Predicting police micro-blog post diffusion on Twitter™: the man or the message?

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Abstract

Message diffusion on micro-blogs such as Twitter™ is still poorly understood. This study aims to develop an explanatory model of message diffusion to understand why some messages are forwarded and others are not. By studying 934 Dutch police force accounts, this study tests previous insights using trace data drawn from the Twitter™ API. Based on an iterative human-calibration procedure, message topics were automatically coded based on customized lexicons. A principal component analysis of message characteristics generated four distinct patterns of use. Message characteristics where combined with user characteristics in a multilevel logistic general linear model. Main results show that URL or use of informal communication increase chances of message forwarding. In addition, contextual factors such as user characteristics impact diffusion probability. Recommendations are discussed for further research into authorship styles and their implications for message diffusion. For practitioners, a list of recommendation about how to increase message reach is presented.

Keywords: Micro-blog; Twitter; Message diffusion; Community Police; Multilevel logistic regression

1. Introduction

The emergence of social media has brought with it new opportunities to reach others. Micro-blogs such as Twitter are an social media platform based on the premise 'less-is-more' (Finin and Tseng, 2007). These platforms limit the amount of characters per message, which leads to bite-sized messages which can easily be consumed by users. This service has been broadly adopted by individuals, but also by companies, non-profit organizations, politicians and government (officials) (Burton and Soboleva 2011, Cho and Park 2011, Li *et al*. 2011, Picazo-Vela and Gutiérrez-Martinez *et al.* 2011, Rojas and Ruiz *et al.*, 2011, Waters and Williams 2011) . Some authors note that the medium can inform about societal trends (Asur 2010, Bae 2011, Khrabrov 2010, Vergeer and Hermans 2011), or discuss how it influences society (Chew and Eysenbach 2010, Christensen and Lægreid 2011). In part through word of mouth processes (Wang and Doong 2010), government agencies like the police have started adopting the medium. In the UK, the London riots became an eye-opener for police officials to use twitter and other social mediums to provide citizens with moment-to-moment updates to combat rumours, discuss incidents and reassure the public (Crump 2011). Elsewhere, police officials have started to adopt the medium to improve their information sharing capacity and thereby actively engage citizens in solving problems (Heverin and Zach 2010). In the Dutch context, police use of micro-blogs is seen as a method to increase both co-production, the feeling of safety and the positive perception of policy legitimacy (Meijer and Grimmelikhuisen *et al.* 2010). Message forwarding in the context of twitter takes place using so called 're-tweets' (abbreviated RT). This is especially important for 'wanted' and 'warning' messages, for which every person reached may entail a crime solved or prevented. However, message diffusion (RT's) on this type of medium is still poorly understood, especially in the context of policing. At this point, it is unclear whether topics such as warnings spread more than talk about the weather.

The body of literature mainly consists of conference papers with explorative data rather than developing an explanatory model. This means many causes have been identified, but have not been tested in a rigorous fashion. Often, interaction effects have been overlooked, and so has the multilevel nature of identified causes. The former means some characteristics might improve reach under some conditions but not in others. Additionally, the absence of testing diverse insights in conjunction may have confounded the effects of various causes. The latter means there has been little theoretical attention to the relation between tweet and user characteristics. Such relations might entail bias towards well connected users and their tweeting behaviour. This study seeks to improve on existing knowledge by integrating previous findings and test their applicability to messages authored by Dutch police officials, in order to understand and explain tweet diffusion among the general public. The research question is: how can differences in the retweet-rate of messages authored by Dutch police officers be explained?

2. Tweet diffusion: literature review of likely predictors of diffusion

2.1 discussing user and tweet characteristics

This section explores the body of knowledge dealing with message diffusion on micro-blogs. Although these studies do not explicitly differentiate message and user characteristics, this study will do so in order to better understand their relation. As mentioned before, the separation has both methodological and theoretical reasons. Mainly, user characteristics are taken to hold across the messages created by that user, which means the effective sample size for these variables is significantly smaller. In a theoretical sense, user characteristics are contextual factors for individual tweets. The messages sent by popular users share a different starting point compared to those of unpopular users which may affect their chances of diffusion regardless of their characteristics. For the sake of clarity, tweet and user[1] characteristics are discussed separately. The insights from literature are summarized in table 1, based on the type of variables discussed by these authors.

2.2 tweet characteristics

Most research has focussed on message characteristics, which are often directly observable. Suh and Hong *et al*. (2010) find that the inclusion of web addresses and hashtags affects the chances of diffusion. The inclusion of hashtags signals the broader discussion a message is part of and increase searchability (Zappavigna 2011), whereas a web address is used to provide readers with additional information. This can be a news articles, picture, video-clip or (longer) blog posts. To this extent, the inclusion of resources like URLs and hashtags provide additional information which may heighten their information value to

[1] 'User' is used synonymous to 'account', as accounts managed by more than one person are still perceived under one name, as one 'source'. This conforms to the literature on organizational use of twitter accounts, which takes the organization as the user. Note that most accounts in this study are tended to by no more than one person.

recipients and thereby increase chances of being forwarded. Such communicative capacity is deemed especially relevant for government actors, who aim to inform citizens (Ampofo and Anstead *et al.* 2011, Picazo-Vela and Gutiérrez-Martinez *et al.* 2011).

Apart from these elements, the topic discussed have been linked to diffusion. Research into twitter activity has shown that popular or current topics can increase both activity and information sharing (Wang and Li *et al*. 2011), especially when it fits with audience expectations (Weng and Lim *et al.* 2010). A study into the use of Twitter by police departments has supported this finding in the law enforcement context (Heverin and Zach 2010). This implies messages may differ in terms of appeal based on the topic they discuss. In the context of law enforcement, it may mean missing person reports garner more sympathy and are therefore more often forwarded compared to traffic information, but small talk may actually reduce chances of being retweeted.

