STAPLE: Spatio-Temporal Precursor Learning for Event Forecasting

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Introduction

Societal event detection can be modeled as a system of inter-connected locations, where each location is recording a set of time-dependent observations. In order to detect event occurrence and automatically reconstruct the precursors and signals, it is essential to model relationships between the different locations w.r.t. how events evolve over time.

We develop a novel multi-task model with dynamic graph constraints within a multi-instance learning framework. Our model tackles the problem of scarce data distribution and reinforces co-occurring location-specific precursors with augmented representations. Through studies on civil unrest movements in numerous countries, we demonstrate the effectiveness of the proposed method for precursor discovery and event forecasting.

Key contributions of this paper

- **Dynamic graph constraints** for precursor learning and event forecasting
- **Augmented representation learning** for precursors
- **Multi-task learning** for precursor mining
- **Comprehensive set of experiments in real-world data**

By taking advantage of spatio-temporal event correlations within a multi-task learning framework, when compared to the best state-of-the-art algorithm:

- 86% of cities have a higher F1 score
- 60% of cities have at least 20% improved F1 score

Formalisms

Objective function

\[
\min_{\theta, \hat{\theta}} \frac{1}{N} \sum_{k \in K} \frac{1}{N_{t_k}} \sum_{t_i \in t_k} L(y, \gamma_k \theta, \hat{\theta}) + \lambda_1 \frac{1}{2} \sum_{k \in K} ||\theta - \hat{\theta}||_2^2 + \lambda_2 \frac{1}{2} ||\theta||_2^2
\]

Here,

- \(k, l\) are the indices for cities,
- \(\theta_k\) is the model parameter for city \(k\),
- \(\hat{\theta}\) represents the global model,
- \(t_i\) is the time index for the current event indicator,
- \(\lambda_1, \lambda_2, \lambda_3\) are hyperparameters.
- \(\alpha_{kl}^t\) is the normalized weight on the edge between city \(k\) and city \(l\) at time \(t_i\), given by:

\[
\alpha_{kl}^t = \left( \frac{1}{\text{min}_{i \in t_k} \|E_k(x_i) - E_l(x_i)\|} \right)^\frac{1}{2} + \frac{1}{\text{dist}(k, l)}
\]

STAPLE: a multi-task spatio-temporal correlation graph model based on a two-level multi-instance learning (MIL) framework for precursor mining coupled with event forecasting. Multiple models for cities are jointly learned together and proven to be effective at both forecasting events and discovering precursors.

Conclusions

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