Credibility of images using textual techniques for Social Media Platforms

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THESIS ACCEPTANCE CERTIFICATE

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Dedication

To my parents,

Without whom this success would not be possible.

Certificate of Originality

I hereby declare that this submission titled "Credibility of images using textual techniques for Social Media Platforms" is my own work. To the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at NUST SEECS or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation and linguistics, which has been acknowledged. I also verified the originality of contents through plagiarism software.

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Abstract

Finding credible information is of paramount importance in the digital-age where massive flow of information is perceived by every internet user. Information shared on social media got potential to manipulate the thoughts and perception of masses which could result in controlled deviation of humans behaviour at large. Images and videos paired with false textual data are often used to spread false information within social media. Finding false location context within such image descriptions is a difficult task. Much of research work is focused towards finding image-location credibility using associated textual data. However, there is a need of having an social-media-eccentric approach where previously ignored social media meta-information can be utilized for the prediction of image-location credibility score based on description or keywords shared with image. We proposed a holistic-view based approach which revolves around the fact that quality of information being shared to a user within social media is directly proportional to the number of users one is in connection with. This led to a proposed method where one can factor-in user credibility parameters such as age, posts, previous credibility score along with the description (keyword) based clustering and matching with similar images to find estimated score. By merging features from multiple approaches, we are able to closely match the prediction rates when compared to conventional location finding methods. For evaluation and verification, hold-out-validation approach is used. In this work, 77%, 66%, 71% accuracy ($\pm 5\% of ground truth$) has been achieved for 11000, 22000 and 43000 images within Div150Cred data-set while raising the F-Score for 5-7% when compared to existing methods.

Chapter 1

Introduction

This chapter states the background and emphasis over need of research regarding social media content verification, which is then followed by problem statement and the associated unresolved hurdles hidden within the questions raised. The statement and its surrounded discussion will lead to research objectives which will lead to help stating with the remaining thesis outline planned for this work.

1.1 Background and Motivation

Social networks and media has become an integral part of an active lifestyle. Unlike traditional media, these digital social networks are very helpful for spreading the news and messages to faraway part of world. Adaption of social media for regular usage has started to impact human lives in more than one ways. One of the impact of social media digitization is the substantiation of geographical politics. In the era of always-connected social media, people are habitually posting all sorts of media to gain more audience, which results in the diffusion of new and sometimes unverified information over the web. Any post containing media content having false claims within is a fake content [1]. There can be other kind of falseness which includes tempering the images or videos with methods like splicing, copy-move image tampering, etc [2]

Its only the past decade where terms like fake news/images started to appear more frequently in media. Recently, fake news were able to derail US Presidential candidates when such news were shared over thousands of times resulting in deviation of opinion among the potential voters. There has been detailed research over how such news are injected within social media and are propagated through networks of friends and/or fake accounts [3] [4]. In 2013, Tang, Mao, Guessoum, and Zhou proposed a model depicting new rumour diffusion which consists of three states (ignorant, spreader, and stifler) and a dynamic friend network which disseminates the information through friends' network [5] which ultimately results in users misinformed at mass-scale having a much negative effect over the community [6]. The spreading of false information can have physical, financial and emotional consequences.

According to some researchers, humans are not efficient regarding separation of real content from fake ones. A research study claims that humans can ony distinguish 70-75 percent of fake news they read [7] [8]. Add more to complexity, another research reveals an astonishing fact that people often tend to label actual content they disagree with as fake one [9]. The lack of authenticity and biasness of users requires the need for verified news from trusted sources.

It has been a huge challenge for popular social media platforms to filter out the massive volume of data being posted by the their users. Hence, there exists a definite threat of publishing fake content over social media, and this research is expected to address an important aspect of this critical problem, which is finding duplicated or altered images being posted with a difference or false caption.

1.2 Problem Statement

Social media consists of all sort of media, which may or may note include verified or correct information. We need to find an efficient way to verify if currently shared images are having correct description and are not propagating false news intentionally or unintentionally. We need to devise a solution which can predict the authenticity score of shared image with description with fair rate of accuracy.

However, Devising such solution can pose following challenges.

1.2.1 Huge Image Corpus

Social media networks are among the most data-intensive services existing right now. According to bondcap report, there are around 3.4 billion users over social media having 7.6 billion social network accounts [10]. Social networks like Facebook and Whatsapp alone handle around 60 billion messages a day [10] while most of them consisting images and videos. This means a proposed system should be capable to index and match millions of images within minimal amount of time.

