Resolving the Bias in Electronic Medical Records

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INTRODUCTION

Electronic Medical Records (EMR Data)

Bias in EMR Data
- Patients tend to visit hospital more often when they feel sick
- Doctors tend to prescribe the lab examinations that show abnormality

METHODOLOGY

EMR Regularization

Inspiration
- EMR Series $\Psi$ is not a randomly sampled subset of Patients’ Hidden Conditions $\Phi$
- Probability that one tuple $<p, t, d, v>$ (p: patient, t: time point, d: feature, v: value) is observed may depend on the medical feature and its value

Target of our work
- Estimate the unobserved hidden conditions $\Phi - \Psi$ using EMR series $\Psi$

Characteristics of Medical Features

Condition Change Rate (CCR)
- How a medical feature is likely to change from its condition in the previous observation

Observation Rate (OR)
- Probability that a medical feature is exposed at a time point based on its actual condition at that time point

A Hidden Markov Model (HMM) Variant for Learning and Inference

Algorithm 1: EMR regularization with smoothing

Input: medical features $\Omega_d$, observations sequences $O_{d} = \{O_{d1}, O_{d2}, \ldots, O_{dN}\}$ for each feature $d$ and for each sequence $s$. $A(s)$ is prior for feature $d$ is Beta$(A_{dp}, B_{dp})$. It’s prior for feature $d$ is Beta$(A_{dp}, B_{dp})$

Output: parameters $\lambda = \{\alpha_{dp}, \beta_{dp}, \theta_{dp}\}$ for each feature $d$ of $\omega_d$, hidden state probability sequence $P_{d} = \{p_{d1}, p_{d2}, \ldots, p_{dN}\}$

1. For each medical feature $d$ of $\omega_d$
2. Initialize $\lambda = \{\alpha_{dp}, \beta_{dp}, \theta_{dp}\}$
3. Iterate $\lambda$ until convergence
4. E-Step:
5. For each observation sequence $s$ of $O_{d}$
6. Compute $q_{d}^{(s)} = \frac{1}{\gamma_{d}^{(s)}}$ (Equation 8)
7. Compute $\gamma_{d}^{(s)} = \sum_{s} q_{d}^{(s)}$ (Equation 9)
8. M-Step:
9. Update $\theta_{dp}$ (Equation 7)
10. Update transition matrix $A_{dp}$ (Equation 6)
11. Update emission matrix $B_{dp}$ (Equation 7)
12. Compute $P_{d} = \frac{1}{\gamma_{d}^{(s)}} \phi_{dp}$ (Equation 8)
13. Return $P_{d} = \{p_{d1}, p_{d2}, \ldots, p_{dN}\}$

EXPERIMENTS

Imputation Accuracy Evaluation

Imputation accuracy evaluation results in two datasets

Benefits for Analytical Tasks

Analytical applications:
- In-hospital mortality
- Diagnosis by category
- Disease progression modelling

CONCLUSION AND FUTURE WORK

EMR Regularization to Resolve Bias
- Consider CCR and OR as characteristics of medical features
- Employ an HMM variant for learning and inference
- Impute missing values in EMR data more accurately
- Improve the analytical performance after resolving the bias

Future Directions
- Model different diseases jointly in the probabilistic graphical model for capturing the relationships in between
- Model the patient personalization as different patients might behave differently in terms of CCR and OR

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