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# **MEDIA SHARING WEBSITES AND THE US FINANCIAL MARKET**

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## **ABSTRACT**

Recently, one of the main issues of concern within the world wide web is the understanding of web 2.0 mass collaboration systems. These systems have emerged in recent years and gained enormous popularity. It must, however, be pointed out, that the potential and practical application of web 2.0 are still not well understood and deserve academic attention. In this paper we investigate the online media sharing collaborative community and its applications for uses in stock market analysis and prediction. Specifically, we look at Youtube.com, one of the most popular social media sharing websites. The association with stock market behaviour and usage patterns are investigated. This work became of more interest and significance with the recent credit crunch crisis. The data under investigation is novel, and to our knowledge, this paper reports the first investigation of its kind to the use of collaborative media sharing website for stock market analysis. We find significant association between video meta-data and textual data using a content driven sentiment text mining approach. The results are very encouraging and importantly highlight efficient information transfer to online media sharing communities as there seems to be predictive value in youtube data.

## **KEYWORDS**

Data Mining, Information Retrieval, Web 2.0 , Mass Collaboration, Finance, News Publishing.

## **1. INTRODUCTION**

With the advent of Web 2.0 systems almost everybody can now update, upload and collaborate on content of webpages (Vossen and Hageman, 2007). Whether these are file, personal detail or news sharing applications. Online community based Media Sharing especially, has in the recent years gained hugely on popularity. With sites such as Youtube.com, MetaCafe.com, Vimeo.com, or Revver.com leading the way in becoming truly “web 2.0 media” phenomenons. At first only intended for entertainment purposes, now these websites are used for news dissemination and individual users partake religiously in media sharing activities. Everybody with an internet connection, whether with or without a camera, can contribute to social video websites, hence the content is highly dynamic with high update frequencies. Users upload every and any kind of imaginable videos, ranging from personal videos, mobile phone videos of US soldiers in Iraq, post election riots in Iran (coverage of the riots has been exclusively from mobile phones) to daily market analyses of the world's economies (Tapscott and Williams, 2008). Moreover press agencies and TV stations like BBC or Bloomberg duplicate their video content from traditional distribution channels. This can have some practical applications, such as whether new trends in music, politics or expected stockmarket activity and other patterns can be detected, the latter being the focus of work, reported herein. Specifically, we explore statistical correlation between stockmarket movement and youtube meta-data.

The rest of this paper is organized as follows: in section 2, background and novelty is discussed, section 3 presents the systems architecture and experimental set-up, with results being demonstrated in section 4, followed by conclusions drawn and further work highlighted in section 5.

## 2. BACKGROUND

Youtube.com was established in February 2005, as an “online video and the premier destination (..) to watch and share original videos worldwide through a Web experience”<sup>1</sup>. It is a free community-driven website through which registered users can upload unlimited number of videos and share them with other users. Each video must be given a title and be assigned to a specified category (e.g. News, Music). A publisher can optionally provide further details (discussed in section 3.1). According to alexa.com, web traffic has been constantly growing since its founding, earning youtube a ranking in top 3 most frequently visited websites in the world. It reaches about 5% of internet users in a day and generates 20% of all http based pageviews on Internet. These figures make youtube most popular community based website.

### 2.1 The Mass Collaboration effect

Mass collaboration or what we like to refer to as knowledge optimisation based on intelligence of crowds, and its benefits, whether in terms of problem solving or simply information gathering and filtering, are very appealing reasons behind the adoption of Web 2.0 systems. In a read and write web the contribution of individual users on a large scale amounts to optimisation in the sense of improving a fitness function (Tapscott and Williams, 2008). Where such a fitness function is understood to be a goal or purpose of the social sharing application, this tends to happen due to emergence of statistical regularities in the evolution of collective choice from individual behavior. To illustrate this idea further, let us look as an example at Wikipedia<sup>2</sup>. Users are encouraged to edit and re-edit this web based encyclopedia in the communal hope of producing an immense body of encyclopedic knowledge. Critics, such as Keen (Keen, 2007) point out the seemingly intrinsic problem, that is such a vast text would clearly have to be riddled with inaccuracies. Quite surprisingly however Wikipedia was found to be an accurate resource and is now becoming a standard encyclopedic reference text. A comparison with encyclopedia Britannica (Giles, 2005) suggests a similar level of information accuracy in both encyclopedias. As was shown, 70%-80% of inaccurate edits on Wikipedia get corrected almost instantly (Adler et al. 2008a/2008b). This can be attributed to the dynamic nature and self-managing environment of collaborative web 2.0. In the case of youtube, numerous users get together to share videos on various topics. Collectively a huge database of videos on wide range of events is built and tagged with meta-data. The quality of content is ensured by a mix of expert and non-expert community participants, that review, rate and comment videos. Since it has become so easy to produce and upload videos, information, opinion and news propagates rapidly throughout youtube. For further examples and case studies of mass collaboration in practice, please refer to (Tapscott and Williams, 2008).

