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Predicting the popularity of TV-show through text mining of tweets: A Drama Case in South Korea☆

Do Yeon Kim[1] Yoosin Kim[2] Sang Hyun Choi[2*]

ABSTRACT

This paper presents a workflow validation method for data-intensive graphical workflow models using real-time workflow tracing mode on data-intensiveworkflow designer. In order to model and validate workflows, we try to divide as modes have editable mode and tracingmode on data-intensiveworkflow designer. We could design data-intensive workflow using drag and drop in editable-mode, otherwise we could not design but view and trace workflow model in tracing mode. We would like to focus on tracing-mode for workflow validation, and describe how to use workflow tracing on data-intensive workflow model designer. Especially, it is support data centered operation about control logics and exchange variables on workflow runtime for workflow tracing.

☞ keyword : Data-Intensive Workflow Validation, Workflow, BPM

1. Introduction

Many changes took place in the interaction surrounding the TV due to the recent emergence and spread of the Internet and SNS, Social Network Service. In the past family members communicated with one another while watching a TV program and nowadays families are used to share their feelings in the Internet space and SNS [1]. SNS has recently emerged as a new means to community members to communicate freely. SNS has an important role in the formation of the discourse to a TV program. Therefore paying attention to communicating data such as SNS is used to discover new values. Most of the current data is increasing exponentially, which is usually unstructured text. Media users created through social media such as Twitter and Facebook. Characterized by a high proximity and simplicity, Twitter has the retweet function of transmitting a tweet bounded to 140 characters of the message. It is possible to diffuse the information via a one-way relationship, and has the advantage of being able to recognize events that are happening in the real world in real time.

Likewise, local media industry needs to make use of big data. Mostly, TV drama series are produced not in advance (i.e. entire production is completed before a show is aired) but in tandem with the organized timeline for each episode. AMR (average minute rating) as a viewer rating data is a quantitative measure with which investors can evaluate the effectiveness of TV programs they invest their capital in. Korean wave called Hanryu, including K-pop and TV soap operas have been spreading globally. At the same time, devices and platforms used for enjoying media contents have been evolving. In this context, an analysis system to evaluate strategies for reducing investors' risks and maximizing marketing effects would need to be introduced to facilitate the production of qualified cultural contents. This study aims to predict the effects of independent variables through a multiple regression analysis of the quantity of Twitter message data, or the number of mentioned keywords. Target variables are AMR and SHR representing viewer ratings in the media industry. We identify correlation between data quantities and viewing rates by matching the quantity of Twitter message data about the episode aired on a given day relative to the AMR and SHR of the next episode. The relation information would be significantly helpful for broadcasters to make or change marketing strategies responsively.

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[1] Department of Information Security Management, Chungbuk National University, Korea
[2] Department of Management Information System, BK21+ BSO, Chungbuk National University, Korea
[*] Corresponding author (chois@cbnu.ac.kr)
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2. THEORETICAL BACKGROUND

2.1 TWITTER CONCEPTS AND FEATURES

Twitter is a micro-blog and mini-blog that was developed in the United States of Jack Dorsey, Evan Williams, BizStone such as jointly in 2006. San Francisco venture company Obvious was first opened. The Twitter is an online open space which messages can be delivered in the light speed. The number of characters that can be written at one time is limited to a maximum of 140 characters. In the disaster or crisis situation, it has played the role of rapid media and can be used as a tool of personal publicity or public relations company due to the huge disseminative property [2].

When they have smartphones, mobile users can freely communicate without being bound by location. As you can send and receive information in real time, there is a large spreading power. Comparing the characteristics of the Twitter with existing social network is shown at <Table 1>.