In addition to the resources and topics of a tweet, the social characteristics are of interest. Suh and Hong *et al*. (2010) found a decreasing effect of mentions on retweet probability. But as with replies, these social factors been linked to user popularity (Burton and Soboleva 2011, Wigley and Lewis 2012). On the tweet level, both are expected to reduce diffusion because of their orientation towards specific rather than broad audiences.

Table 1: overview of micro-blog literature discussing diffusion or related concepts

	Independent	Dependent	Source
Tweet characteristic	URL inclusion	Diffusion	(Hansen and Arvidsson, *et al.* 2011; Suh and Hong *et al*, 2010)
	Hashtag inclusion	Diffusion	
	Mention	Diffusion	
	Reply	Audience size	(Burton and Soboleva, 2011; Wigley and Lewis, 2012)
	Topic discussed	User activity	(CHeverin and Zach, 2010*,Crump 2011*, Wang and Li *et al*. 2011)
User characteristic	Organization type	Replies to audience	(Cho and Park 2011, Golbeck and Grimes *et al*. 2010; Rojas and Ruiz *et al*. 2011, Waters and Jamal 2011, Waters and Williams 2011)
	Organization type	Mentioning of others	
	Engagement	Diffusion	(Wigley and Lewis 2012, Zhang and Jansen *et al.* 2011)
	Informativeness	Decreased audience	(Kwak and Chun 2011)
	Account age	Diffusion	(Suh and Hong *et al.* 2010)
	Total messages posted	Diffusion	
	In-links	Diffusion	(Lussier 2011; Suh and Hong *et al*. 2010)
	Out-links	Diffusion	
*=Article specifically discusses police or police officer use of the medium.			

2.3 user characteristics

In terms of user characteristics, there has been considerable attention to the style of communication employed on the medium. Such stylistic differences can be divided into roughly two kinds: interactivity and authorship. Interactivity refers to the extent to which a user uses conversational tools such as mentions and replies. A number of studies show that organizational accounts often lack such interactive elements, opting instead for classic one-way communication (Cho and Park 2011, Golbeck and Grimes *et al*. 2010, Rojas and Ruiz *et al*. 2011, Waters and Jamal 2011, Waters and Williams 2011). This contradicts the advice of studies into business engagement, which finds significant positive effects of interaction on message diffusion (Wigley and Lewis 2012, Zhang and Jansen *et al.* 2011). This study will employ the use of on interactive style as engagement, which in turn is expected to predict message diffusion. Authorship is another way for users to distinguish themselves. Research has shown the role of users as information channels in part determines the retention of their audience (Kwak and Chun 2011). This raises a point about the role of accounts as conduits for new information. Some users will frequently forward messages from others, thereby providing information from various sources, whereas others are expected to use their accounts mainly for their own information.

A user also brings some experience to the table. Although Suh and Hong *et al*. (2010) do not distinguish user and message based causes of diffusion, they do find a significant influence of both account age and number of messages posted. Such influences may be the result of a learning effect. Prolonged use has been linked to socialization or adaptation to audience preferences (Marwick and Boyd, 2010). Because of this, experienced users are more capable of connecting with their audience. In addition, it allows for users to become accustomed to the medium and feel more secure in its use (Chen, 2011). These factor should therefore increase message quality and thereby the chances of diffusion.

In addition to the type of relations a user has built, the quantity of relations has been connected to message diffusion (Suh and Hong *et al*. 2010). A user has a number of in-links, from which messages are received automatically. This provides a user with information about what is going on in their network and the ability to forward interesting news and expectations (Marwick and Boyd 2010, Weng and Yao *et al*. 2010). A benefit which has been linked to increased retweets (Lussier 2011). A higher number of in-degree links is therefore hypothesised to increase the ability of a user to serve his or her followers. These followers form the audience of a twitter user. They don't just receive messages posted by a user, but also have the ability to forward these messages, thereby making them available to all of their followers (Bae 2011). In this way, followers are gatekeepers who decide whether or not to spread a message to their own audience. Having more followers is thereby expected to increase the chances of having a message forwarded.

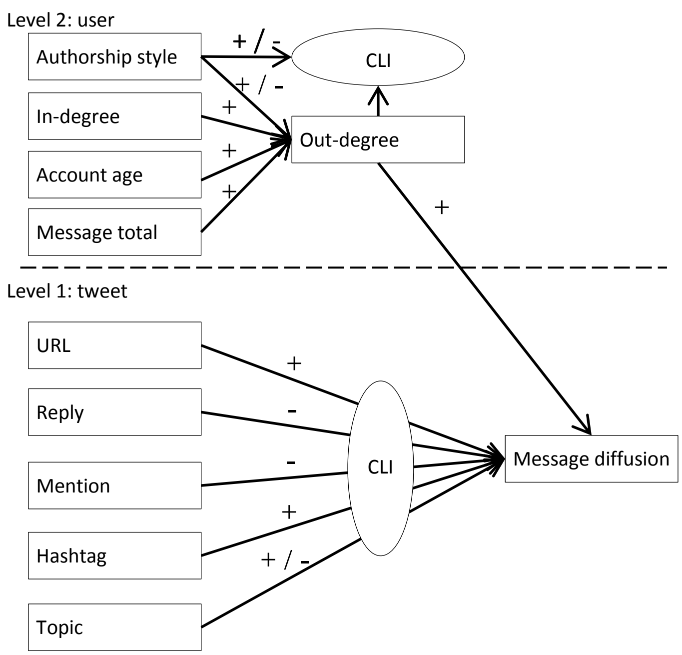

Figure 1:Model of message diffusion on the Twitter micro-blog service

2.4 building a model of message diffusion

Together, the outlined elements are combined in the explanatory model of message diffusion shown in figure 1. In addition to relationships within each level, the model includes interaction between levels. The direct interlevel relation is represented with an arrow crossing the levels, the moderating effect uses the Cross Level Interaction (CLI) ellipse. Two of these indirect effects have been hypothesised. The first is the moderating relation between authorship style or out-degree on each of the tweet level characteristics. The second is the direct mediating effect of out-degree on message diffusion.

