MULTI-TASK LEARNING FOR DISASTER IMAGE MINING

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OUTLINE

- Introduction
- Multitask Learning
- Feature transfer
- Study Case
- Summary


**Introduction**

- Multi-task learning offers the capabilities in learning features that are similar across classes (tasks).
- Quantified based on the similarity between the distributions that underlie these tasks.
- Improves performance relative to single task learning when the tasks are related.
- Also improves the learning of the tasks by shared models or representations.
- Goal is to achieve good feature representation for the target domain which can be transferred.
- The learning process aims to understand those features which are common, and those that will help in learning the specific tasks.
REMOTE SENSING APPLICATIONS

- Disaster scenarios
- Change detection studies
- Geospatial database updating
- Rapid response applications

For example, in a coastal disaster event, an ‘agriculture land’ could map into a ‘flooded agriculture land’. Here, the data distributions would be different, but the underlying concept is very similar.
**APPLICATION SCENARIO**

- In a coastal disaster, event such as a hurricane, floods, and other weather events, it is important to provide rapid response.

- Normal machine learning algorithms require a **good amount of training data** to develop a reasonable good classification model.

- Immediately after a disaster, the data are scarce, and only few samples are available to train the classification algorithms.

- To provide rapid response using maps updated by remote sensing imagery, there is a need to build models using small samples.

- Using **prior knowledge** in such a way as to enhance the learning of a new class proves to be very useful.
During a flood disaster, there is a lack of ground truth data, and also we have very small number of samples by which it is necessary to predict various classes (e.g. Flooded agriculture areas, flooded urban areas).

Can we predict a particular disaster affected area (Class) by understanding the composition of the various classes through which this affected area is related?
**Problem addressed**

- Paucity in ground truth during a natural disaster (flood) and the need to build models for new classes that arise during these events is addressed.

- Multi-task learning simultaneously learns different tasks and one can take advantage of closely related tasks in learning a new task.

*From a remote sensing perspective, knowledge learned from one region can be transferred to a spatially or temporally separated region whose spectral signature is different.*
Multi Task Learning

Learning
The prerequisite in traditional supervised and semi-supervised learning methods is that the training and the test data distribution and feature space should be the same. When the distribution changes the statistical models need to be rebuilt using newly collected training data.

Multitask learning
Transfer learning, learns from closely related tasks having similar or slightly different data distributions. This helps is some ways to mitigate the paucity in training data in learning a new class (e.g. flooded affected class). Multitask learning is one such method where different tasks are learnt simultaneously.
**Methodology**

- Transfer learning enables learning in closely related domains and can be achieved via
  - Instances
  - Features
  - Parameters

- Labeled data is available in the source domain, supervised methods are used to construct feature representations.

- This feature representation transfer is called multitask learning.

- In feature representation-transfer, “good” feature representations are found to minimize domain divergence and classification or regression model error.
Knowledge for transfer is represented by features (Sinno et al, 2010). Each task (class) has different features that are representative of the task.

The tasks when not related, feature transfer in learning actually induces a negative effect in learning.

The adapted method for this study is based on a convex multi-task generalization of the 1-norm single-task regularization. (Andreas et al, 2007)

Features and tasks are learned through the tasks' regression functions and by a low-dimensional representation for these task parameters. Different features in each task are learnt in this process and is called feature representation transfer.
The process is done by the following optimization problem

\[
\min \left\{ \sum_{t=1}^{T} \sum_{i=1}^{m} L(y_{ti}, \langle a_t | x_{ti} \rangle) + \gamma \|A\|_{2,1}^2 : A \in \mathbb{R}^{d \times T} \right\}
\]

The minimization function has matrix, 'A' having the regression entities 'a'. T, denotes the number of tasks and m the number of samples in each task. 'x_t' denotes a sample of dimension, d=10. outputs of task 'y' is a numeric identifier distinct to each class.

The minimization function,

- Learns few features that are common across multiple tasks
- Controls the number of common features learned by a regularization parameter, γ
- Error, across the tasks is measured according to a prescribed loss function L
## Case Study (Feature Transfer) Datasets

### Tasks Considered

<table>
<thead>
<tr>
<th>Task</th>
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<tbody>
<tr>
<td>Agriculture</td>
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<tr>
<td>Flooded agriculture</td>
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<tr>
<td>Barren lands</td>
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<tr>
<td>Water</td>
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<tr>
<td>Urban settlements</td>
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### Features Considered

<table>
<thead>
<tr>
<th>Feature</th>
<th>Type</th>
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<tbody>
<tr>
<td>Texture</td>
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<tr>
<td>Contrast</td>
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<tr>
<td>Angular second moment</td>
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<td>Maximum probability</td>
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<td>Correlation</td>
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<td>Saturation</td>
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<td>Value</td>
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### Datasets used

Earth Observing-1 (EO-1) satellite acquired pre-flood and post-flood Imageries for coastal flood event occurred in Thailand, 2011.
Figure 1 depicts the Pre- and Post-flood images showing Agriculture, Flooded agriculture, Barren lands, and Water which are nearly related tasks.

Urban settlements are unrelated when learning the task of Flooded agriculture.

Classes considered for this multi-task learning:
- Agriculture (231 samples)
- Flooded agriculture (91)
- Barren lands (158)
- Water (40)
- Urban settlements (58)

Number of features used: 10
RESULTS

Figure 2. Test error vs. Dimension ($\gamma = \{10^{-1}\}$) of the input tasks. Feature (Feat) learning by four tasks compared with Independent (Inde) learning (without feature transfer).

Figure 3. Test error vs. Dimension ($\gamma = \{10^{-1}\}$) of the input tasks. It shows the impact of the number of tasks simultaneously learned on the test performance as the number of features (dimensions) increases. The comparison is of feature transfer in both 4 tasks and 5 tasks case.
RESULTS

Figure 3. Quality of the learned features: Frobenius norm vs. Dimension of the input tasks.

- Four and five different tasks are used to learn *Flooded agriculture*
- Performance improvement in feature learning than that of Independent learning is observed.
- Illustrates the negative impact of the considered tasks
- Quality of features learned. This is further used to assess the number of features learned during the process of multi-task learning (Future work).
DISCUSSION

- Remote sensing based disaster management applications will benefit from Multi-task learning through which it is possible to transfer knowledge between multiple related tasks and perform simultaneous learning.

- Further study includes understanding the effect of the features considered and their impact on multi-task learning will be evaluated.

- More number of diverse tasks needs to be considered, and their interactions studied to provide a better assessment of the approach.

- The number of features and type of features involved in the transfer process will have to be identified.