w_{C1} \underbrace{(0.80 + 0.9 \sim)}_{F_1} + w_{C2} \underbrace{(0.400 - 0.5\theta)}_{F_2}$$



MTL by sharing priors

Alice: $0.7 \cdot O + 0.6 \cdot \sim -0.2 \cdot \theta$ Bob: $0.6 \cdot O + 0.8 \cdot \sim -0.4 \cdot \theta$ Caleb: $0.6 \cdot O + 0.7 \cdot \sim -0.3 \cdot \theta$

Method

Model the parameter of all tasks by some prior distribution(eg. $N(\mu, \Sigma)$), then μ , Σ are hyper-parameters shared across all tasks. To estimate hyper-parameters:

- Calculate the average and variance directly based on multiple tasks.
- ② Formulate the likelihood of data in all tasks; maximize it or (penalized likelihood) with respect to hyper-parameters. penalized likelihood = likelihood × prior(hyper-parameters)

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MTL by constructing manifold in predictor space

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One commonality shared by all the tasks is that

$$w_1 + w_2 - w_3 = 1.1$$

- Manifold actually represents a pattern in the predictor space.
- It can be a line, a curve, a hyperplane, a complicated manifold etc.
- Usually formulated as an optimization problem.
- Perform SVD in the predictor space; specify a required manifold etc.

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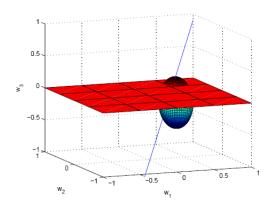
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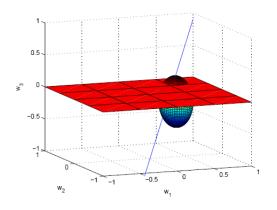
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Pros

- Improve classification accuracy (or some other similar measure) as a more reliable.
- 2 Improve learning speed.

- No general conclusion about approaches of MTL.
- Assumption: all the tasks are related. What if there are some unrelated tasks? unfortunately, dissimilar tasks might hurt the performance, the same as introducing noise.
- Existing methods treat all tasks equivalently, what if some tasks are more reliable? Need uneven task weighting.
- What if no related tasks are in hand? Generate automatically?
- Existing methods show that MTL improve performance mostly when data are scarce (Some papers just use 1-10 examples for training). What if I have 100, 200, 500, 1000, 1000, 1000000 data?

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Let's rock!!

Multitask learning is not new. Its original idea dated back to 1980s. But still lots of open problems.