User characteristics such as authorship style, in-degree and experience are expected to contribute indirectly to message diffusion. Out-degree is expected to mediate their influence, and is itself expected to have a direct relation to diffusion, because in-degree and experience an authorship help build an audience. A direct effect is not expected, as these are reflected in the composition of tweet characteristics. Instead, in-degree and experience are expected to enable a user to serve his / her audience, thereby increasing the out-degree. Similarly, authorship style is expected to impact the number of followers based on the personal or original nature of the user's tweets. Such stylistic properties may increase or decrease relational value for followers. The out-degree is expected to have a direct effect on message diffusion. This is because tweets which do not feature URLs, mentions or hashtags, nor reply to a user or discuss a measured topic, may benefit from greater exposure and thus greater likelihood of diffusion.

Lastly, an interaction effect between levels is hypothesised to moderate the effect of tweet level variables on message diffusion. The CLI ellipse denotes this cross-level moderating effect. The out-degree interaction is based on a logic of increasing returns. When the audience size increases (big out-degree), the effect of a tweet level characteristic is applicable to more ‘gate-keepers’. This means that for each person reached, the effect of such a characteristic again applies. Authorship style is expected to moderate the effect of these characteristics based on audience expectations; Users who have a more personal style are likely to draw more attention when compared to impersonal users. Because of this, their use of message elements such as URLs or Hashtags may result in stronger effects.

3. Methods

3.1 Operationalisation

3.1.1 tweet level independent variables

In inclusion of directly observable elements such as hastags, URLs and mentions are operationalized as their presence or absence in a given message. Replies operationalized as given by twitter, defined by the inclusion of a mention in the first character-space of the message. Mentions were recoded to 0 if a message was a reply to reduce confounding mentions and replies. URL and mention variables are coded 1 if present and 0 if absent. Only hastags where counted based on the use of symbol ‘#’ in the message text in order to gauge the added effect of multiple hashtag inclusion.

To measure the influence of topics, the qualitative framework of police message subjects listed by Heverin and Zach (2010) is adapted for the Dutch context, which yields eight topic categories dealing with crime/incident reporting, department (activity) information, event information, traffic information, prevention aimed information, (witnesses) wanted requests, missing person information and small talk. These topics are operationalized based on word-use. In the exploratory phase, 200 tweets where coded for their main topic, which were operationalized based on Heverin and Zach (2010). For each topic, a list of often used words was formulated.

Crime and incident reports contain tweets which state a crime or incident which has occurred, this the lexicon of this topic includes terms such as ‘apprehended’, ‘burglary’ and ‘investigate’[2]. Departmental information covers tweets about meetings, office hours, upcoming projects and internal affairs. This list includes ‘meeting’, ‘project’ and ‘office hours’.[3] The event topic considers tweets which discuss current or upcoming events like marathons, parades and demonstrations, but also information events. This wordlist includes ‘campaign’, ‘strikes’ and ‘educate’.[4] The traffic topic includes tweets about crashes, traffic jams and traffic controls and tweets which deal with driving. Keywords in this list are ‘traffic’, ‘speed’ and the abbreviation of ‘near’.[5] Tweets discussing prevention include warnings and suggestions to prevent crime. This wordlist includes ‘tips’, ‘prevent’ and ‘warning’.[6] Messages which call for witnesses or tips concerning suspects are coded by their use of police hotlines and words such as ‘witness?’ and ‘seen something?’.[7] Missing person related tweets are coded using ‘missing’ and ‘last seen’.[8] Small talk is perhaps the broadest category and includes tweets in which officers tell what they

[2] ‘aangehouden’, ‘inbraak’, ‘onderzoek’.
[3] ‘overleg’, ‘project’, ‘spreekuur’.
[4] ‘campagne’, ‘acties’, ‘voorlichting’.
[5] ‘verkeer’, ‘snelheid’, ‘thv’ (ter hoogte van)
[6] ‘tips’, ‘voorkomen’, ‘waarschuwing’
[7] ‘0900-8844’, ‘getuige? ‘, ‘iets gezien?’
[8] ‘vermist’, ‘vermiste’, ‘laatst gezien’

are doing, respond to others, and communicate about their state-of-mind and opinions. Words in this category include smiley symbols, 'fun' and 'nice'.[9,10] Tweets where then automatically coded 1 on a topic if it contained an exact match of a topic word. In an iterative calibration process, a random sample of 100 tweets was checked for human-computer coding congruence. Based on the resulting insights, wordlists where updated and the comparison was repeated.[11] After four rounds of calibration, the error rate was reduced to 4,3-10,7% false positives (α=0.05, n=200). This means messages are unlikely to be wrongfully attributed to a topic. [12] Due to the chances of false negatives, the influence of topics is expected to be deflated. The false positive rate may reduce statistical power to detect topic influence, but the low false positive ratio preserves reliability.

