The growth of Web3 techno-social systems through graph evolution rules

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In recent years, novel paradigms that contrast the over-centralization of the current Web 2.0 are emerging. In this context, Web3 is a trending idea, based on blockchain technologies. From a researcher's point of view, Web3 services are resourceful because they offer publicly available, validated, temporal data that can be accessed through a blockchain interface. Blockchain Online Social Networks (BOSNs) are an example of platforms belonging to the Web3 ecosystem; they represent complex systems that include both social and financial dimensions. Non-fungible tokens (NFTs) are another example of Web3 service; they are data units that guarantee a unique certificate of ownership for a digital object together with a digital asset's uniqueness and non-transferability.

Given the complexity of such techno-social systems, it is essential to study how they evolve over time, to get deeper insights into their internal growth mechanisms. In the literature, there exist many models and measures that describe network growth by observing the link formation process, such as preferential attachment, homophily, and triadic closure. However, network evolution, especially in the Web3 context, cannot be explained by a single a-priori mechanism. More realistic models might adopt a mesoscopic approach, observing how small frequent subgraphs evolve.

Methodology A valuable option is graph evolution rules mining, a frequency-based method for evaluating network evolution. A graph evolution rule (GER), inspired by the association rules concept, is composed of a precondition - body- and a postcondition - head, suggesting that a subgraph matching the body frequently evolves into the head. Among the method for GER mining proposed in the literature ([1, 2, 3]), we focus on the method developed by Scharwächter *et al.*, named EvoMine, because it is one of the most recent ones, it allows the detection of edge deletion/relabeling, and it proposed a novel support metric, namely*event support*. In this work, we describe the evolution of several Web3 services, offering readable results and a way to compare how two o more temporal networks evolve.

Datasets We apply the EvoMine method to different Web3 platforms: Steemit, one of the most popular BOSN and a collection of NFT sales transactions. Specifically, we model both datasets as multilayer networks. In the Steemit case, layers correspond to transfer or social operations realized in a 3 months period. As regards the NFT sales dataset [4], we focus on trades made on two popular markets in a 50-days period: Cryptokitties and OpenSea. Since each graph presents its own features, we apply the GER mining method to each layer separately.

Results The starting point for analyzing the evolution of networks is the *GER profile*, a vector that defines a distribution over the different kinds of evolution rules found on one graph. Basically, each element of the vector represents the relative frequency of a specific rule over the graph, obtained through the event support measure. Note that we first identify all temporal subgraph isomorphism classes of the results, then compute the vectors, accordingly. The GER profile contributes to understanding the evolution of a graph in two directions: *(i)* by computing an appropriate distance measure between vectors, we are able to measure if two networks evolve in a similar way, and *ii* looking at the values, we can identify sets of GERs that might have a stronger impact on the graph evolution. Fig. 1 shows the GER profiles for all the four graphs in analysis. We investigate the specific rule types, to explain why the GER profiles have points with evident differences. An aspect of Web3 platforms that emerges is some evolution rules are common in all platforms, regardless of the system specificity. For instance, GERs that present an expanding behavior of nodes are frequent in all graphs. On the other hand, in some cases, the frequency of graph evolution rules is influenced by the nature of the platform. The cryptokitties case - the NFT trading network where only kitties NFTs are exchanged - offers an example because rules based on the triadic closure process are not present.

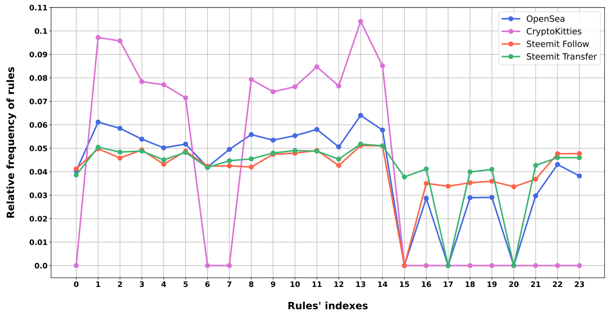

Fig. 1. GER profiles

Conclusions Results suggest that the GER profile is a good starting point to get insights into the evolutionary behavior of a network. We are going to use the vectors as starting point to define a classification of graph evolution rules. The classification will provide a topological and semantic interpretation of patterns, that will be essential to understand the evolutionary mechanisms that rule a network.

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