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# **Influence Model Based on Actions and Reactions in Social Networks**

- Technical Report -

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# Technical Report: Influence Model Based on Actions and Reactions in Social Networks

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**Abstract**—Today’s social networks allow users to react to new contents such as images, posts and messages in numerous ways. For example, a user, impressed by another user’s post, might react to it by liking it and then sharing it forward to her friends. Therefore, a successful estimation of the influence between users requires models to be expressive enough to fully describe various reactions. In this article, we aim to utilize those direct reactive activities, in order to calculate users impact on others. Hence, we propose a flexible method that considers type, quality, quantity and time of reactions and, as a result, the method assesses the influence dependencies within the social network. The experiments conducted using two different real-world datasets of Facebook and Pinterest show the adequacy and flexibility of the proposed model, that is adaptive to data having different features.

**Index Terms**—influence, social scoring, social network analysis

## I. INTRODUCTION

Nowadays, due to the increasing number of people using social network sites, the number of careers created using networking sites such as Youtube has risen as well. The majority of such businesses made via social networking are involved with creators generating content for their audiences, i.e. youtubers, bloggers, instagrammers, earning fame and influence, as well as revenue from advertisement. However, one of the concerns of both creators and advertising companies that collaborate with Internet creators is how to measure, prove and sustain their influence on audiences. To illustrate the problem, let us consider the network that consists of different users - proactive and reactive ones, having different interests, and having various numbers of connections to others. Now, we want to target the social campaign to people, using limited resources. The question is how to select creators to share the event, which not only have (possibly large) audiences, but also the audience that would be involved in the campaign?

The topic of *Influence Maximization* [4] is not new in the literature, however, the proposed methods focus more on the spread of the information in the network already assumed to be indicating influence. Hence, such works suppose to have users influencing others, basing on "friend" relations on Facebook, sharing posts or even calling each other. While these approaches focus on expanding the reach of information within the network (i.e. the possibility of user *seeing* some content), none of them actually guarantees that we have actual influence

between users (that is engaging with the message). However, while only the pairwise relation between two users seems to be insufficient to immediately implicate the impact, analyzing and evaluating the engagement and reactions concerning a particular user seem to be good basis for evaluating the influence.

In this paper, we present a simple, general model, which we called ARIM (Action-Reaction Influence Model), for evaluating influence between users using one (any) on-line social network platform. In the model, we base on the users’ proactive and reactive behaviors, that can be found on basically any social networking site. We concentrate on data flexibility aspect of the model, so that the model can be used with different datasets. Our focus is to create a model which uses data features that are possible to obtain for research, and in which each of the properties is connected to its overall expressiveness. Our contributions are as follows:

- We analyze characteristics of different social network sites, establish the key influence-related terms and present the simple social network sites interactions schema (Section II),
- We propose a simple, general influence model ARIM, that focuses on three influence aspects important for model expressiveness namely *intensity* of users’ reactions, *spread* and *audience engagement* differentiation and *time dependency* (Sections II and III),
- We additionally propose a submodel based on ARIM, that is focused on trends in time intervals, called Inic – **Interval Specific SubModel** (Section IV),
- We built a framework based on the proposed models and test it using two real-world datasets, that allow us to validate the two models (Section V).

## II. DESCRIPTION OF ACTION-REACTION INFLUENCE MODEL

In this section, we firstly define the basic notions and the core of our idea. Then, we describe three components of ARIM model and explain their importance for the model expressiveness.

### A. Definitions

The aim of this work is to create a general model for evaluating influence, that is independent of the data platform

on which it is applied on. On top of that, we focus on the simplicity of the model on both abstraction and data levels, for two reasons: to be compatible with the intuitive understanding of influence, and to be able to operate on the minimum features expressive enough to evaluate influence.

We define the influence from the perspective of Actions and Reactions on social network sites, which goes with intuitive understanding of influence, and the way we tend to evaluate influence in real world. The core of the **Action-Reaction Influence Model (ARIM)** consists in the simple schema of information exchange on social network sites, depicted in Fig. 1. We base on the situation in which one user is performing an Action by generating the content, i.e. posting photo or post. The second user, being (a part of) audience, is performing Reaction<sup>1</sup>) to the content. We follow the categorization of the relation from social networks that distinguishes upvotes, comments, etc. (see Section II-B). We aim to measure the influence between Action generating user – the Subject of Influence – and the reacting user – the Object of Influence. In the following, we formally define the notions of influencer, reaction and the influence starting with a social network:

**Definition 1: Action:** An entity  $e \in E$  such as a person (user), a group of people (e.g. company) or an object (content, conference, etc.) performs an action  $a \in A$  such as posting, photo-sharing etc.