3.1.2 user level independent variables

In terms of in-degree and out-degree contacts, twitter data offers elegant solutions. In-degree contacts come in the form of 'friends'[13]. This metric is the count of twitter users whose posts are automatically forwarded to a user. Out-degree contacts are registered in a similar statistic called 'followers' and are the logical opposite of friends. This is the number of accounts which receive a posted message. Similar will be used for experience. The collected data lists the creation date of each account and the number of statuses since creation. The former provides an operational measure of time spend on the medium and the latter reflects previous experience. Both are used as interval level variables with respect to their impact on message diffusion. All these variables are measured at the time of data collection and are therefore constant for each tweet of a user.

Authorship is the only indirectly measured concept. Different styles are operationalized as recurrent use of message types, topics and elements[14]. In terms of types, a message can be a reply (as on the tweet level) or a retweet. If a message is a retweet, we draw the distinction, a retweet can be internal (retweeted from another police account) or external (from general public). To enable this distinction, both types are separated. Internal retweets are coded 1 if the message is a retweet and the source is an account from the police account list used in data collection. Retweets which are internal are coded as 0 to maintain the reduce confounding. The messages types, topics and elements used are aggregated to the user level as averages. Styles are then defined using an explorative principal component analysis, in order to re-express the use of message types and characteristics (Lattin and Carroll *et al*. 2003). This principal component analysis is applied to a subset of the data, of which duplicate users are removed. This is done to prevents bias towards users with more tweets. Components are selected based on the

[9] ';-)','leuk', 'mooi'

[10] For the complete wordlists used for each topic, consult appendix B.

[11] This approach was deemed most feasible considering the amount of data (130.000+ tweets) and vertical nature of semantic entities (all drawn from police-authored communication). The latter provides less ambiguity and thus increased reliability for simple coding.

[12] Due to the rudimentary approach of this method, between 27,5 and 40,5% of the messages are not attributed to the right topic and thus default to 'generic' tweets.

[13] These are the accounts followed by a user, contrary to following the user.

[14] As an example: mentions often denote conversation (Honeycutt and Herring, 2009), users with a high mention average can therefore be characterized as more interaction oriented relative to those who do not use mentions. By examining such signals across multiple variables, the reliability of stylistic distinctions is increased.

scree-plot method (Lattin and Carroll *et al*, 2003:114) and variables loading more than 0.3 on a component are scaled together and used as authorship dimensions. These are subjected to a Guttman lambda six test to ensure coherence. For the statistical tests, these items are combined into a scale based on their average. These scales are normalized in order to avoid multicolinearity issues.

3.1.3 Message diffusion

We define the dependent variable, message diffusion, as the reach of a message beyond its initial audience. As such message diffusion is understood in a binary fashion, either a message is forwarded or not. This decision is made to deal with the extremely skewed distribution of retweets, making the data unsuitable for reliable normal regression. A message which has been forwarded corresponds to a retweet on twitter, as declared by the integrated retweet function. These are considered diffused whereas a messages which has not been 'retweeted' are considered non-diffused. The retweet variable is coded 1 if forwarded and 0 if not.

3.2 data collection

For data collection the Twitter™ REST API was used, which provides a maximum of 200 of the most recent messages posted by an unshielded user. A list of accounts was provided by Dr. A. Meijer of Utrecht University[15]. For each of the 1000 accounts in this list, a request was made for their messages, including retweets and user characteristics. The requests to this service where made on 27-4-2012, using a custom program which saved the responses in a comma separated file. Message and user characteristics were used as supplied by Twitter™, including retweet counts, message text, followers, friends, creation date, total number of statuses and whether a message contains a URL, mention or reply.

3.3 statistical model employed

Because message diffusion is a binary variable, the model will be tested using a logistic regression model. This method is designed to estimate the odds of either value of a dichotomous dependent variable (Pampel 2000), in this case the chance of diffusion. During this analysis, a subset of the data is used which excludes tweets which are themselves retweets. This is because this study is interested only in tweets authored by police officials, not diffusion of messages which are only forwarded by police officials. The collection of data gives us multiple tweets per user, a form of cluster sampling. Because the sample is clustered, a multilevel model is used to control for dependent sample bias (Bickel 2007, Khan and Shaw 2011). In addition this method allows cross-level interaction to be modelled using variables from different levels in conjunction (Bliese 2012). In this way, contextual variables can be tested which are aggregated from individual level raw data. This prevents problems estimating the effect of authorship style, which is aggregated from individual level data. In terms of the required sample size, our data fits the 10 observation per independent variable rule on both levels (level 1 n = 106 462, level 2 n = 964) (Garson 2009). The sample size is also bigger than the minimum of 20 groups with 30 observations required for multilevel regression (Bickel 2007). In addition, multilevel logistic regression requires the

[15] http://www.albert-meijer.nl/, last visited 28-5-2012.

fulfilment of regular logistic assumptions on each level (Gelman and Hill 2007). These are normality for continuous variables[16], low multicolinearity, non-additivity and linearity (Hosmer and Lemeshow 2000). To deal with inflated deviance due to non-normally distributed values, a logarithmic transformation was applied to previous messages, friends and followers. Multicolinearity was checked using correlation tables and yielded no highly collinear relations. Lastly, interaction effects and non-linear relations were taken into account by exploring all possible additions to the model. In addition, running a Cook's test indicated no influential outliers (Cook's distance >0.02). Time of day and characters in a message where added as control variables. All relations improving model fit are adopted in the final model. [17]

Moderating effects are checked using interaction terms, which shows how differences in variable A impact the relation between variable B and C (Whisman and McClelland 2005). When these interactions prove significant, the relation is interpreted as moderating. For mediating effects, the Baron and Kenny's test is applied, which uses tests the direct effect of independent variables, the relation between independent and mediating variables, and the decrease in effect of the independent variable when the mediator is included in the model (Baron and Kenny 1986).

