Application of Random Forests and Deep Neural Networks to Survival Data

STAT-6494 Project Proposal

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Abstract

The classical survival models, such as Cox proportional hazard model, often require extensive efforts on variable selection or prior medical information to model interaction between patients' covariates and treatment covariates. While nonlinear models, such as neural networks and random forests, are able to model high-order interaction terms. It is of interest to apply these machine learning methods to survival data and compare their performance with classical statistical models.

Keywords: Cox Model, Machine Learning, Suicide Prevention

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1 Introduction and Objects

For survival data, medical researchers' interests often lie in discovery of significant treatment effects and important diagnosis covariates of patients. The classical survival models, such as Cox proportional hazard model, assume risk function in a simple linear form of covariates, which can be too simplistic to capture the underlying relationship between response and covariates. In addition, they often require extensive efforts on variable selection or prior medical information to model interaction between patients' covariates and treatment covariates. While nonlinear models, such as neural networks and random forests, are able to model high-order interaction terms. It is of interest to apply these machine learning methods to survival data and compare their performance with classical statistical models. It would be even more interesting to discover nonlinear relationship by machine learning methods and build a statistical model for better interpretation and capability for statistical inferences.

The specific objectives include:

- Explore and review existing machine methods for survival data including random forests and deep neural networks.
- Apply these methods for CT suicidal data.
- Compare the out-of-sample model fitting or prediction performance of these methods with classical survival models, such as Cox model.

2 Random Forests for Survival Data

Main reference includes

- Ishwaran et al. (2008)
- Mogensen et al. (2012)

3 Deep Neural Networks for Survival Data

Main reference includes

- Katzman et al. (2016)
- Nair and Hinton (2010)
- Ioffe and Szegedy (2015)
- Klambauer et al. (2017)
- Srivastava et al. (2014)
- Kingma and Ba (2014)
- Nesterov (2013)
- Pascanu et al. (2012)

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