**Definition 2: Reaction:** An entity  $e_1 \in E$  can react to an action  $a \in A$  performed by other entity  $e_2 \in E$

**Definition 3: Social Network:** A social network  $SN$  is a triple  $SN \langle E, A, R \rangle$  where  $E$  is a set of entities,  $A$  is a set of actions performed by entities from  $E$ , and  $R$  is a set of reactions of entities from  $E$

**Definition 4: Influencer:** We say that  $e_1 \in E$  is an Influencer iff:

- 1)  $e_1$  performs actions  $A' \subseteq A$  observable in  $SN$
- 2) Actions from  $A'$  are recognized by other entities  $e_{i \geq 2}$  using reactions from  $R$
- 3) Actions from  $A'$  have an impact on the behavior or structure of  $SN$ .

**Definition 5: Influence:** Let  $e_1, e_2 \in E$  from  $SN \langle E, A, R \rangle$ . We say that  $e_1$  influences  $e_2$  iff actions  $A' \subset A$  performed by  $e_1$  affects the behavior of  $e_2$  resulting in the influenced entity  $e_2$  engagement demonstrated in reciprocal actions–reactions  $R' \subset R$ .  $e_1$  is then called the subject of influence and  $e_2$  the object of influence.

**Proposition:** The relation of influence is asymmetric, time-dependent and oriented. It involves actions generating content (proactive) and reactions (reacting on content).

**Remark:** Importantly, we do not assume that the Subject and Object of Influence have a relation between each other, i.e. follow, friendship, etc. Obviously, the actions of the Subject of Influence must be visible by the Object of Influence in order to the Object to be able to react. However, this assumption

<sup>1</sup>In the Action-Reaction schema, we refer to an Action as a self-activity of user  $u$ , while Reactions symbolize activities overtaken by other users in response to the user  $u$  Action.

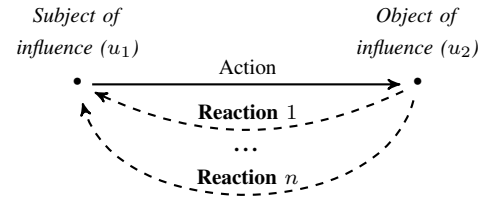


Fig. 1. The Action-Reaction schema. Subject generates content visible to the Object who reacts to the content, possibly by using multiple types of reactions several times.

implies only the visibility of the actions performed by the Subject, and represents more flexible approach in terms of the data requirements and applicability to various social network platforms without a notion of direct relation between users.

The presented general influence definitions and schema aim to cover three degrees of expressiveness, namely: intensity of influence depending on the reactions, influence spread and audience engagement and influence time dependency, which we discuss in the next section.

### B. Intensity of influence depending on reactions

The fact that our model is based on the Action-Reaction schema (Fig. 1) implies the flexibility in terms of the number of features the data can include. Obviously, by minimum, the data is required to have the users and reactions of one kind (e.g. comments). Considering the existing to-date potential sources of data, we enlisted most of major social network sites in order to gather all the similar features categorized to Action and Reaction. The results are presented in Table I. From this comparison, it can be seen that most omnipresent reactions available to the users to perform upon the generated content are *upvotes* (also named *likes*, *claps*, *hearts*, etc. – in this work, all one-click reactions that imply appreciation of the content will be called by the general name *upvote*), and comments, and then shares (the action of sharing the content originally posted by other user). In this article, without loss of generality, we concentrate on these three reactions due to their ubiquity.

In particular, we want to focus on the implications that different types of reactions have on the influence strength. Indeed, upvotes, comments and shares have various functions and meanings within social networks. According to [10], the upvote is treated as a lightweight reaction, easy to perform to acknowledge the posted content, similar to "wordless nod". In comparison, comments are regarded as "more satisfying to receivers" [10]. Moreover, because of the quickness and easiness of upvoting, it may also be regarded as less meaningful than other reactions. Clearly, reacting using comment involves both effort (writing comment content in comparison to "default" value of upvote) and time (writing and answering versus just one-click). Furthermore, a study [1] has shown that the majority of people share content due to its value – 94% of subjects share "valuable or entertaining content with others", 84% share to support causes and issues they care