4. Results

4.1 descriptive statistics: what are the police doing on Twitter?

The 966 accounts gathered range from street cops (76%) to district level managers (3%). Their specific functions range from general community officer (65%), other (14%)[18], youth officer (4%) , manager (2%) to PR representative (1%). As such, this study had a high percentage of local accounts as compared to the sample examined by Crump (2011). This could be the result of the strong change in the force-to-local accounts ratio discussed by this author, or cultural effects (Poblete and Garcia *et al.* 2011). The total amount of posts per account ranges from 1 to 10357, with a mean of 802 (SD=1098). The oldest account is 1645 days old, whereas the newest account started 35 days before collection. The amount of followers range from six to 21084, which is positively skewed with an average of 1152 and a median of 560 (SD=1125), just like friends, which vary between zero and 5715, with a mean of 252.7 (SD=470).[19]

The most discussed topic matched that of earlier studies (Heverin and Zach, 2010), which is crime and incident reporting (25%). In our coding scheme, this topic is followed by small talk (15%) and (witnesses) wanted / 'look out for' messages (11%). About 23% of these messages contain a URL, which most oftenly link to the official police website (27%), followed by the yfrog™ and twitpic™ picture sharing service (12% and 3%), and the Youtube video sharing at 3%. Hashtags use averaged at 0.67 per tweet, with a

[16] Although not a hard requirement (Harrell 2001), non-normal distributions may inflate coefficients.

[17] Although our software noted false convergence, the multicolinearity check produced no problems. In addition, coefficients nor standard errors are visibly inflated (Hosmer and Lemeshow 2000), nor do iteration reports show deviance between iterations. Lastly, the R packages applied is known to be stringent with estimation procedures, which often yields false-positives on convergence checks (Bates 2009). In such cases, deviance is overestimated, making the results more conservative than optimal, but equally reliable.

[18] Ranges from animal to team-loverboy cops.

[19] Both follower and friend counts where normalized to compensate for their skewed distribution, see the methodology section.

maximum of 7 in one tweet. In all messages, 20% formed a reply but only 5.5% used a mention. Most tweets (41%) where send in the afternoon, 28% in the evening, 26% in the morning and 5% at night. [20]

The first two components estimated by the principal component analysis conform to theoretical expectations. On the first component there are four elements which load above 0.3. The user average of small talk and replies load positivily. Negatively contributing are URL use and crime/incident reporting. Both reply and small talk are means of communicating on a personal level, by addressing one specific person or discussing topics more personal in nature. In this sense, the use URLs (which mostly refer to the official police website) and crime reporting are more impersonal in nature. Combined, the first component is taken to cover the personal (positive) to impersonal (negative) dimension (Guttman's lambda 6=0.716). There are three variables which load on the second component. These are internal retweets, external retweets and mentions, which all load negative. As a combined measure, these items are taken to denote the authorship-messenger dimension (Guttman's lambda 6=0.919). The higher the scale, the less a user forwards messages or mentions others. As such, the higher a user scores on the authorship scale, the more the more tweets are self-authored and the less reference is made to others. Together, these stylistic dimensions explain the extent to which a user chooses an (in)personal tone and acts more as a messenger. In our sample, there is a tendency towards a personal style (negatively skewed distribution). In terms of authorship, the distribution strongly negatively biased in favour of authorship over messenger properties (negatively skewed). Both these dimensions will be used in the model.

4.2 Model results: predictors of retweets

The observed best-fit model significantly reduced variance compared to a null-model ($\rho<0.01$, McFadden's pseudo-R^2 = .14). All effects mentioned are significant at the $\alpha=0.01$ level unless specified otherwise, insignificant predictors are predictors with a ρ-value greater than 0.05. The effect sizes mentioned are deviations from a 'joe average' user's tweet, with average characteristics and lacking any specific topic or element (which has a base chance of 1.26% of being retweeted). Such comparisons to a baseline tweet take non-linear and interaction effects into account. For comparisons concerning continuous variables, the difference between the first and third quartile are used. Note that all estimates are based on a logarithmic scale and can therefore not be directly added.

4.2.1 User level effects

Findings support the expected direct effect of followers on retweet probability, with an increase of 0.56% over generic tweets. In addition, the number of friends has no statistically significant direct effect on retweet probability. Contrary to the expectations of the theoretical model, experience in terms of days active has a strong direct negative effect on retweet probabilities (-1.17%). This is also true for the total number of messages posted by a user, although this effect is smaller (-0.25%). There was also a direct effect of authorship, contrary to the theoretical model; Original authorship reduces retweet

[20] Morning is 06:00-11:59:59, afternoon is 12:00-17:59:59, evening is 18:00-23:59:59 and night is between 0:00-05:59:59

chances (-0.40%). The effect of more sending more personal messages is smaller (-0.03%). The effect of authorship styles diminishes as a user gets more followers.

4.2.2 Tweet level effects

Supporting the theoretical model, URLs and hastags have a positive effect on retweet probabilities with 1.77% and 0.24% to 0.38% respectively. Contrary to the model, mentions also contribute to message diffusion, with an increase of 1.04% over generic tweets. Replies do conform to theory and reduce the chances of a retweet with 0.39%. In terms of topics, significant effects are observed for all but event related messages. The strongest effects are related to missing person (+3.04%) and (witnesses) wanted (+1.56%) tweets. [21]In terms of interaction effects, combinations of replies and URLs increase chances of diffusion. URLs in traffic messages and replies about (witnesses) wanted combinations have diminished effects of diffusion.