〈Table 1〉 Twitter and existing social networking services [3]

Item	Twitter	Facebook/ My Space	Portal site
Information type	Text	Picture, Text	Picture, Text
Information Characteristics	Simple, Personal	Complexity, Personal	Complexity, some professional
Device range	Web Mobile Instant Message	Web Some Mobile Extensions	Web
Way relationship	Following One-way	Invitation -Allowed	Sign-Approval
Information spreading rate	Very fast	Fast	Primarily spread inside the Community
Business Model	No business model	Banner advertising revenue and paid applications	Banner advertising revenue

2.2 LITERATURE REVIEWS ON SOCIAL MEDIA AND TV WATCHING

Social media refer to platforms where users of SNS (social networking services) such as Twitter and Facebook share information and comments, broadening their relational networks (Communication Books, Feb. 05, 2013). According to a study on variables affecting the AMR or SHR of a local TV drama series based on data collected from social media including Twitter, Me2day and Daum Yozm [4], local SNS better indicated the AMR of the local TV drama series. Lee (2013) explored the word-of-mouth (WOM) effects on TV soap operas, analyzing the word-of-mouth activities arising in the course of Twitter communication [5]. In short, messages on such key components as plots, themes and materials were found to spread most actively, suggesting consumers' WOM information served as a determinant in their choice of a TV drama series. Also, no significant difference was found in the word of mouth on Twitter over time, whereas differences were found in word-of-mouth acts and diffusion activities between on the day a show was aired and on the days following.

Investigating the relationship between TV programs' AMR and Twitter buzz, Lee (2014) found Twitter buzz and AMR were temporally accompanying variables, and their relationships varied with program genres [6]. Bai & Choi (2013) reported that active SNS interactions about TV programs occur before, during and after the programs being aired [7]. Interactions happening before TV programs being aired were mainly about sharing information about and watching such programs. Interactions on SNS while TV programs being aired resulted from a desire to watch TV with others and maximize the pleasure. Interactions occurring after TV programs were aired included opinions, ratings and reviews, and formed diverse discourses on given programs. Lee & Jung (2014) extracted topic key words representing Tweet context to reveal which filmic properties reflect the interest of the audience. By analyzing the reaction of those properties by the audience, they suggested factors that influenced box-office hits of movies [8]. Kim et al (2012) used Core-Topic-based Clustering to analyze tweets of particular dramas and extracted significant topics [9]. (Ni et al, 2011) extracted core words from Twitter to suggest movie contexts frequently referred by users and clustered similar tweets following topics [10].

2.3 LITERATURE REVIEWS ON ONLINE WORD OF MOUTH AND SOCIAL IMPACT

Online word of mouth refers to the word which is spreading via online users' postings (Nilsen KoreanClick). With the advent of social media, WOM (word-of-mouth) marketing has become highly sought out. As a means of communication where consumers informally share positive or negative information about certain matters based on direct or indirect personal experiences [11], WOM communication often takes place between family members or close friends with strong ties. Over recent years, the rising influence of SNS has highlighted the importance of and attention to the word of mouth [12]. In light of the conformity phenomenon most frequently cited in socio-psychology referring to social influence, the more a WOM message, the stronger the tendency to conform to the message [13].