TABLE I  
SOCIAL NETWORK ASPECTS DEPENDING ON THE TYPE AND/OR SITE

Social Network Type	Action	Reaction
<b>Social Network Sites</b>		
Facebook	posts, photos	comments, likes ( $\approx$ upvotes), shares, mentions
LinkedIn	posts, updates	comments, likes ( $\approx$ upvotes), shares
G+	posts, photos	comments, +1 ( $\approx$ upvotes), shares
<b>Content-sharing</b>		
<i>Microblogging</i>		
Twitter	tweets ( $\approx$ posts)	replies ( $\approx$ comments), likes ( $\approx$ upvotes), retweets ( $\approx$ shares), mentions
Weibo	posts	replies ( $\approx$ comments), likes ( $\approx$ upvotes), retweets ( $\approx$ shares), mentions
<i>Bloggng</i>		
Medium	posts	comments, claps ( $\approx$ upvotes), shares to outside platform, e.g. twitter/fb, bookmark
Politico	posts	comments, shares to outside platform, e.g. twitter/fb/g+
<b>Creative content</b>		
Youtube	videos	comments, likes ( $\approx$ upvotes), dislikes, shares, views
Instagram	photos, stories	comments, hearts ( $\approx$ upvotes)
<b>Collaborative sites</b>		
Yelp	reviews	upvote review, upvote profile

about. This means that when we see content that is highly impacting we are more willing to share it. This phenomenon is much different to the "casual" upvoting. It was also observed that receiving more complex reactions from acquaintances is corresponding to increase of relationship strength and closeness, as opposed to getting upvotes where no such association was noticed [2].

Taking all the above into consideration, we assumed the hierarchy of the reactions, in which the reaction of sharing is regarded as better descriptor of influence than comments and comments implying higher influence than upvotes. To illustrate, let us consider the following example: user  $u_1$  created the post. User  $u_2$  liked the post, while user  $u_3$  commented on the post. The hierarchy aims to evaluate influence according to the importance of the reactions, in this case evaluating the influence of user  $u_3$  higher than user  $u_2$ . Moreover, for each generated influencer content, we can specify several combinations of reactions of the influencee – user can *only* upvote, comment or share the content, can upvote and comment, upvote and share, comment and share, and obviously, all three at the same time, meaning user is upvoting, commenting and sharing the same content.

We do notice that one might argue that the importance of combinations could be modeled by using the linear combination of weights and vector of reactions. However, we aim to put different importance to each of the reactions (and their

possible combinations) by not only using weights vector but also by utilizing non-linear multiplications corresponding to reaction combination, so that the importance of existence of two or three reactions at the same time can be stressed, and have greater value on final score. In order to achieve this, we need to model reactions with the use of a non-linear function.

### C. Spread and engagement

The reaction schema presented in Fig. 1 is a simple, but important generalization of interactions on social networks sites. However, further consideration involves the case of multiple reactions to the same user's content.

Let us imagine a user  $u_1$  performs an action – creates a post. The users  $u_2, u_3$  can react differently, as pictured in Figure 2. In two cases (Fig. 2 A and Fig. 2 B), only user  $u_2$  reacted to the post. Intuitively, the comparison of these two situations leads to the conclusion that the influence of user  $u_1$  should be higher in the Fig. 2 B, as the user  $u_2$  has stronger response in this case. In other two cases (Fig. 2 C and Fig. 2 D), both users  $u_2, u_3$  reacted. We can say that the overall influence of user  $u_1$  in Fig. 2 D should be higher, because of more reactions obtained. While it is fairly easy to compare these pairs of situations, the  $a$  and  $b$  or  $c$  and  $d$ , the issue starts to be complicated when we want to order influence from highest to lowest in all the presented situations. Intuitively, without any particular model we can state that influence in case  $a$  will be the lowest, while influence in case  $d$  the highest. However, it is not that obvious in case of  $b$  and  $c$ . Is the fact that user  $u$  gets reaction from two separate users important enough to evaluate influence of  $u$  in situation  $b$  higher? Or is the strength of particular reaction more important than the spread of the audience?

In order to tackle this problem, we propose to differentiate two components of influence, namely influence spread and audience engagement. Intuitively, in the example above, the user  $u_1$  in situation  $c$  would have higher spread, while in situation  $b$  would obtain higher audience engagement value.

**Definition 6: Spread:** property of influence which determines how many users were actually affected with the generated content.

The idea behind the spread is to calculate the active audience (meaning the one that is reacting to the initial activity), in order to determine the actual overall broadcast range. We define spread as a number of users that made reaction at least once, i.e. general audience cardinality.

**Definition 7: Audience engagement:** property of influence determining the strength of the reactions obtained from the reached audience.

The audience engagement notion aims to conceptualize how powerful is the user's influence, therefore evaluates the overall involvement of already active users reacting to the content.