### 2.2 Previous Work and Literature

Arguably, quantities of potentially useful content are locked up on Web 2.0s “architecture of participation”<sup>3</sup> and recently quite interesting work was done to identify and bring some of this content to the surface. Adamic and Glance (Adamic and Glance, 2005) for example analysed links between liberal and conservative blogs during the 2004 US presidential elections. There is strong evidence that political opinion is represented in online media sentiment (Mullen and Malouf, 2006; Malouf and Mullen, 2007; Johnson et al., 2007; Farrell and Drezner, 2008). Naturally, this could have number of applications, such as commentary and analysis of political opinion, or forecasting. More generally, Mishne and de Rijke attempt to identify overall topic independent mood sentiment represented on blogs and in their textual posts (Mishne and de Rijke, 2006a/2006b; Balog et al., 2006; Mishne et al., 2007) and classify them into mood categories such as tired, cheerful, happy, calm, angry, etc. This is possible via semantic text analysis and tags. It has been shown that mood is intrinsically present in informal text posts and we, as well as previous authors, hypothesise, this information if extracted, may be of some value.

Of most interest to us is sentiment analysis related to stockmarkets. (Choudhury et al., 2008) investigated

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<sup>1</sup> According to youtube [http://www.youtube.com/t/about?hl=en\\_GB](http://www.youtube.com/t/about?hl=en_GB) (consulted on 2 April 2009)

<sup>2</sup> Wikipedia is an online, publicly maintained encyclopedia. It covers millions of topic definitions.

<sup>3</sup> A poignant term coined by Tim O'Reilly on his blog, (O'Reilly, 2005) on 1st October 2005.

correlations of tech-companies on stockmarket with activity on the blogosphere. Using a Support Vector Regression model, they found very encouraging associations with stock magnitude and price direction advances. As early as 1999, (Wysocki, 1999) and then Jones (Jones, 2006) analysed the impact of posted discussion board messages onto stock moves. They found that after online forums were introduced to world wide web, trading volume and volatility have significantly increased and daily absolute returns on average decreased. This is an interesting observation as it highlights strong effect online information seems to have on the stockmarket. (Tumarkin and Whitelaw, 2001) found correlations between abnormal activity on popular online forum Raging Bull ([www.ragingbull.com](http://www.ragingbull.com)), and abnormal share returns. (Thomas and Sycara, 2000) implemented a simple text processing (bag-of-word frequency) GA based trading system, using the very same discussion board and reported successful trading performance. (Antweiler and Frank, 2004) applied text analysis techniques to capture semantic meaning of forum posts, and also achieved significant correlations. (Das et al., 2005) investigated message board posting and news correlations with stock returns, but at same time investigated the disagreement between news and message board postings. Gloor et al. (Gloor et al., 2008) and others (Fung et al., 2005; Clarkson et al., 2006; Sabherwal et al., 2008) also found statistically significant association with stockmarket moves.

All of this work however was performed with either blogs, online news websites or discussion boards. To the knowledge of the authors however, no investigation into video media sharing systems for financial market prediction is in existence. Hence we consider this work to be novel and original in respect of reported results and the uniqueness of dataset under investigation.

## 2.3 Market Predictability

Price movements in financial markets are consequences of decisions taken by both stockholders and stock buyers based on how they perceive market, sector, company or asset. Actions taken by them are not only influenced by the rational information on market but also what actions other investors took, what somebody said or wrote, and simply sentiment and emotion. According to the recently emerged field of behavioral finance (Siegel, 2002), feelings of anger, fear, uncertainty or confidence and subjective perceptions of financial perspectives of economic agents have real impact on entire markets and therefore price movements.