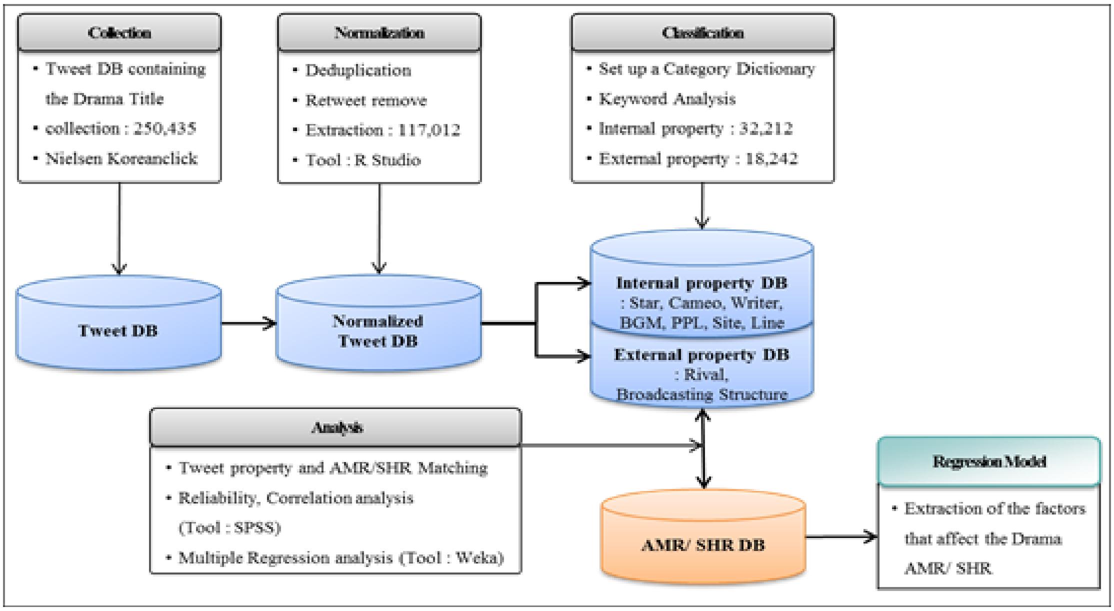
Meanwhile, as a determinant of a film's box-office hit, the effects of total online WOM have drawn much attention [14]. The frequency of online WOM of a film was found to have significant effects on its box-office performance. Particularly, online WOM exerted substantial effects in the first to second weeks of a film's release. Verifying the effects of online WOM on box-office performance of 68 local films released in 2010, Park & Song (2012) compared the influence of online WOM with that of the previously verified traditional factors including production cost, genre, star power, rating, distributor power, number of screens and critics' opinions, and found the effects of online WOM, or frequency of netizens' reviews and comments came second after the number of screens [15]. Differently put, buyers tend to rely on the information of others' experiences in order to lessen the perceived risks and uncertainties in making decisions on buying things in the absence of their direct experiences.

3. RESEARCH METHOD

3.1 ANALYSIS PROCESS

The present study tests hypotheses by comparatively analyzing the Nielsen Korean Click's data concerning content-related Twitter and the AMR

and SHR data from AGB Nielsen Media Research, the world's best AMR research firm operating in 46 countries, or 76% of global market. The detail analysis process is shown at Figure 1.



(Figure 1) Analysis process

3.2 EXPERIMENTAL DATA (CONTENT & DATA)

3.2.1 Content

As shown at Table 2, "My Love from the Star" is a TV drama series consisting of 21 episodes aired on SBS from December 18, 2013 to February 27, 2014. It is an SF romance soap opera based on a story of an unidentified flying object witnessed in Gangwondo on September 22, 1609 as recorded in king Gwanghaigun's diary documented in the Annals of the Chosun Dynasty (Newsjelly, Feb. 09, 2014).

(Table 2) Analyzed Content

Item	Details
Content	My Love from the Star (21 episodes)
Channel	SBS
Timeline	Wednesday and Thursday nights (10 p.m.)
Period	Dec. 18, 2013 ~ Feb. 27, 2014
Writer	Park Ji-eun
Cast	Jeon Ji-hyoen, Ki Soo-hyeon, Park Hai-jin, Shin Seong-lok, Yu In-na, etc.

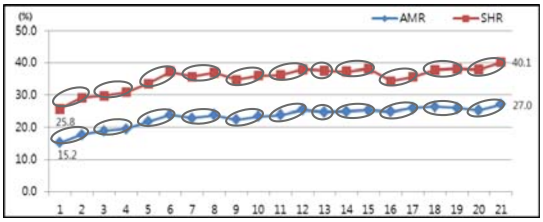
3.2.2 AMR and SHR data

The AMR (Average Minute Rating) and SHR (Share Rating) data from AGB Nielson Research were used as shown at Table 3. The trends of AMR and SHR for each episode of "My Love from the Star" are as in Figure 2.

(Table 3) Scope of Data Yielded

Item	Details
Content	AMR (Average Minute Rating) and SHR (Share Rating)
Target	Households nationwide
Period	18/12/2013 ~ 27/02/2014
AMR	Households watching a certain channel out of all households having TV sets
SHR	Households watching a certain channel out of all households watching TV

For the duration of analyzing "My Love from the Star", its AMR and SHR were 26.1% and 39% on average, respectively. Excluding the AMR and SHR on January 8, 2014 (Ep.7) slightly lower by 1% and 1.5%, respectively, than those for episodes 1 to 6, overall AMR and SHR data showed upward trends. The last episode recorded the highest AMR (27%) and SHR (40.1%). Due to the cancellation on January 30, 2014 (Ep.14), the AMR and SHR for Thursdays were excluded.



