The role of geography in the complex diffusion of innovations

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Collective behaviour, like massive adoption of new technologies or their quitting (also called "churn" in business), are social contagion phenomena and as such they are complex [1]. Individuals are influenced in their decision, both by media and by their social ties. This feature was first modelled in the 60s with the Bass model of innovation diffusion [2]. The differential equations of the Bass model have been extensively used to describe diffusion process and forecast market size of new products and the peaks of their adoption. Only in the last two decades, the importance of the social network structure has become increasingly clear in the mechanism of peers' influence. Complex contagion models, in which adoption depends on the ratio of the adopting neighbours, have been efficiently applied to characterize diffusion of on-line behaviour and on-line innovations [3]. In this work we analyse the spatial dimension of the complex contagion dynamic, using ten years of a large scale online social network (OSN). We analyse adaption dynamics of iWiW a social media platform that used to be popular in Hungary over its full life cycle (2002-2012). IWiW reached up to 300 million friendships at the peak of its popularity and subsequently disappeared after its failed competition with international OSN platforms.

This allows us to systematically measure spatial diffusion and uncover relevant empirical features of the contagion dynamics. The data also allows us to explore the opposite spatial process of quitting, or churning the product [4]. Recent studies have shown that in such cases the contagious mechanism of churn is similar to the one of diffusion [5]. While it has been argued in early works on innovation diffusion that social contagion occurs first between two large settlements located at large distances and then becomes more local reaching smaller towns and short distance paths [6]; how churn happens in geographical space is unknown.

We find empirical evidence that diffusion as well as churn start across distant big cities and become more local over time as adoption and quitting reach small towns in different time-scales. Taking towns as isolated systems, the Bass model describes adoption dynamics, while churn scales exponentially over time. To study the spatial characteristics of complex contagion, we develop a Bass ABM of new technology's adoption preserving the community structure and geographical features of connections within and across towns. This exercise allows us to measure how spatial interaction and similarity of peers in terms of adoption tendency in towns influence local diffusion dynamics [7].

We disentangle the superlinear relation of Innovators and Early Adopters as a function of the town population. This highlights the importance of urban settlements in the adoption of innovations [8]. In early stages of the life-cycle, complex contagion is likely to occur across distant peers [9]. By combining complex diffusion with empirical scaling from urban science, we proposed a modelling framework that corresponds with the early notion of Haegerstrand [6]. Adoption peaks initially in large towns and then diffuses to smaller settlements.

Our work contributes to the recent discussion on the increasing urban-rural divide in modern societies that influences economic- and social inequality, and political radicalization. These observed trends are deeply rooted in the spatial patterns of society, and require geographical extensions in network models of social influence. Better understanding how new technologies and new ideas diffuse across locations will provide us with new insights into information spreading, technological progress and economic development. With aforementioned empirical findings, we enrich standard models of complex diffusion by introducing novel features that depend on geography.

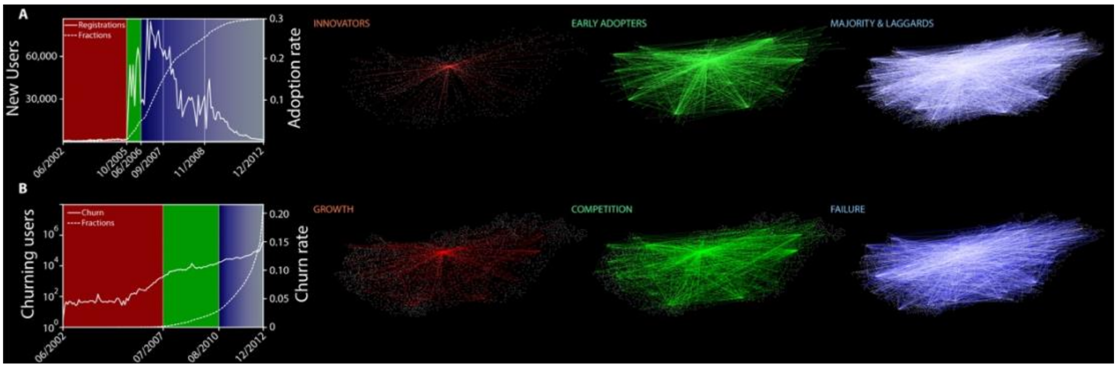

Figure 1: Adoption and churn in the OSN. A. Number of new users and the cumulative fraction of registered individuals among total population over the OSN life cycle. Spatial networks depict the number of invitations sent between locations over the corresponding periods of the OSN life cycle. B. Number of churning users and the cumulative fraction of churned individuals among total population over the OSN life cycle. Spatial networks depict the number of social ties of churning users between locations over the corresponding periods.

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