BT users are targeted in individual level. Tyler et.al. [19] solve audience selection as a ranked retrieval problem. Fuxman et. al. [10] present an audience selection method that focuses on modeling user interests to infer targeting. Archak et.al. [4] describe ad factors based aggregation of user information that the advertiser can use to extract deeper insights about the effects of their ads. Bilenko et. al. [5] present a user personalized advertising model that build a user profile under the user's privacy control. Provost et. al. [18] suggest extracting quasi-social networks from browser behavior on user-generated content sites, to find good audiences for brand advertising. Kanagal et.al. [13] propose a focused matrix factorization model to learn user preferences towards specific campaign products, while also exploiting information about related products. Also, Aly et. al. [3] build a web-scale user modeling platform for optimizing display advertising targeting. Finally, Grbovich et. al. identify users to target based on advertisers expectation about user behavior using (manually defined rules [11].

Research on reputation systems is related to our work, as we build a reputation system for advertisers, and we derive reliability scores for users. In reputation systems, several works propose systems that represent the quality of the involved parts and methods to compute reputation scores along with bias. In [8] and [9], Daltayanni et. al. propose WorkerRank, a reputation system to score workers and employers in an online labor marketplace. This work is also based on bipartite relations, similar to the approach in the current study. Auto-segmentation is one case of reputation systems in two-sided marketplaces as described in[7]. In [15], Kokkodis et. al. address data sparseness in building reputation systems in labor marketplaces. In [20], Weng et. al. build reputation scores such that they represent an influence measure for Twitter users. In [6], Chen et. al. discuss how to de-bias reputation in a comments rating environment. Finally, the works of Adler et. al. in [1] and [2] study reputation in the Wikipedia environment and they achieve to measure the quality of contributions.

6 CONCLUSIONS

Audience selection is a hard problem that advertisers do not have good enough data to solve; the available user behavior data is too large and sparse and there are not enough informative signals to use in order to constrain the user space and select the best users suitable for a campaign. In this study, we showed how a DSP that has data from many advertisers and users can help advertisers solve the above problem. We proposed Auto-Segmentation, a novel approach to combine the signals that we take from users and advertisers, and to use them within the context of a reputation system to automate user segmentation. We showed experimentally how to use auto-segmentation for audience selection; first, we showed the contribution in recommending optimal conversion segments to new advertisers, improving the performance for new campaigns that face the cold start problem by $40 - 450\%$. Second, we showed how the recommended segments can replace existing ones, contributing to refining the advertisers' campaigns and achieving better conversion rates. In future research, we would explore using advertiser targeting decisions as signals in bidding optimization.

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