(Figure 2) AMR and SHR data trend circled by a week

3.2.3 Twitter message data

For the purpose of this study, online buzzword data were collected by Nilsen Korean Click, 21 episodes of the TV soap opera "My Love from the Star" were selected as the content for analysis. Twitter data generated for 91 days (December 2, 2013 ~ March 2, 2014) were investigated. Postings mentioning the title were extracted, whereas those not mentioning the title were excluded. Tweets at Table 4 were collected a total of 250,435 tweet. Duplicate content and retweets are removed and analyzed for 117,012 tweet.

(Table 4) Scope of Data Yielded

Item	Detail
Target	Twitter
Condition	My Love from the Star, You Who Came from the Stars, MLS (My Love from the Star), #My Love from the Star, #MLS → The title must be mentioned.
Amount	250,435
Period	00:00:00 02/12/2013 ~ 23:59:59 02/03/2014 (91 days)

3.3 Noun extraction & Categorization

R package was used to calculate the frequency of the tweeter word. The following Table 5 is intended to indicate the nouns corresponding to the most frequent 1 Ranked to the 20 Ranked. Words that showed the highest frequency corresponds to the main character of the drama is a “Soo Hyun Kim, Ji Hyun Jeon ”. In addition was a lot of talk about characters. The viewer can know that it is showing a high interest to the actor in the drama.

⟨Table 5⟩ Base frequency of Noun Extraction

Rank	Noun	Frequency
1	Soo Hyun Kim	4,931
2	Ji Hyun Jeon	3,776
3	SBS	1,802
4	Yi Chun Song	1,703
5	Tue	1,497
6	Wed	1,415
7	Jun Do Min	1,398
8	OST	1,293
9	Forewarning	1,181
10	Youtube	975
11	Naver	928
12	Average minute	866
13	Time	754
14	News	746
15	Jae Hyun Ahn	643
16	Sung Rok Shin	638
17	Epilogue	630
18	Performance	629
19	Love	595
20	Kiss	555

Category classification table, according to the previous studies about the properties of the message, were divided into internal and external attributes [16][17][5].

Table 6 shows 9 variables which represent the number of twitter comments about each variable. For example, X1 means the number of comments in twitter about stars shown at the drama. Types of opinion are divided into cognitive interaction, emotional interaction, and act interaction based on the attributes of the message. There are 3 kinds of articles in accordance with the content and theme of the articles. First types are directly related to the specific program. Second ones are no direct relevance and writings about the program. Lastly a variety of tearing is on viewing function and so on [18]. However, variables used in this study are largely divided into internal properties (The main character, Cameo, Writer, BGM, PPL, Filming Site, Dialogues) and external properties (The same time drama, Broadcasting Structure) to reflect the characteristics of the Twitter and drama. Character was composed main character, cameo (Special appearance, Appearances friendship) and writer.

3.4 MATCHING ANALYSIS OF AMR/ SHR WITH BUZZ

Based on the “My Love from the Star” category dictionary, we placed the average minute rating(AMR) and share rating(SHR) at the dependent variable Y1 and Y2. The nine independent variables including the structure of the main character, broadcasting structure, and so on were denoted as X1~X9.

⟨Table 6⟩ AMR/SHR and Twitter attribute matching table

Twitter	Variable	Variable Name	Measurement Time	Internal	External	Episode	AMR	SHR
In ternal	X1	Star		$X_1, \cdots, X_7$	X_8, X_9		Y_1	Y_2
	X2	Cameo	Thu (23:10) ~ Fri (24:00)	$X_1^1, \cdots, X_7^1$	X_8^1, X_9^1			
	X3	Writer	…					
	X4	BGM	Wed (00:00 ~ 22:00)	$X_1^2, \cdots, X_7^2$	X_8^2, X_9^2			
	X5	PPL	Wed (22:00 ~ 23:10)	…		e_1	Y_1^{e1}	Y_2^{e1}
	X6	Site	Wed (23:10) ~ Thu (22:00)	$X_1^3, \cdots, X_7^3$	X_8^3, X_9^3			
	X7	Dialogue	Thu (22:00 ~ 23:10)	…		e_2	Y_1^{e2}	Y_2^{e2}
Ex ternal	X8	Rival	…					
	X9	Structure						

