

Urban Water Quality Prediction based on Multi-task Multi-view Learning



Ye Liu*, Yu Zheng**, Yuxuan Liang**, Shuming Liu***, David S. Rosenblum* *SoC@NUS, {liuye, david}@comp.nus.edu.sg,

** Urban Computing@Microsoft Research, {yuzheng,v-yuxlia}@microsoft.com

*** School of Environment@Tsinghua University, shumingliu@tsinghua.edu.cn



Methodology

Motivation

- **O** Urban water quality is of great importance to our daily lives.
- **O** Predicting the urban water quality plays an essential role in
 - Informs waterworks' decision making 0
 - Affects governments' policy making 0
 - **Provides maintenance suggestions** 0

Goal

O Predicting urban water quality from multi-sources urban data



O Multi-task Multi-view Learning

- > Multi-View: For each station, there are two views
 - ✦Spatial view: predictions based on its neighbors
 - ✦Temporal view: predictions based on its own history
 - ✦Alignment between two views

 $\|\mathbf{X}_{l}^{s}\mathbf{w}_{l}^{s} - \mathbf{X}_{l}^{t}\mathbf{w}_{l}^{t}\|_{2}^{2}$

→ Multi-Tasks:

The prediction at each station is a task All stations do the co-prediction Alignments among multiple tasks

$\sum C_{l,m} \|\mathbf{w}_l - \mathbf{w}_m\|_2^2$ l,m=1

Global Prediction

Local Prediction

Insight

Urban water quality is impacted by usage patterns and structure of pipes



Overview



$$\min_{\mathbf{W}} \quad \frac{1}{2} \sum_{l=1}^{M} \|\mathbf{y}_{l} - \frac{1}{2} \mathbf{X}_{l} \mathbf{w}_{l}\|_{2}^{2} + \lambda \sum_{l=1}^{M} \|\mathbf{X}_{l}^{s} \mathbf{w}_{l}^{s} - \mathbf{X}_{l}^{t} \mathbf{w}_{l}^{t}\|_{2}^{2}$$
$$+ \gamma \sum_{l,m=1}^{M} C_{l,m} \|\mathbf{w}_{l} - \mathbf{w}_{m}\|_{2}^{2} + \theta \|\mathbf{W}\|_{2,1},$$

Evaluations

Models	1 hour	2 hour	3 hour	4 hour
RC Decay Model	3.51 <i>e</i> -1	3.53 <i>e</i> -1	3.59e-1	3.68 <i>e</i> -1
ARMA	1.86 <i>e</i> -1	2.18 <i>e</i> -1	2.46e-1	2.78 <i>e</i> -1
LR	1.68 <i>e</i> -1	1.99 <i>e</i> -1	2.09 <i>e</i> -1	2.10 <i>e</i> -1
LASSO	1.23 <i>e</i> -1	1.42e-1	1.52e-1	1.56e-1
MRMTL	1.32 <i>e</i> -1	1.48 <i>e</i> -1	1.56e-1	1.58e-1
regMVMT	1.06 <i>e</i> -1	1.15 <i>e</i> -1	1.18 <i>e</i> -1	1.19 <i>e</i> -1
stMTMV	9.33e-2	9.66e-2	9.80e-2	9.90e-2



Performance comparison among various approaches



Model components comparison