4.2.3 Cross-level interaction effects

Conforming to the model, the data supports the strengthening effect of followers on the relation between replies, URLs and message diffusion. But contrary to the model, mentions become less, rather than more influential when an account has a bigger audience (a -0.82% decrease in likelihood). The moderating role of authorship is supported. Personal authorship increases the effect of URLs beyond the decrease resulting from the direct effect of this style. Crime and incident related messages are by contrast less likely to diffuse if send by personal type authors. The moderating role of original authorship is statistically significant but small and only applicable to the use of mentions. Both experience measures have an unexpected moderating effect, with the number of messages reducing the effect of mentions by 1.55%, yet increasing the chances for replies by 0.25%. The age of an account also increases chances for replies to diffuse, perhaps suggesting reputation effects. By contrast, both experience variables are negatively linked to traffic message diffusion.

4.2.4 The mediation effect of out-degree connections

In addition to the moderating effects, findings support a moderate mediating effect between followers, account age and in-degree (friends). When not controlling for the effect of followers, both these variables get higher coefficient estimates. In addition, a separate general linear analysis showed the experience and in-degree variables to be significant predictors of followers. Together, this conforms to Baron and Kenny's statistical operationalization of mediating variables. Figure 2 summarizes the observed results.

[21] Other effects are: department (-0.73%), small talk (-0.51%), prevention (+0.39%), Crime or incident (+0.16%) and traffic (+0.05%, $\rho<0.05$).

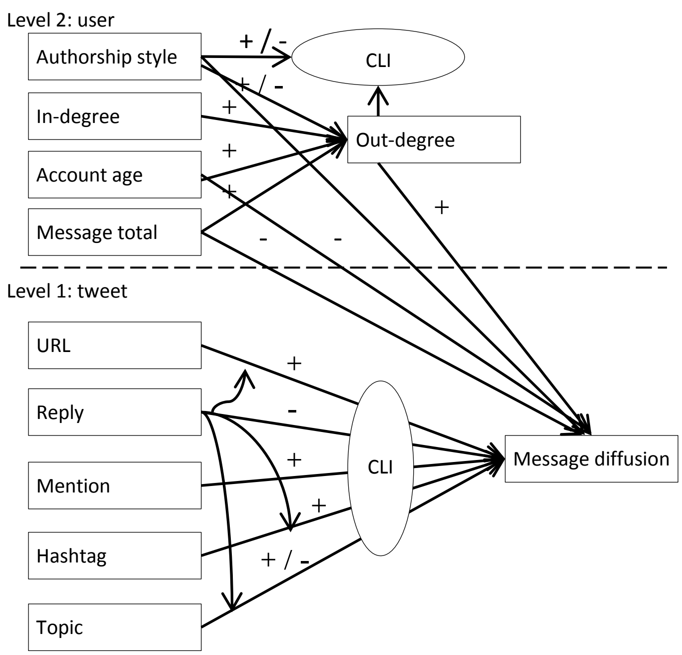

Figure 2: Model as observed

5. Discussion

5.1 additions to theory

This study integrated theories from a broad range of source. In terms of tweet level characteristics, findings deviate from the model of Suh and Hong *et al* (2010). Mentions were found to have a significant positive effect on retweet probablilties in both statistical and practical terms. The same is true for replies, which may decrease retweet probabilities, but diminishes as followers increase. This raises new questions about the role of social signs in communicative reach. In addition to these direct effects, this study presents supporting evidence of interaction effects on replies, URL inclusion, various topics and mentions. Such interaction effects have remained largely untested in the message diffusion literature dealing with micro-blog use.

Drawing from descriptive analyses by Crump (2011) and Heverin and Zach (2010), tweets where coded for topics often discussed by police officials. This study used these topics in a quantitative analysis in order to predict retweets and found supporting evidence to their effect. The strongest effects are missing person reports, tweets with URLs and wanted messages stimulating message forwarding. The positive interaction between personal messages and URLs and high message counts and mentions also increase the odds of retweets. Small talk has the strongest diminishing effect. Based on these findings, this study adds another factor to the causes of message diffusion in the form of topics.

A third addition to the model is drawn from qualitative and descriptive studies concerning audience engagement on the platform, such as those by Kwak and Chun (2011) and Zhao and Zeng *et al.* (2011) . By aggregating the use of specific tweet characteristics for employed by a user, this study sought to quantitatively operationalize authorship style. Findings support the hypothesis that differences in authorship style significantly impacts retweet probabilities. Apart from direct effects, authorship has been observed to interact with the diffusion probability of specific topics, as with URL inclusion. This adds another dimension to predictive models of message diffusion, based on the distinction between tweet and user level characteristics.

5.2 Suggestions for further research

For future research, further analysis of user aggregated data may yield interesting results. Such analyses may uncover learning effects, such as diminished effects of URLs for users which often employ this feature. Understanding of authorship style can perhaps be enhanced with the application of sentiment analysis (Barbosa 2010), social network theory (Butts 2008) and improved topic detection (Cataldi and Caro 2010). In addition, the role of authorship may differ by cultural setting, as research points out international differences in twitter use (Poblete and Garcia *et al.* 2011) and e-governance in general (Zhao 2011). Lastly, this study has observed the relation of authorship and retweet probability in the context of police officials. Further research is required to understand the extent to which authorship is applicable to message diffusion in general.