### D. Time dependency

The third crucial factor we consider as an influence component is time. As it was mentioned in the influence definition, we acknowledge that influence is occurring in time, hence

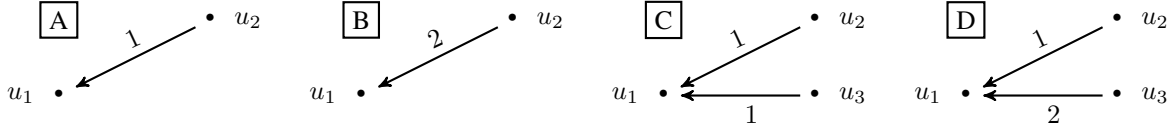


Fig. 2. Examples of different scenarios of users ( $u_2, u_3$ ) reacting to the content generated by user  $u_1$ . The arrow symbolizes the reaction (e.g. comment) and the number signifies the number of reactions

it is necessary to examine and include different aspects of time in the influence estimation process. Here, we present the approach to include time dependency within ARIM.

Gaining the influence is a long-term and continuous process. Therefore, in many cases, considering the whole available dataset gives the best estimation of users influence to-date. However, while considering the whole data time period for calculation, including time aspects connected to actions occurring within this time is still valid.

To illustrate, let us consider two situations, in which users  $u_1$  and  $u_2$  are posting content for time period  $(t_1, t_{10})$ , and content is visible to the same number of users (audience). In the first situation, user  $u_1$  is posting in each of the time points  $t_1, \dots, t_{10}$ . In the second, user  $u_2$  has posted only two times, in  $t_1$  and  $t_{10}$ . Additionally, both users  $u_1, u_2$  received during this time the same amount and type of reactions. While evaluating influence, the question is whether user  $u_1$  posting much more ("constantly") should have equal value of the influence (as we count only the reactions that both users received), or should user  $u_2$  indeed have higher influence? We propose to tackle this issue by introducing the component that favors lower frequency of performing actions. This is in accordance with the fact that we tend to appreciate more users with less posts but with higher quality and possible maximum gain for reactions.

The presented idea aims to incorporate time-dependency aspect into ARIM without the need to divide the data according to the time. However, we do acknowledge that temporal changes are also of importance. Therefore, in Section IV, we additionally show the second proposed model, basing on ARIM, that is especially dedicated only to examine the short-term influence trends.

### III. SPECIFICATION OF ARIM MODEL

In this section, we present the formulas used for the model that are combined for the final calculation of the influence. All the notions used in this section were previously described in Section II.

First, in order to deal with distinction of different types of reactions (see Section II-B), we propose a *Reaction Strength Per Reacting User* function that combines all reactions done by particular reacting user  $ru$  on particular action  $a$  for user  $u$  using the following formula:

$$\begin{aligned} Strength(u, a, ru) = & w_1 * upvotes + w_2 * comments + \\ & w_3 * shares + w_4 * upvotes * comments + \\ & w_5 * upvotes * shares + w_6 * comments * shares + \\ & w_7 * upvotes * comments * shares \end{aligned} \quad (1)$$

where  $upvotes, comments, shares$  are the number of each of the reactions for each actor respectively and  $w_1, \dots, w_6$  are the weights that introduce additional hierarchy of the reactions. The weights should be tuned to emphasize each reaction combination (lower weight – less emphasis). The number of possible reactions can obviously be higher or lower depending on the types of reactions the dataset includes. The function includes the multiplication of each pair of the reactions, so that in the case in which there is a combination of reactions the overall value of the measure increases. Inclusion of these combinations – cases when two or three reactions were done by one reacting user concurrently – reflects the fact, that Reaction Strength is considered per Reacting user.

Then, we measure the *Post Reaction Intensity (PRI)* metric, which specifies how much, on average, appraisal (in the form of reactions) a post received, formally defined as:

$$PRI(u, a) = \frac{\sum_{ru=1}^{|RU(a)|} Strength(u, a, ru)}{|RU(a)|} \quad (2)$$

where  $Strength(u, a, ru)$  is the defined above (*Reaction Strength Per Reacting User*), and  $RU(a)$  is the set of Reacting Users on the action  $a$ .

Next, the two influence components, *Engagement* and *Spread*, are defined (in accordance to their definition presented in Section II-C) as follows:

$$Engagement(u) = \frac{\sum_{i=1}^{|A|} PRI(u, i)}{|A|} \quad (3)$$

where  $A$  is the set of actions performed by user  $u$ .

$$Spread(u) = |RU|_{\neq} \quad (4)$$

where  $RU$  is the set of Reacting Users from the whole considered data, and index  $\neq$  implicates the distinct set.