AMR and SHR of Wednesday matched through Friday after data on Thursday broadcast and Wednesday broadcast before the data (1). AMR and SHR Thursday matched through after data on Wednesday broadcast and Thursday broadcast before the data (2).

$$[X_1^1, \ldots, X_9^1, X_1^2, \ldots, X_9^2] \xrightarrow{\text{Multiple Regression Analysis}} [Y_1^{e1}, Y_2^{e1}] \quad (1)$$

$$[X_1^3, \ldots, X_9^3] \xrightarrow{\text{Multiple Regression Analysis}} [Y_1^{e2}, Y_2^{e2}] \quad (2)$$

4. PREDICTION OF AMR/SHR

4.1 RELIABILITY ANALYSIS OF MEASURING ITEMS ANALYSIS

To analyze the reliability of testing, SPSS 18 was used. To measure the reliability, Cronbach's alpha was used. An alpha above 0.6, or more strictly above 0.7, is considered to indicate a high reliability. For nine properties of Twitter messages and AMR, SHR Alpha value of 0.710 at Table 7, since satisfy the reliability, it was performed multiple regression analysis.

(Table 7) Reliability Analysis of Measuring Items

Variable	Cronbach Alpha	Number of items
Twitter and AMR/SHR	0.710	10

4.2 INDEPENDENT VARIABLES CORRELATION ANALYSIS

In this study, by using the SPSS18 to figure out correlation between independent variables were performed correlation analyzes. The results are Table 8, the closer to 1.00 indicates that the correlation is very high. Correlation between the two variables are highly The Star (main character), the correlation value of the BGM and the Broadcast Structure variable is the highest as 0.780.

4.3 MULTIPLE REGRESSION MODEL FOR PREDICTING AMR AND SHR

For the multiple regression analysis of Twitter data satisfying the TV program's AMR and SHR as well as reliability, WEKA 3.4.1 was used as a mining tool. Table 9 show the findings from the multiple regression model analyzing the relationship between the Twitter data variables and the AMR and SHR by dividing the entire data set Cross-validation Folds 6.

(Table 8) Independent variables correlation analysis

X	1	2	3	4	5	6	7	8	9
1	1								
2	.476*	1							
3	.035	.325	1						
4	.666**	.235	-.137	1					
5	.586**	.161	-.106	.307	1				
6	.312	.332	-.155	.314	.215	1			
7	.249	.053	-.369	.264	.218	.214	1		
8	.360	.076	.544*	.348	.027	-.042	-.023	1	
9	.619**	.271	-.113	.780**	.201	.173	.362	.176	1

** $p < 0.01$, * $p < 0.05$

(Table 9) Multiple Regression Analysis Results of AMR and SHR

Statistics	AMR	SHR
Linear Regression Model	AMR = 0.007 * Star + 0.090 * Dialog + -0.02* Rival + 21.234	SHR = 0.007 * Star + 0.127 * Dialog + -0.023 * Rival+ 33.9745
Correlation Coefficient	78.95%	68.05%
MAE	1.5406	2.1824
RMSE	1.8884	2.6746
RAE	61.479%	72.3345%

Table 9 shows overall indices of the precision of prediction. The correlation coefficient represents the correlation between predictor variables and target variables. AMR is 78.95%, SHR is 68.05%. Based on the RAE (Relative Absolute Error) of the two models' actual values and predictive values, AMR proved to be less prone to error by 10% on average than SHR. In view of the regression coefficient for AMR, out of the entire Twitter data, Dialogues (0.0904), Rival (-0.02) and Star (0.0067) were found to serve as the principal factors influencing AMR. Likewise, SHR was influenced principally by Dialogues (0.1269), Rival (-0.0234) and Star (0.0065) the order named.