Besides additional research into user-level characteristics, increased specification of topics may be beneficial. The rudimentary coding employed by this study suggests topics can be successfully applied in quantitative research. Besides testing the influence of topics for police officials of different nationalities, an improved method of topical coding might yield additional insights into this phenomenon. Although vertical coding, such as employed in this study, are supported as viable options for well-defined populations, more general approaches may be developed to understand general topics of interest. Some studies aimed at methodological development show promising inroads into broader application of topic based research (Michelson and Macskassy 2010, Yang and Chen *et al.*2011).

5.3 Advise for police officers & other practitioners

For police twitter users, this study has generated some applicable insights to increase retweet odds. Findings show some message characteristics which may be manipulated to increase the probability of message diffusion. Note that even messages with high probabilities may not be retweeted, and messages with low probability can be retweeted. Tweet characteristics to maximize are, in order of effect size:

- Send Replies with URLs, especially with new accounts.
- Include URLs.
- Use Mentions to show you are socially engaged.
- Include Hashtags to increase searchability.
- Longer tweets, rather than shorter tweets
- Tweet in the afternoon or evening, when more people listen.

In terms of user characteristics:

- More followers is better, but reduces the effect of replies and mentions
- Older accounts have less chance of getting retweets, unless there are enough followers.
- Having posted a lot reduces the chances of being retweeted
- Adopting a personal style increases chances for messages containing a URL, but decreases retweet probability for those without one. This is especially relevant for street level cops.
- Avoid retweeting others more often than sending original tweets, especially in combination with URLs

6. CONCLUSION

This study aimed to explain why some police authored tweets are forwarded whereas others are not. Results show both the (wo)men and message matter, as tweet and user characteristics both influence the chances of being retweeted. Differences in retweet probability for diverse topics were found. In addition, the inclusion of web addresses, hashtags and mentions were significantly related to retweet probabilities. Interaction with the audience by way of replies was also related to message diffusion, which emphasises the effect of engagement. Various user level characteristics such as audience size, previous experience and authorship style were of direct influence on retweet probabilities. In addition, user level characteristics significantly influence the effect of tweet level characteristics such as topics discussed, elements included and interactivity. These insights are also applicable by practitioners. Future research into the role of authorship style, user-averages and the role of topics may improve understanding of learning effects, audience expectations and online culture with regard to message diffusion.

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Appendix A: Best linear unbiased estimator model

AIC	BIC	logLik	deviance		
97624	98093	-48763	97526		
Random effects:					
Groups	Name	Variance	Std,Dev,		
name	(Intercept)	0,024146	0,15539		
Number of obs: 106462, groups: (name), 964					
Fixed effects:					
	Estimate	Std, Error	z value	Pr(>|z|)	
(Intercept)	-7,93E+00	2,45E-01	-32,37	< 2e-16	***
dayscale	4,81E-02	9,65E-03	4,98	6,24E-07	***
Char	9,58E-03	3,09E-04	31,04	< 2e-16	***
Hash	1,98E-01	1,75E-02	11,31	< 2e-16	***
Reply	1,29E+00	3,08E-01	4,2	2,70E-05	***
Url	1,29E+00	1,57E-01	8,21	< 2e-16	***
log(stats + 1)	-1,95E-01	6,54E-02	-2,98	0,0029	**
log(friends + 1)	6,74E-02	5,36E-02	1,26	0,209068	
log(followers + 1)	1,43E+00	5,01E-02	28,47	< 2e-16	***
CI	1,23E-01	1,89E-02	6,53	6,73E-11	***
DP	-8,72E-01	4,65E-02	-18,76	< 2e-16	***
TR	6,49E-01	2,70E-01	2,41	0,01616	*
PR	2,74E-01	3,91E-02	6,99	2,69E-12	***
LOF	8,22E-01	2,86E-02	28,78	< 2e-16	***
MIS	1,26E+00	9,18E-02	13,73	< 2e-16	***
ST	-5,23E-01	2,69E-02	-19,46	< 2e-16	***
c,pers	-2,06E-01	2,29E-02	-8,97	< 2e-16	***
c,auth	-3,64E-01	7,21E-02	-5,06	4,27E-07	***
Clmention	1,26E+00	2,64E-01	4,77	1,82E-06	***
days	-3,29E-03	2,73E-04	-12,04	< 2e-16	***
I(log(stats + 1) * log(stats + 1))	-3,33E-02	6,42E-03	-5,19	2,14E-07	***
I(Hash * Hash)	-2,28E-02	2,48E-03	-9,2	< 2e-16	***
log(stats + 1):Clmention	2,40E-01	3,63E-02	6,62	3,48E-11	***
log(followers + 1):Clmention	-4,40E-01	5,20E-02	-8,46	< 2e-16	***
DP:Clmention	5,48E-01	1,46E-01	3,75	0,000176	***
c,auth:Clmention	1,05E-01	2,95E-02	3,54	0,0004	***
log(stats + 1):log(friends + 1)	4,02E-02	9,11E-03	4,42	9,96E-06	***
Reply:log(stats + 1)	2,70E-01	4,91E-02	5,5	3,75E-08	***
Url:log(stats + 1)	1,53E-01	2,44E-02	6,26	3,76E-10	***
log(stats + 1):TR	1,61E-01	3,87E-02	4,17	3,01E-05	***
log(friends + 1):log(followers + 1)	-5,42E-02	1,04E-02	-5,19	2,07E-07	***
Reply:log(followers + 1)	-9,14E-01	5,72E-02	-15,99	< 2e-16	***
Url:log(followers + 1)	-2,73E-01	3,37E-02	-8,12	4,58E-16	***
log(followers + 1):c,auth	3,39E-02	1,15E-02	2,95	0,003199	**
dayscale:c,pers	-4,35E-02	1,13E-02	-3,85	0,000119	***
Char:TR	-8,04E-03	1,44E-03	-5,57	2,50E-08	***
Hash:Reply	1,46E-01	2,76E-02	5,29	1,22E-07	***
Reply:Url	6,10E-01	1,22E-01	5,01	5,36E-07	***

