A Probabilistic Framework for Land Deformation Prediction (Student Abstract)

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Abstract

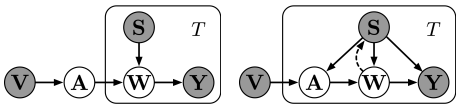
The development of InSAR (satellite Interferometric Synthetic Aperture Radar) enables accurate monitoring of land surface deformations, and has led to advances of deformation forecast for preventing landslide, which is one of the severe geological disasters. Despite the unparalleled success, existing spatio-temporal models typically make predictions on static adjacency relationships, simplifying the conditional dependencies and neglecting the distributions of variables. To overcome those limitations, we propose a Distribution Aware Probabilistic Framework (DAPF), which learns manifold embeddings while maintaining the distribution of deformations. We obtain a dynamic adjacency matrix upon which we approximate the true posterior while emphasizing the spatio-temporal characteristics. Experimental results on real-world dataset validate the superior performance of our method.

Introduction

Landslides are among the most common geological hazards, and can result in significant economic losses and casualties. They occur often because of heavy rain, rock erosion, or other natural disasters in mountainous area (Huang and Fan 2013). Monitoring deformations of the land surface is critical for preventing landslides and has gained great attention recently in both academia and industry (Zhou et al. 2021).

The prediction of land deformation is similar to most spatio-temporal tasks, such as traffic flow and trajectory prediction (Mohamed et al. 2020). It has been in the spotlight, especially with the recent advances in Graph Neural Networks (GNNs). Although prior studies have made significant improvements in modeling spatio-temporal data, existing models are still facing several challenges.

First, existing approaches lack a dynamic adjacency matrix and only catch static spatial interactions. However, the truth is that neighboring nodes may share similar temporal patterns, which can inform the trend of temporal features. Modeling temporal similarities between nodes allows obtaining a more informative adjacency matrix, thus better measuring the similarity between nodes. Second, most existing methods simplify the conditional dependencies, which inevitably cause information loss. Third, prior distributions of variables, i.e., node embeddings, are also ignored, resulting in an over-smoothing problem of GNNs (Zhao and Akoglu 2020). In a word, these methods are not fully exploited due to inadequate probabilistic modeling.



(a) Existing models (b) DAPF

Figure 1: Comparison of graphical models.

Methodology

Definitions: Denote N monitored locations as $\mathbf{V} \in \mathbb{R}^{N\times d}$, each with $d = 3$ coordinates (longitude, latitude, elevation). We consider the observed deformations as $\mathbf{S} \in \mathbb{R}^{N\times T}$, where T is the duration of the observation. In GNN-based models, we have adjacency matrix $\mathbf{A}$ and the aggregated spatio-temporal features $\mathbf{W} \in \mathbb{R}^{N\times M}$. Our task is to forecast deformations $\mathbf{Y} \in \mathbb{R}^{N\times T'}$ in future time periods T', defined as:

$$\begin{aligned} p(\mathbf{Y},\mathbf{W},\mathbf{A}|\mathbf{V},\mathbf{S}) &= p(\mathbf{A}|\mathbf{V},\mathbf{S})p(\mathbf{Y},\mathbf{W}|\mathbf{A},\mathbf{V},\mathbf{S}) \\ &= \underbrace{p(\mathbf{A}|\mathbf{V},\mathbf{S})}_{\textbf{Adjacency}}\underbrace{p(\mathbf{W}|\mathbf{A},\mathbf{V},\mathbf{S})}_{\textbf{GNN learning}}\underbrace{p(\mathbf{Y}|\mathbf{W},\mathbf{A},\mathbf{V},\mathbf{S})}_{\textbf{Prediction}}. \end{aligned} \tag{1}$$

As illustrated in Figure 1(a), there are many assumptions about conditional independence in the existing literature, i.e., $\mathbf{S} \perp\!\!\!\perp \mathbf{A}$ and $\mathbf{A},\mathbf{V},\mathbf{S} \perp\!\!\!\perp \mathbf{Y}|\mathbf{W}$, which all have the aforementioned drawbacks. In contrast, we argue that $\mathbf{S}$ is indispensable in learning adjacency relationships and making predictions, and Figure 1(b) presents the dependencies in our DAPF. In particular, we aim to learn dynamic embeddings and adjacency matrices conditioned on temporal features. Besides, we propose a variational framework to approximate the true posterior while learning the distributions of latent representations.