The component that favors lower frequency of performing actions (Section II-D), called *fc* (frequency component), is defined as:

$$fc(u) = e^{\frac{1}{|A|}} \quad (5)$$

where  $A$  is the set of actions performed by user  $u$ . Finally, the influence for user  $u$  can be described using the formula:

$$Influence(u) = Engagement(u) \times Spread(u) \times fc(u) \quad (6)$$

The formula calculating the final value of influence is using the whole available data, in order to achieve the best estimate. Formula 6 binds all the measures presented before using the

multiplication. Thanks to this, the contribution of spread and engagement to the final influence score depends on their value. Therefore, the user with high engagement and low spread will have the same influence as the user with low engagement and high spread, assuming that they have equal amount of posts. This is important, as being the better spreader does not straightforwardly implies being more influential (as shown in e.g. [5]). Additionally, the  $fc$  component penalizes the users with bigger number of posts, which means that for two users with equal spread and engagement, we prefer user that posts less.

#### IV. INIC: INTERVAL SPECIFIC MODEL

As mentioned before, time is an important aspect of influence. ARIM presented in the previous section is focused on the frequency problem for the whole dataset. However, we also want to examine the short-term, temporal changes in reactions, that would give us the possibility of observing the trends of users' reactions in terms of potential influence. In order to be able to observe these trends, we propose a second sub-model, **Interval Specific Model (Inic)**, that bases on ARIM model, however it is dedicated only to dealing with the influence trends within time windows. Inic uses constant time windows, i.e. it will consider each time period resulting from time window separately. As we utilize the same concepts as presented in previous sections, here we will only precisely present the way Inic is dealing with time.

First, it is important to notice that in many cases the length of the time window should be tuned to the specific portal characteristic, from which the data come. This is due to the fact that there are sites with a very rapid information exchange patterns, e.g. Twitter, where posts and reactions can be done in minutes and even couple of seconds, and there are those that have instant but more steady exchanges, e.g. Instagram. Moreover, the time window will also be highly dependent on the data granularity – data collected daily and aggregated into one snapshot will be by default unable to capture more rapid changes in the network.

It is crucial to notice that there are two time-lines of the data to consider: the action time-line and the reactions time-line. For instance, presented before ARIM model is basing on the Action-Reaction schema, hence it uses the information about the time of occurring reactions to estimate influence. Any influence model focused on time that utilizes quantities such as post engagement, spread or target audience has to determine a time period in which reactions targeted towards the post. For example, if a user posts some news (performs action) on social network portal, the impact of this post on the user's audience is not immediate. Instead, the influence on the user's audience is stretched in time, over the period from the post creation until the last audience reaction, e.g. last comment. Therefore, the question would be: is the post influential at the creation moment or when the reaction occurs? We propose to assign the influence value to time window, considering the reactions time-line (and not the time-line of

TABLE II  
STATISTICS ABOUT USED FACEBOOK [11] AND PINTEREST [13] DATASETS

	Parameter	Number
Facebook	Number of users	1 067 026
	Number of users that reacted	23 426 682
	Number of posts	25 937 525
	Number of comments	104 364 591
	Time span of data	15/10/14 - 11/02/15
Pinterest	Number of users	1 307 527
	Number of users that reacted	8 314 067
	Number of posts	2 362 006
	Number of shares	37 087 685
	Number of upvotes	19 332 254
	Time span of data	03/01/13 - 21/01/13

action occurrence). In particular, we propose two alternative ways of assigning influence value to time window:

- Using only reaction time-line – We assess the influence value for each window in which the reactions to particular action occurred. In that way, although we do ignore the moment when the post was created, we correctly find the particular time window for which the influence (coming from reactions) have surfaced. For instance, let us assume that the action (e.g. post creation) was performed in time window 1, and reactions (e.g. comments and share) occurred in respectively time window 2 and 3. In this case, Inic would associate time windows 2 and 3 with respective influence values (and none in time window 1).
- Using point in time resulting from median of Action and Reaction times – The idea is to chose the time window according to both action time, and the time of receiving the reactions. In particular, we determine the time window according to the median of time series consisting of delay between publishing the post and publishing the reaction. The calculated influence value for this action and reactions is placed in the time window which includes this "median" time. In that way, we bind influence value to the time window in which already half of all reactions towards the action have occurred.

The choice of one of these methods will depend on the time window length and the social network site characteristics<sup>2</sup>.

#### V. EVALUATION

This section describes experiments conducted in order to validate and check the proposed models, namely general ARIM and interval specific Inic showed in previous sections.

##### A. Datasets

In order to evaluate our proposed approach, we performed the experiments using two real datasets. The first consists of data from Facebook [11] containing information about posts and their comments (without the text content) with precise information about the time of each of action/reaction.

<sup>2</sup>For example, the median method will be insufficient in the case in which the average reaction time for the action will be short (minutes, some hours), and the time window will be longer (as we want to consider a big enough sample for the trends, e.g. couple of days), in which case the median will be included in the time window.