Reply:LOF	-7,74E-01	2,06E-01	-3,77	0,000165	***
Reply:ST	5,90E-01	9,96E-02	5,93	3,09E-09	***
Url:TR	-5,35E-01	9,32E-02	-5,74	9,19E-09	***
Url:c,pers	5,35E-01	2,33E-02	22,99	< 2e-16	***
CI:c,pers	1,53E-01	1,71E-02	8,94	< 2e-16	***
DP:ST	4,02E-01	1,11E-01	3,62	0,000296	***
PR:LOF	-6,11E-01	1,44E-01	-4,25	2,18E-05	***
Reply:days	7,18E-04	1,81E-04	3,96	7,63E-05	***
log(followers + 1):days	3,60E-04	4,14E-05	8,69	< 2e-16	***
TR:days	-5,13E-04	1,50E-04	-3,42	0,000628	***

Signif, codes: 0 ‘***’ 0,001 ‘**’ 0,01 ‘*’ 0,05 ‘,’ 0,1 ‘ ’ 1					

Appendix B:Wordlist

wanted

2298	zoekt
1848	bel 0900-8844
264	bel 09008844
1081	situatie
3294	getuige?
1667	iets gezien
467	opsporing verzocht
0	#####
55	SMS-Alert
36	Allert
309	help
258	signalement
28	weet meer
116	bellen met
1371	gezocht
779	alert
23	getuige gezocht
110	herkent u
66	herken je
0	####
8	informatie is welkom
18	vluchtauto
180	verdachts gezien
26	bel of mail
10	uit kijken naar
229	wie herkent
161	verdachte personen
27	verdacht persoon

department

2934	overleg
139	discussie
324	buro
393	opleiding
19	excuses voor
1	manual
1	gratis hulp
3	beslis mee
60	procedure
406	project
150	cijfers
48	assisteren
3	diensten zijn druk
3389	verleg
77	aftrap
1035	spreekuur
30	extra inzet
9	collegas in dienst
84	teamchef
72	praten over
662	briefing
20	om de tafel
71	focus

Prevention

55	bedenk
79	folder
2	empty
1105	waarschuw

Missing

2200	vermist
877	vermiste
59	laatst gezien

Event

32	deelname
1100	campagne
206	acties
333	evenement
326	opstelten
14	actie voeren
429	voorlichting
104	opkomst
21	live tijdens
22	EK
22	WK
725	actie
55	demonstratie

Smalltalk

0	zo ga hierna
4	nice!
21	prima!
235	heerlijk
1726	leuk
833	lekker
61	genoten
604	vrij
203	einde dienst
2	begin dienst
311	bang
143	goeie
14	oh ja
1	meningen
1040	(winks)
516	:-)
116	vriendin
8	success
19	tot ziens
0	wrijf het maar in
1017	fijn
27	gecertificeerd
747	dagdienst
2372	mooi
1124	aanwezig
205	zometeen
1800	rustig
148	enthousiast
64	ha

Crime / Incident

99	aanhouden
5953	aangehouden
4	houdt aan
376	vlucht
2390	gestolen
432	opgepakt
162	opengebroken
324	opgelost
66	gearresteerd
324	opgelost
19	veroordeling
1008	rijbewijs
312	arresteer
83	opstoot
2390	gestolen
973	drug
24	explosieven
132	opgerold
1258	mishandeling
1241	ongeval
1010	brand
811	anhoudingen
7	ontruimt
44	explosief
3074	onderzoek
209	verklaring
28	aan te houden
2112	anhouding
2151	melding

	traffic	17	riskeer	365	late dienst	652	overvallen
77	fietscontrole	32	houdt rekening	183	prachtig	3167	overval
2	aanrijding plaatsgevonden	36	oppassen	945	de wijk in	80	ontruimd
2826	verkeer	168	denk aan	154	toetsen	2154	aangetroffen
70	radarcontrole	119	opvallende	72	weet ik	848	ingebroken
293	a6	1127	toezicht	349	geniet	21	escalatie
337	thv	168	NIET!	4	briefings	10	pakt op
103	a1	38	géén	20	goed om te zien	10	opvarende
95	a2	8	ga niet in op	593	ik heb	20	betrapte
33	a3	240	goed op	386	jammer	324	opgelost
120	a4	489	preventie	538	bezig met	15	geruime tijd
19	a5	498	vooral	1499	bezoek	1656	nieuws:
75	a6	5	voordoen als	14	je bent welkom	34	omgekomen
63	a7	0	voordoet als	1040	gezellig	135	geruimd
22	a8	18	zegt het voort	359	gefeliciteerd	2767	overlast
43	a9	3	pas ook op	271	trots	112	overgedragen
3	u mag hier	21	reken op	310	koffie	3	niet in gevaar
1	je mag hier	88	levensgevaarlijk	67	voelt	1356	hennep
16	aanrijding geweest	156	gevaarlijke	25	#loesje	3	achtervolgen
8	total loss	3	verassen	56	zonde	847	slachtoffer
23	busbaan	38	niet toegestaan	199	afscheid	5012	inbraak
110	aanrijding:	0	wordt hier vaak	56	drukke dienst	591	gepleegd
1329	snelheid	972	voorkom	91	kennis gemaakt	2332	inbraken
10	doorstroming	190	meld misdaad anoniem	499	surveillance	284	vechtpartij
33	dichte mist	33	fraudealert	529	:)	24	wiet