In its simplified form, Efficient Market Hypothesis, originally proposed in the 60s (Fama, 1965), essentially states that market participants have equal access to information, and as new information affecting a market comes out, this information is counted-in into the market almost instantly. An offshoot of this hypothesis is the Adaptive Market Hypothesis (Lo, 2004). AMH takes behavioral finance into account, and it is within this framework that it is acceptable to expect some short to medium term predictability, based on the information we extract from youtube. This is possible, however, only if assuming information propagates into youtube quickly enough, and can be filtered well from non relevant information. Since all these assumptions cannot be guaranteed we decided to concentrate our main efforts into researching whether a relationship between youtube and stockmarkets is present and if so of what strength and in what form. Indeed, we discovered a strong relationship in number of cases. Our findings are encouraging.

## 3. SYSTEM ARCHITECTURE

The goal of our experiments is to show there is correlation between changes in stockmarket prices and community submitted information on the youtube platform. In order to show this relationship we took a set of steps to extract, prepare and analyse youtube data. We were interested in answering two questions. **First**, *whether it is possible to relate intensity of content submissions with market volatility*. **Secondly**, *whether it is possible to quantify sentiments of videos and relate them to directional market moves*.

### 3.1 Input Data

We are interested into as much youtube meta-data as possible. Every uploaded video on youtube is in the form of a video file and a set of related meta-data describing the file. Such meta-data contains video title, description, category, date of submission, view count, duration and author. Since youtube is a social website it also allows users to comment, rate (1 out of 5) and submit response videos. Videos can also be tagged with

arbitrary tags that might help identify a video better. The meta-data attached to a file, shown in Figure 1.

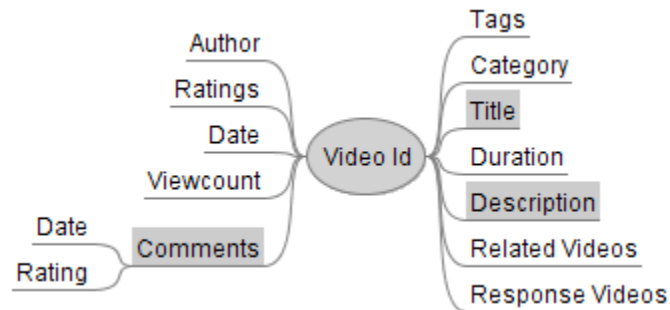


Figure 1. Video meta-data associated with a youtube file. Highlighted fields represent three main streams of textual data

Title, Description, Category and Tags provide basic information as to the content of a video clip. Author, Date, communicate who and when submitted the file. Ratings and Duration tell us a little bit more about the video. Viewcount and Comments are quite important for our analysis, the former can be important in judging the popularity of a video and the latter also provides us with collective opinion about a video contribution in textual form. Related videos are video recommendations that might be of similar content to the target video. This is done by an algorithm that is kept secret<sup>4</sup>. Response videos are actual file responses to the original clip, and are usually used to create a so called “video-debate“.

Stockmarket indices were used as proxies for financial markets. For some keywords, tags, time periods, especially early periods, there is little number of youtube clips available. Hence stock indices are ideal.

### 3.2 Data Collection

In November 2006 youtube was acquired by Google, Inc. after a few months Google implemented their API called GDATA, enabling developers to integrate systems with youtube platform. We made use of this API to extract as many financial market related videos as possible for the entire available time period. Videos based on search keywords FTSE, DOW JONES, NASDAQ, NIKKEI, CAC, DAX<sup>5</sup>, and also related and response videos were retrieved (see section 3.1). Since each of these videos has a lot of meta-data associated, we extracted altogether about, 90'400 videos, 89'000 tags and 3'749'000 comments on submissions related to finance news.

A number of issues with API were encountered, some errors were discovered and some limitations imposed by the youtube terms and conditions. It was ensured that terms and conditions were complied with by an appropriate implementation of our scripts. Main bulk of data extraction process took over 7 days. After this we run extraction scripts daily to ensure database was kept up to date with recent video submissions. Since our system required manipulation of large amounts of data, a powerful server set up; DELL PowerEdge 1950 III with two CPUs Intel Quad Core Xeon 2.66GHz, 8GB of RAM memory and SAS hard drives running Linux Debian OS and MySQL was used in experiments.