TABLE III  
TOP 10 INFLUENTIAL USERS FROM FACEBOOK [11]

#	Engagement	Spread	#Actions	Influence Score
1	1.039	66181	96	69478
2	1.216	19793	549	24116
3	1.208	18093	148	22012
4	1.204	17030	103	20701
5	1.071	17817	200	19183
6	1.097	17040	941	18717
7	1.092	16087	263	17637
8	1.413	11086	67	15899
9	1.053	14185	998	14953
10	1.066	12678	34	13924

Second dataset includes data from Pinterest [13], that contains repins (shares) and likes (upvotes). Table II presents the basic statistics about the both used datasets.

We conducted three sets of experiments: two resulting in general influence score using ARIM model, utilizing datasets of Facebook and Pinterest, and one involving trend examination within time using Inic model, utilizing Facebook dataset, due to the fact that only this dataset includes precise time stamps for each action and reaction. The implementation was done using PostgreSQL ver 9.6 and R language ver 3.3.1.

### B. Results of ARIM

1) *Facebook*: The experiments performed on Facebook dataset, due to the nature of the data that contained one relation - comments, were done using all weights equal to 1. Table III shows the Top 10 ranking of the most influential users. It can be observed that the user in the first place, while having low (relatively to other top 10 users) engagement rate, is having exceptionally high spread. At the same time, this person has created 96 posts, which is also relatively low. Despite the fact that the audience is not very reactive, i.e. commenting only once, and not entering into discussions, the user is considered very influential due to the user's huge spread for very few actions. Complementary to Table III, the Figure 3 presents a comparison of Top 3 users in terms of influence score, engagement and spread rate, and number of posts. The high spread rate of top 1 user relative to two other top users can be easily noticed.

Another interesting case can be observed on the 8<sup>th</sup> position in the ranking, with the person having the lowest spread rate in the ranking, significantly lower than both users on 9<sup>th</sup> and 10<sup>th</sup> position. Interestingly though, this person engagement rate is very high (highest value in the ranking), with additionally small number of posts. Therefore, this user higher place can be explained with the fact that ARIM is not only focused on both engagement and spread equally, but also it favors the low post number (see Section III). Hence, the user on the 8<sup>th</sup> position in the ranking surpasses the next user (9<sup>th</sup> position) that although having high spread, he/she has also lower engagement and very high (998) number of posts (the biggest number of posts in the whole ranking).

2) *Pinterest*: The second set of experiments was conducted on Pinterest database, containing two types of reactions, namely shares (called on the site "repins") and upvotes

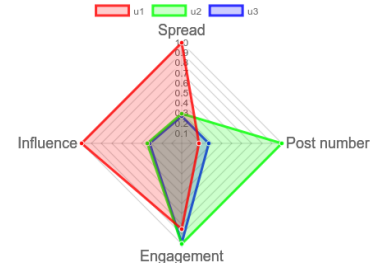


Fig. 3. Detailed comparison of top three users from influence score using Facebook dataset

TABLE IV  
TOP 10 INFLUENTIAL USERS FROM PINTEREST DATASET OBTAINED USING ARIM WITH EQUAL WEIGHTS (ALL REACTIONS CONSIDERED EQUAL)

#	UID	Engagement	Spread	#Actions	Influence Score
1	2777	1.314	23386	1282	30743
2	20703	1.249	19777	566	24747
3	2367	1.367	13512	1025	18487
4	5656	1.314	9843	535	12958
5	4000	1.286	9908	360	12778
6	1731	1.442	8553	328	12372
7	5074	1.389	8876	465	12358
8	820	1.262	9735	615	12304
9	4968	1.301	9013	569	11742
10	993	1.344	8580	387	11559

TABLE V  
TOP 10 INFLUENTIAL USERS FROM PINTEREST DATASET OBTAINED USING ARIM WITH WEIGHT EMPHASIS ON SHARE REACTIONS

#	UID	Engagement	Spread	#Actions	Influence Score
1	2777	2.263	23386	1282	52961
2	20703	1.935	19777	566	38329
3	2367	2.283	13512	1025	30877
4	820	2.224	9735	615	21690
5	4000	2.133	9908	360	21196
6	5656	2.133	9843	535	21032
7	4968	2.262	9013	569	20422
8	1731	2.360	8553	328	20245
9	5074	2.256	8876	465	20067
10	993	2.258	8580	387	19427

TABLE VI  
ADDITIONAL INFORMATION ABOUT USERS GAINED REACTIONS FROM TWO RANKS USING PINTEREST DATASET

UID	Shares Sum	Upvotes Sum	#Shares and Upvotes Concurrently
20703	15944	11467	1066
820	12617	4184	219
993	9251	4159	583
5074	8897	4816	694
2777	28920	10863	1358
1731	9242	4665	829
2367	19404	9028	1203
5656	10695	5786	885
4000	10729	5245	618
4968	10709	3621	466



