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Fast Approximate Bayesian Contextual Cold Start Learning (FAB-COST)

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Abstract : Cold-start is a notoriously difficult problem which can occur in recommendation systems, and arises when there is insufficient information to draw inferences for users or items. To address this challenge, a contextual bandit algorithm – the Fast Approximate Bayesian Contextual Cold Start Learning algorithm (FAB-COST) – is proposed, which is designed to provide improved accuracy compared to the traditionally used Laplace approximation in the logistic contextual bandit, while controlling both algorithmic complexity and computational cost. To this end, FAB-COST uses a combination of two moment projection variational methods: Expectation Propagation (EP), which performs well at the cold start, but becomes slow as the amount of data increases; and Assumed Density Filtering (ADF), which has slower growth of computational cost with data size but requires more data to obtain an acceptable level of accuracy. By switching from EP to ADF when the dataset becomes large, it is able to exploit their complementary strengths. The empirical justification for FAB-COST is presented, and systematically compared to other approaches on simulated data. In a benchmark against the Laplace approximation on real data consisting of over 670, 000 impressions from autotrader.co.uk, FAB-COST demonstrates at one point increase of over 16% in user clicks. On the basis of these results, it is argued that FAB-COST is likely to be an attractive approach to cold-start recommendation systems in a variety of contexts.

Keywords : cold-start learning, expectation propagation, multi-armed bandits, Thompson Sampling, variational inference
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