### 3.3 Data Preprocessing

One of main challenges in building the model was to classify sentiment in the three textual data fields highlighted in Figure 1. In order to run classification on these fields, the text had to be preprocessed using standard text processing techniques, tokenising, stemming (finding the root form of words), stop word removal, etc.. Comments are full of difficult expressions and jargon, such as emoticons :-), forum talk “gr8”, rude language, negations “not good”, etc... these had to be handled appropriately. For example emoticons were quantified as they express sentiment, or rude language was filtered.

<sup>4</sup> According to youtube support section, <http://help.youtube.com/support/youtube/bin/answer.py?hl=iw&answer=95612> (Consulted on 2 April 2009), this algorithm is kept secret.

<sup>5</sup> These represent UK, USA, Japanese, French and German stock indices respectively

### 3.3.2 Stockmarket Prices

Stock prices tend to be very noisy, especially at high frequencies, i.e. hourly or daily prices. In such data the prevailing short to medium term trend can get lost within the data. Therefore we smoothed the noise using timeseries segmentation. A percentage based segmentation algorithm was used, that is price trends of at least 5% moves in magnitude must occur in order to be detected, Figure 2. illustrates this step. The first chart in Figure 2. shows an original stock index with daily fluctuations. As stock time series have rising and falling trends, some daily fluctuations can have opposite direction to direction of the segment. The second chart represents post processed, segmented and smoothed data, which eliminated noise. Start date and end date of segment 1, for example are  $t_1$  and  $t_2$  respectively, in Figure 2. second chart. Price movement  $m$  of a segment is computed as follows:

$$m = \frac{p_i - p_{i-1}}{p_{i-1}}$$

where  $p$  is a price at time  $i$  ( $t_1 \leq i \leq t_n$ ,  $n$  being total number of prices in the timeseries)

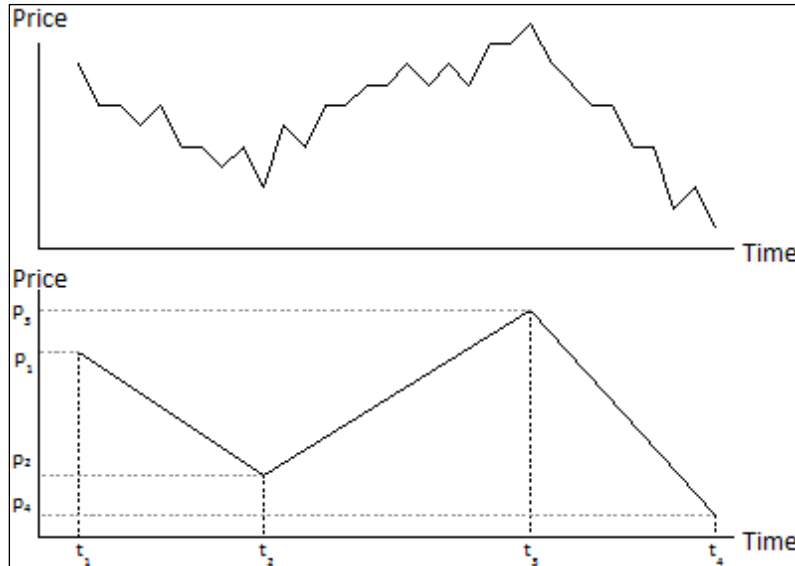


Figure 2. Segmentation of Stock Index (original and segmented price data)

### 3.4 Our Model

Three sentiment classification models were implemented. A simple score based technique for good and bad words was used within all three models. The idea behind the scoring function is to provide quantitative indication of sentiment for textual information of a clip. The scoring function is of the form,

$$s = \frac{p - n}{p + n}$$

where  $s$  is the score,  $p$  is number of positive words and  $n$  is number of negative words in the text,  $p \geq 0$ ,  $n \geq 0$ ,  $-1 \leq s \leq 1$ . A simple method yet robust and powerful. Three dictionaries of positive and negative words were created for each model, using a semi automated process based on most common occurring words in each stream of text. This was necessary as each stream of texts tends to use different vocabulary and phrasing to express a message. The scores are then combined and with an appropriate threshold a sentiment classification is made over an aggregated time period or segment.