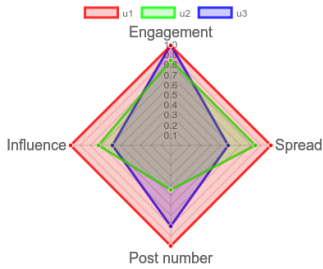


Fig. 4. Detailed comparison of top three users: 2777 (u1 – red), 20703 (u2 – green), 2367 (u3 – blue) from both influence scores using Pinterest dataset

(“likes”). In order to show the results difference when considering shares to be of more significant value than upvotes, we used ARIM model with: (1) equal weights for all reactions,  $w_1 = w_2 = w_3 = 1$  (see Equation 1 in Section V-B), and (2) higher weight for shares,  $w_1 = w_3 = 1, w_2 = 2$ . Tables IV and V present the obtained results from both runs. Additionally, the complementary Table VI presents the detailed information about the users, containing the aggregated sums of upvotes and shares (2<sup>nd</sup> and 3<sup>rd</sup> column) and the number of times that both of the reactions occurred simultaneously (for the same post and from the same user). The information about the latter number (4<sup>th</sup> column) is important, as the Equation 1 (Section III) in ARIM model includes an addition component in the formula regarding cases of simultaneous occurrence of the reactions (as was described in Section II-B).

Going back to the Top 10 rankings (Tables IV and V), it can be seen that for both experiment executions, the first three positions are unchanged. This can be explained by a very high spread value of each of the users, which is the predominant component for their high influence. Figure 4 shows in detail the ratios of spread, engagement and post number for each of the top 3 users. Moreover, from Table VI we can see that all of the top 3 users have a very high “combination” number, which means that they were appraised by other users simultaneously using upvotes and shares.

The use of the emphasis on the shares can be clearly seen by the example of user 820. In the first rank with equal weights, this person position is low (8<sup>th</sup>). However, the stress by using the higher weight for share reactions results in increase of the position of user 820 to 4<sup>th</sup>, jumping ahead of users like 5656 who, while having higher spread value, has less shares in total. Similarly, user 4968, who also has a high number of shares, is promoted from 9<sup>th</sup> to 7<sup>th</sup> position. Interestingly, in the case of second rank (Table V), the emphasis on the shares also resulted in the top user 2777 having much higher influence score in comparison to all other users. Indeed, the gap between users 2777 (1<sup>st</sup>) and 20703 (2<sup>nd</sup>) significantly rose (two fold), while the gap between users on second and third position (20703 and 2367) stayed similar. This is due to the fact that user 2777 has significantly higher share sum (28920 versus 15944 and 19404 for users 20703 and 2367 respectively), along with the high spread rate.

#	user	Engagement	Spread	#Posts	Influence Score
6	$u_6$	1.10	17040	941	18717
89	$u_{89}$	1.19	3131	13318	3728

TABLE VII

INFORMATION ABOUT TWO SELECTED USERS FOR TREND ANALYSIS

### C. Results of Inic

Experiments involving the trend analysis using Inic were done using Facebook dataset, due to the fact that only this data included time information for actions and reactions. Importantly, in Section IV, we presented two methods for assigning influence, using reaction time-line and using time resulted from median of time series of action and reaction. However, after initial analysis of the data, we noticed that for the majority of users, the time to obtain comment after posting is less than 200 minutes. Such a short time is not sufficient for observing the trends and obtaining conclusions about one’s influence. Therefore, in the experiments, we used only the first method, while using arbitrary chosen time window of 7 days. Due to the space limitation, we present the trend analysis for only two, interesting users, selected from the list of top 100 influentials, obtained from previous experiments with the dataset (see Section V-B1). The information about the two selected users can be seen in Table VII. The results in the form of trends are presented in Figure 5 for user  $u_6$  and Figure 6 for user  $u_{89}$ , and include the trend of post count, engagement and spread ratio trends and influence trend. The dotted line in an approximation of the trend done using Linear Regression.

It can be seen that, in case of user  $u_6$ , while the amount of created posts varies, both spread and the engagement decrease in time. On the contrary, user  $u_{89}$  gains not only spread for his/her posts, but also the users that are commenting are highly active - the engagement ratio equals at the beginning 4 and is rising with time. In the case of user  $u_6$ , the possible explanation for such trend is that independently from the number of posts that the user is generating, the audience is gradually losing interest. Additionally, we can observe one significant peak in the spread and one time window, which suggests that the person was very popular (maybe controversial?) at one particular moment, which spiked the number of users reacting to the content. However, after that the user was not able to maintain such an audience. The case of user  $u_{89}$  shows how the user is systematically gaining popularity (increasing the spread value). Moreover, observed increase of spread is simultaneous with the increase of audience engagement. This shows that Inic was able to determine influence evolution would be particularly helpful for campaigns in which the audience should be an active collaborator, for example giving feedbacks about the product.

