Learning to rank for uplift modeling and heterogeneous treatment effect estimation

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The purpose of machine learning often is selecting targets for some action such as a medical treatment or a promotional campaign. Typical applications include personalized or precision medicine and direct marketing optimization. Unfortunately, classical machine learning is not suitable for the task since it is unable to determine the true effect of the action. The reason is that it does not take into account what would happen has the action not been taken. A solution to this problem is including a second training dataset containing the control group which has not been subjected to the action. The goal is to build a model which predicts the difference between behaviors of individuals subjected and not subjected to the action: that is the true benefit from performing it. Such approaches have been known as **uplift modeling** or **heterogeneous treatment effect estimation**.

While most classical machine learning models have been adapted to uplift modeling [2, 3], there are several areas which have not been addressed. One of them is **learning to rank**. Machine learning models are typically used to rank potential targets (patients, customers) by predicted probability of success. Learning to rank allows for directly learning the correct ordering of cases instead of learning some score by which they can be sorted [1]. Since most uplift modeling methods are used to select best targets for an action, adapting learning to rank methodology to uplift modeling is important from an application point of view.

Other possible research topics include developing learning theory for uplift modeling or designing more advanced uplift tree and ensemble methods.

References

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