## 4. RESULTS

Before our text sentiment classification models were built we first needed to find out whether there is a standing connection between stock data and youtube. Therefore, monthly aggregated time series were built from video submissions and total posted comments per month, between the period from January 2007 to April 2009 (months before January 2007 contained too little video submissions). Figure 3. compares intensity of video submissions against absolute value of price movements of the Dow Jones index. As can be appreciated from Figure 3., in the second half of 2008 there is a strict relationship between intensity of video and the market. The Pearson correlation coefficient for the whole period is 0.745 for video and 0.697 for comments submissions. Both values are statistically significant and point towards a relationship between stockmarket and youtube. Of course causality of relationship presented above cannot be deduced from Pearsons' correlation alone. In the data presented, there is a rapid increase of financial (Dow Jones) related youtube activity beginning in September 2008. It could be linked with the fact that awareness of crisis and risk of recession became widespread throughout youtube (for example. bankruptcy of Lehman Brothers at this time dragged attention of many reporters to financial collapse and economic instability). However it could just be the rapid increase in overall popularity of youtube. Therefore benchmark data was needed to associate this trend with one or the other reason. We hence retrieved similar quantity of videos from 3 categories, namely; music, entertainment and sport. A comparison of monthly time series data for each category showed that only the financial video submissions experienced a rapid increase in the fourth quarter of 2008, which is also statistically significant. This can be appreciated in Figure 4.

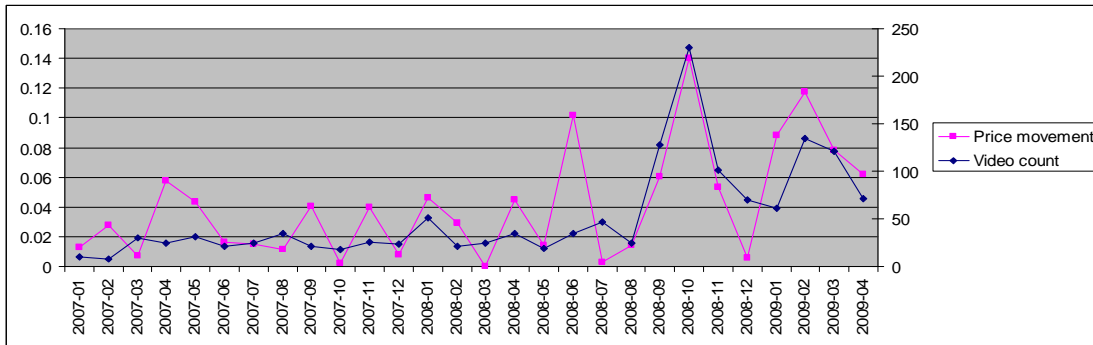


Figure 3. Video submissions related to Dow Jones clips and absolute Dow Jones price movements

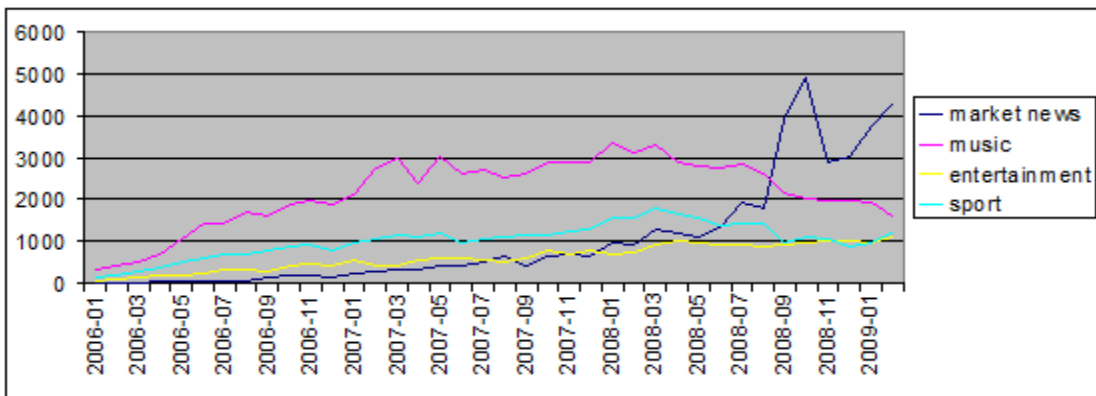


Figure 4. Comparison of video submissions over various categories on Youtube

Once it was established that a relationship is present we were further interested into whether there is a correlation between sentiment and directional price movement of the stockmarket data. Three models were built as described in sub-section 3.4, when aligned against stock index returns, correlations of 0.423, 0.387, 0.033 were measured for title, description and comment models respectively, where the first two correlations