5. CONCLUSIONS AND FURTHER STUDIES

In general, contents for TV shows are not produced in advance in Korea. Rather, the production process goes in tandem with the organized timeline for each episode to be aired. If the marketability of contents about each episode could be identified, it would be viable to decide on whether to invest in contents including advertisements and sponsorships within the shortest time possible. Contents may be evaluated based on quantitative social interactions they generate [18]. The present study performed the multiple regression analysis to predict AMR and SHR, both of which serve as quantitative measures for investors to determine the performance of contents relative to the production cost. The quantity of Twitter data associated with cumulative interactions about contents was used as the independent variable. The present study is significant in that it explored the relationship between AMR and SHR based on online Twitter data, which approach was hardly taken by previous studies. In brief, the findings of this study are as below.

First, as we got the value of 0.7 as reliability between nine properties of Twitter messages and dependent variables, a multiple regression analysis was performed. The correlation coefficient represents the correlation between predictor variables and target variables. AMR is 78.95%, SHR is 68.05%. Based on the RAE (Relative Absolute Error) of the two models' actual values and predictive values, AMR (61.479%) proved to be less prone to error by 10% on average than SHR (72.335%). Accordingly, Twitter message data will have implications for AMR and SHR in practice.

Second, although factors influencing AMR and SHR varied daily, the present study empirically proved Dialogues on internal data and Rival on external data, Star on internal data influenced AMR and SHR. The TV drama is visual arts and visual media where the story is drawn through the words and actions express. This means that words and actions of the characters in the drama is the most important factor. The fact that the TV dialogues play an important role in AMR and SHR was confirmed empirically.

Third, the multiple regression analysis dialogues and star on internal data had positive effects on AMR and SHR, whereas the Rival as part of the external data had negative effects on AMR and SHR. Thus much buzz of content receivers on dialogues and star of an episode on a given day predicts high AMR and SHR of the following episode. In contrast, frequent mentioning of Rival on a given day when an episode is scheduled to be aired is likely to lower the AMR and SHR of the following episode.

Fourth, the present study contributes to addressing the practical difficulties in predicting AMR in the field of content production, investment and organization. Reflecting such big data analysis results as the present findings in the scale, method and content in the course of producing TV soap opera series, the present analysis may be used as a reference tool to carry out strategies for reducing investors' risks and optimizing marketing effects. Moreover, the present findings will be significantly conducive to further studies on quality content production.

Yet, the present study has the following limitations, which warrants further studies. As the reference data for predicting AMR and SHR, the present study drew on Nielsen Korean Click's collection of open postings relevant to the TV drama series as Twitter message data. It should be noted that these reference data are separately yielded based on a collection of sites having a large number of unique visitors or many postings generated, and thus may differ from the numerical data returned on portal searches. Also, as for the SNS, the data on the world's most widely used Facebook were excluded because the amount of data open to the public was considered limited on Facebook. Future studies may add implications to the present findings by isolating the SNS component item to analyze its relationship with AMR.

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◐ Authors ◑

김 도 연 (Do Yeon Kim)
2014년 한국교통대학교 경영학과 졸업(학사)
2016년 충북대학교 정보보호경영학과 졸업(석사)
2016~현재 한국직업능력개발원 자유학기·진로체험지원센터 연구원
관심분야 : 정보보안, 빅데이터 활용, 데이터마이닝
E-mail : lloook91@krivet.re.kr

김 유 신 (Yoosin Kim)
2000년 국민대학교 정보관리학과 졸업(학사)
2009년 국민대학교 비즈니스IT학과 졸업(석사)
2013년 국민대학교 비즈니스IT학과 졸업(박사)
2015~2016 충북대학교 경영정보학과 연구교수
관심분야 : 소셜미디어 데이터 분석, 빅데이터
E-mail : akilleo@naver.com

최 상 현 (Sang Hyun Choi)
1991년 한양대학교 산업공학과 졸업(학사)
1993년 한국과학기술원 산업공학과 졸업(석사)
1998년 한국과학기술원 경영정보학과 졸업(박사)
2011~현재 충북대학교 경영정보학과 교수
관심분야 : 데이터마이닝, 빅데이터 활용, 지능정보시스템
E-mail : chois@cbnu.ac.kr