Direct and Indirect Approaches to Finding Optimal Dynamic Treatment Regimes

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Dynamic regimes are employed when decisions have to be made reactively as data becomes available though time. As an example consider the problem of dosage selection for any of the two million European patients who are provided with long term anticoagulation. Optimal dose does not just vary between patients, it varies within patients over time in response to short-term changes in lifetsyle or diet. At a clinic visit at timepoint t_j the physician needs to review the state S_j of the patient and then make a decision as to what what action A_j, is needed, such as what dose to prescribe. We assume that the goal of the actions/treatments is to maximise some final quantity Y, which depends stochastically on the sequence of states and actions $\{S_1, A_1, \ldots, S_K, A_K\}$.

Dynamic programming methodology provides the traditional approach to determining decision rules to optimise Y. This requires a model of the consequences which an action at t_j will have on both the final value Y and all interim states S_k $(k > j)$. This is a *direct* approach. However, there are many computational problems unless there are only low numbers of possible states and actions. An alternative approach, designed to be applicable to complex observational data, is to avoid modelling the direct consquences of an action but instead to take an assumed parametric form for the *difference* in expected final outcomes Y given two possible decisions. Thus the model does not anticipate $E[Y|S_1, A_1, \ldots, S_j, A_j]$ directly but instead provides information on the *change* in this quantity should A_j be changed to some other action A_j^* say. Modelling and estimation under such an *indirect* approach is described clearly in [1].

Both approaches rely heavily on the accuracy of the assumed models. In this presentation we investigate sensitivity to model misspecification and demonstrate how relatively minor error can propagate in determining optimal allocations. We consider how robustness can be improved and argue that in realistic applications myopic strategies are likely to perform well. The ideas are illustrated through an analysis of data from 303 patients on maintenance anticoagulation therapy [2].

References

[1] Moodie, E. E. M., Richardson, T. S., and Stephens, D. A. (2007) Demystifying optimal dynamic treatment regimes. Biometrics, 63:447-455

[2] Rosthøj, S., Fullwood C., Henderson, R. and Stewart, S. (2006). Estimation of optimal dynamic anticoagulation regimes from observational data: a regret-based approach. Statistics in Medicine, 25, 4197-4215