are statistically significant. These varying strengths of correlations are due to the fact that there is noticeable difference between the three streams of text. Title often expresses the main content message of the video in a concise manner, e.g. “Dow Closes Below 10'000, a four-year low”. It often represents facts, as in the former example (Dow fell to the 10'000 level). The description gives more insight as to the video content, and words such as downtrend, suffer, hope, opportunity would occur. Comments on the other hand are filled with subjective opinions of users as to their interpretation of videos. The problem we faced with comments was that sometime users would comment on the quality of video rather than the message conveyed (e.g. the video was well done, the guy has amazing presentation skills, ...). We tried to take this into consideration when constructing the model vocabulary, however filtering comments from noisy contributions can be difficult.

Improved results were achieved when the scores were combined into a single indicator by averaging the individual scores. See Figure 5. for this statistically significant 0.543 correlation. As one can see, the resulting score tends to correlate in local turning points to the market very consistently.

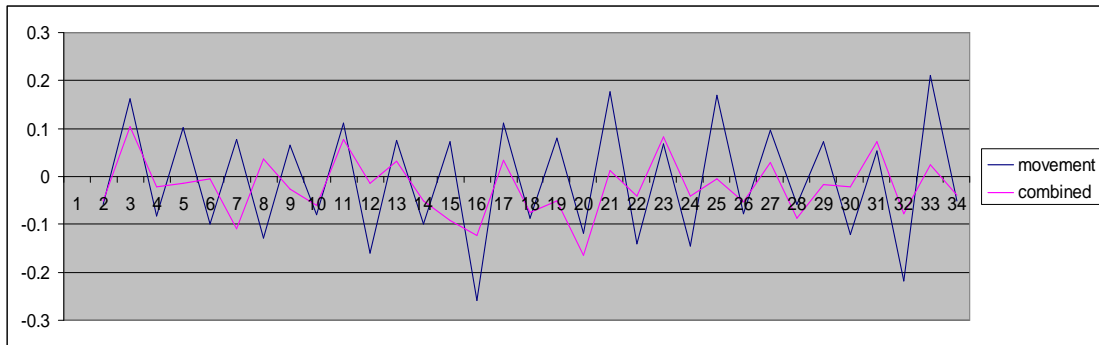


Figure 5. Combined (mixed) scores and segmented price data

Finally we employed thresholds to the combined score, in order to change soft classification to proper classification. Since scores are distributed normally with a mean ( $\mu$ ) of -0.021 and variance ( $\sigma^2$ ) of 0.0037, we used this to eliminate some of the more frequent values close to the mean. Table 1. illustrates the rather good (76% up to 89%) model accuracies of directional move forecasts.

Table 1. Classification of how often the sign of score is in agreement with directional market movement

Scenario	Lower and upper limit	Matches / Hits	Hit rate
No limits	None	25/33	76.00%
$\mu \pm 1/4\sigma$	-0.0367 to -0.0059	21/25	84.00%
$\mu \pm 1/2\sigma$	-0.0521 to 0.0094	16/18	89.00%
$\mu \pm \sigma$	-0.0829 to 0.0402	6/7	86.00%

## 5. CONCLUSIONS

A strong and statistically significant connection between stock market returns and youtube meta-data was found. Directional correlation was also proved to exist, as a text classification system for sentiments was applied to youtube meta-data. A classification system solely based on the text analysis of youtube data, managed to anticipate stockmarket trends with impressive accuracies of between 76% and 89%. These results are significant since our work points out, that there is potentially much hidden value in media sharing web 2.0 systems, this is further backed up by the fact that information must indeed travel very efficiently throughout youtube in order for us to be able to anticipate stockmarket moves from this data.

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