## VI. RELATED WORK

Much of the current research is focused on the problem of Influence Maximization, in which the aim is to find the group of nodes in the social network for which the information spread will be maximal. The systems, e.g. [3], [4], targeting influence maximization problem are focused on selecting a

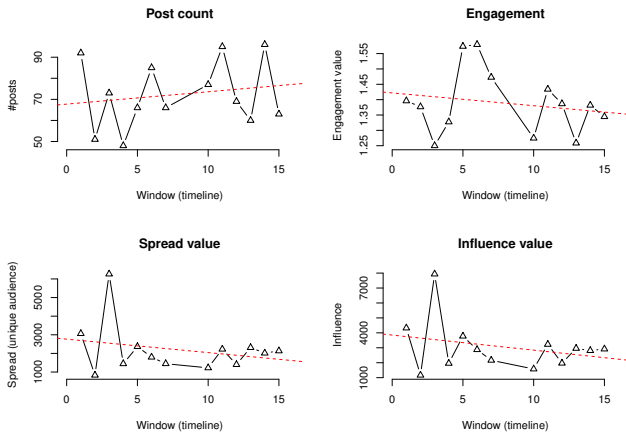


Fig. 5. Falling trend of user  $u_6$

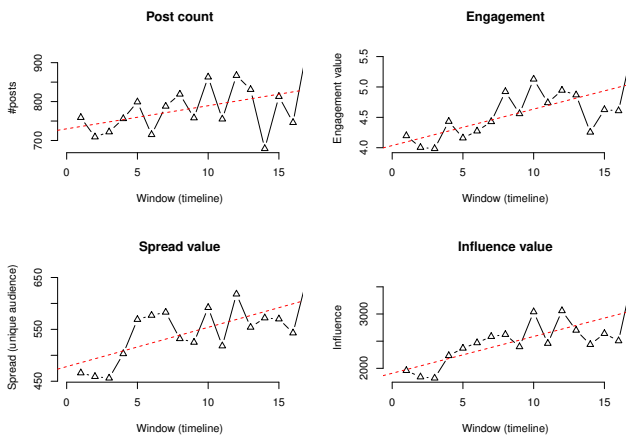


Fig. 6. Rising trend of user  $u_{89}$

subset of users basing on the graph, where users are already connected via influence relations. In comparison, in this work we target evaluating the influence between the users and establishing a rank for them.

There are several works proposing various influence metrics for ranking influential users in social networks. Many of them are platform specific, for example operating on Twitter [6], or job portals [8], as opposed to this work, which aims to propose the general approach that can be tuned to any social network site. Few of the well-known, well-established influence metrics base their model only on the typology of the network, i.e. PageRank [7], or centrality measures [12]. However, these methods do not consider deeper network characteristics, such as differences between types of reactions between the users, or the aspect of time dependency.

To the best of our knowledge, the work of Rao et al. [9], [11] is the closest to our approach. However, there are several key differences between the methods. Rao et al. system called Klout focuses on being multi-platform, while our ARIM is build for single platform, targeting a platform-specific influencers' analysis. This means that ARIM not only

needs less data, but also it can be more helpful to use it in practice, i.e. for small advertiser companies. On top of that, probably due to the company privacy, none of the articles published by Klout reveals enough details about the metric to really have inside into their work, e.g. in their article they mention using both weights and more than 3 thousand features to calculate the final score, however, they do not include any details about them.

## VII. CONCLUSION

In this paper, we presented the Action Reaction Influence Model that evaluates influence for each user basing on the proactive (actions) and reactive (reactions) behaviors of social network participants. The model targets three aspects of influence, namely intensity of influence, spread and audience engagement in the context of influence value, and time. Importantly, the model is flexible in terms of features that may or may not be available for particular social network site. Moreover, it also embraces the fact that different reactions types should be differently considered and should have various significance for the final influence score of a particular user. Furthermore, we have proposed an additional model, Inic, that focuses solely on influence trends in time. We have performed experiments on two real-world datasets including data from two well-known social network sites, namely Facebook and Pinterest. The results present interesting discoveries about the users influence and indicate the adequacy of the proposed ARIM model. They also show how different emphasis on various types of reactions can change overall influence rank.

As future work, we intend to deepen further analysis of influence trends. In particular, we want to focus on users that, while being not at the highest positions in influence ranks, show the potential to gain the influence with time.

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