More specifically, $p(\mathbf{A}|\mathbf{V},\mathbf{S})$ in Eq.(1) consists of a normalizing flow (Kim et al. 2020) and a probabilistic adjacency matrix construction:

$$p(\mathbf{A}|\mathbf{V},\mathbf{S}) = \sum_{\mathbf{U}} p(\mathbf{A}|\mathbf{U})p(\mathbf{U}|\mathbf{V},\mathbf{S}), \tag{2}$$

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where $\mathbf{U}$ is the latent manifold embedding with a simple distribution. At a certain time step $\tau \in [1, T]$ on the i-th monitored location, a deterministic mapping $f(\mathbf{V}^\tau, \mathbf{S}^\tau | \mathbf{S}^\tau)$ transforms the coordinates $\mathbf{v}_i$ and deformations $\mathbf{s}_i^\tau$ to $\mathbf{u}_i^\tau$:

$$\log p(\mathbf{v}_i + \mathbf{s}_i^\tau) = \log p(\mathbf{u}_i^\tau) - \log \left| \det \frac{\partial f^{-1}(\mathbf{u}_i^\tau | \mathbf{s}_i^\tau)}{\partial \mathbf{u}_i^\tau} \right|. \tag{3}$$

Then, for any two points with learned embeddings $\mathbf{u}_i$ and $\mathbf{u}_j$, the mapping $p(\mathbf{A}|\mathbf{U})$ can be directly computed as:

$$p(A_{ij}^\tau = 0 | \mathbf{u}_i^\tau, \mathbf{u}_j^\tau) = \text{sigmoid}(\|\mathbf{u}_i^\tau - \mathbf{u}_j^\tau\|_2), \tag{4}$$

where $A_{ij}^\tau \in \mathbf{A}^\tau$, and the similarity between two points is estimated by a distance in the manifold space.

Let $\boldsymbol{\Omega} = \{\mathbf{A}, \mathbf{V}, \mathbf{S}\}$ for simplicity, the $p(\mathbf{Y}, \mathbf{W}|\boldsymbol{\Omega})$ in Eq.(1) is approximated by $q(\mathbf{Y}, \mathbf{W}|\boldsymbol{\Omega})$ and the variational inference of the true posterior can be derived as follows:

$$\begin{aligned} & D_{\text{KL}}\left(q(\mathbf{Y}, \mathbf{W}|\boldsymbol{\Omega}) \| p(\mathbf{Y}, \mathbf{W}|\boldsymbol{\Omega})\right) \\ =& D_{\text{KL}}\left(q_\varphi \| p(\mathbf{W}|\boldsymbol{\Omega})\right) + D_{\text{KL}}\left(q_\phi \| p(\mathbf{Y}|\mathbf{W}, \boldsymbol{\Omega})\right) \\ \simeq& D_{\text{KL}}\left(q_\varphi \| p(\mathbf{W})\right) - \mathbb{E}_{q_\varphi}[\log p(\mathbf{A}, \mathbf{S}|\mathbf{W})] \\ & - H[q_\phi(\mathbf{Y}|\mathbf{W}, \mathbf{S})] - \mathbb{E}_{q_\phi}[\log p(\mathbf{Y})], \end{aligned} \tag{5}$$

where D_{KL} is the KL-divergence and H is the entropy, φ and ϕ are parameters of $q(\mathbf{W}|\boldsymbol{\Omega})$ and $q(\mathbf{Y}|\mathbf{W}, \boldsymbol{\Omega})$ respectively, and denoted as q_φ and q_ϕ for simplicity. With Eq.(5), the distributions of $p(\mathbf{W})$ and $p(\mathbf{Y})$ are constrained.

In practice, the densities must be easily obtained, therefore we specify q_φ as a variational graph auto-encoder (Kipf and Welling 2016), and q_ϕ as a dynamic system of $\mathbf{W}^\tau$ and $\mathbf{S}^\tau$, which can be solved by ordinary differentiable equations (Grathwohl et al. 2018). Finally, the model is optimized by minimizing the bound Eq.(5) and the mean square error (MSE) between the predicted and true deformations.

Experiments

Dataset: We conduct experiments on real-world InSAR data of slopes in a large-scale hydropower station Pubugou Dam[1] in the southwest of China. There are 8,671 monitored locations, each has deformation observations spanning from Nov 17, 2017 to Jan 04, 2020, and the range of displacements is [-29.06, 30.50] (mm).

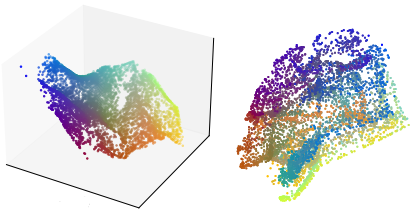
Performance Comparison: We report the results of different methods on deformation prediction in Table 1. The first group of approaches is time-series based, and the second group is spatio-temporal based. Obviously, the second group achieves better performance because of modeling spatio-temporal dependencies critical for deformation prediction. Besides, DAPF achieves significant improvements over the baselines. These results verify our motivation to construct a dynamic adjacency matrix and emphasize the importance of distribution learning in prediction.

Figure 2 plots the learned 2D embeddings via Eq.(3), colored by geographical coordinates. It tells us that DAPF can obtain clustered embeddings successfully.

[1]https://en.wikipedia.org/wiki/Pubugou_Dam.

Method	RMSE	MAE	ACC	EVS
Historical Average	6.067	4.010	0.050	0.164
GRU	0.200	0.160	0.540	0.137
(Chen et al. 2018)	0.053	0.041	0.710	0.412
(Wu et al. 2020)	0.041	0.027	0.854	0.426
(Zhou et al. 2021)	0.024	0.018	0.956	0.478
DAPF	**0.016**	**0.013**	**0.978**	**0.496**

Table 1: Overall performance comparisons.



(a) Original surface (b) DAPF

Figure 2: Visualization of surface and manifold embedding.

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