1.2.2 Image Alterations

In order to avoid detection, users may share tempered, modified or merged images so that they appear true to most users [2]. With the advancements in image processing tools and techniques, its becoming difficult to recognize tempering of image content through both human and automated methods. A devised system should attempt to detect if image has been tempered with.

1.2.3 Matching Textual Description with Image Content

Finding relevant images has been researched over extensively due to its close nature with image search engines [11] [12]. However, it can be difficult to maintain the balance between accuracy and efficiency when there be infinite possibilities and nature of descriptions/keywords. Finding important keywords from user-entered description is also an important step towards labelling relevant images within same topic [13] [14].

1.2.4 Factoring in User's Information

Social media networks usually maintains and provides comprehensive data of user's information and its behaviour or usage trends [15]. This can be helpful for predicting user's potential to share false information [16]. Conventional authenticity methods usually ignore such information as they are not tailored to execute with social media information usually.

1.3 Research Questions

Evaluating credibility of social media content is of paramount importance. In order to evaluate the credibility of social media content, one must factor in all the possible information at hand in order to predict the best possible validity score. Based on the problems highlighted above, aim of this research is to study currently proposed systems for social media images credibility evaluation and to find if existing systems can be improved upon. This motivation leads to following research questions.

- **RQ1** What are the existing parameters to evaluate the credibility of location information associated with images being posted over social media with respect to its post content?
- **RQ2** How existing methods are faring with such problem of description location credibility evaluation?
- **RQ3** Is there any correctable gap within existing methods to improve the process of social media image-posts location evaluation?

1.4 Research Objectives

Current researches and solutions are able to differentiate between real and fake content involving same or different location details with good efficiency. But not all existing solutions seem to be targeting social media content as they don't leverage the information available at disposal in a correct manner. Moreover, the solutions are not impartial in regard to covering most of the unverified content types. There is need of a system which can look through image information along with user's relevant data to predict authenticity score for each description shared along the image. Hence following research objectives can be summarized.

- **RO1** Find existing parameters to measure social media image post location credibility.
- **RO2** Compare existing methods targeting the problem of image-post location credibility evaluation.

- **RO3** Find any correctable gap within existing methods to improve the process of social media image-posts location evaluation.

1.5 Proposed Solution

With the combination of efficient keyword generation, matching technique and weighing scores based on user's existing authentic score, one is expected to predict the accuracy of image description with fair accuracy. However the exact model and its specifications will be discussed in upcoming Chapter.

1.6 Thesis Outline

The thesis is organized in the following manner.

Chapter 2 consists of relevant research literature study which encompasses the domain of evaluating the location information within the image description of associated or posted image. This chapter also enlists the the advantages and shortcomings of existing systems and why it is important to have a different approach for social media image location credibility evaluation. This chapter would also discover few credibility factors of social media information.

Chapter 3 include the proposed methodology of devised social media solution. This may include up-to trivial details regarding each sub-module which includes purpose and working along with the details which should lead up to its execution.

Chapter 4 contain the execution details, and the results of the proposed methodology while having the comparison of proposed methodology with existing solutions in order to state its contribution among existing literature of similar work.

Chapter 5 conclude the work by answering each research objective through the work done, along with the discussion of future research direction and the limitations of the proposed system which can be worked upon in future.

Chapter 2

Related Work

This chapter discusses the factors discovered for measuring credible posts and the existing work done regarding automated detection of image description credibility score. This chapter will then compare existing work to find possible gap in work leading to proposed methodology.

2.1 Factors of Social Media Post Credibility

Research on content credibility has been an active research area since the for past half decade [17] and remains a hot domain even today[18]. With the rise of social media popularity, finding credible source of information is becoming more important [19]. Early years of social media were limited to connect and share personal and social content. However, with the passing of time, social media applications became multi-purpose networks. Users share both personal and world-made content which can influence audience at large scale [20]. Extensive amount of research has been done to find the factors behind the credibility of both generic and social media content [21] [22].

Content credibility is the believing ability of the users on information based over some subjective and objective factors [23]. These factors are generally partitioned into seven domains which are accuracy, impartiality, quality, currency, professionalism, popularity and authority [24]. These factors are the basis of every research regarding credibility of information shared over internet. Since Image description is the focus of this research, these factors are also helpful for defining credibility of im-

Credibility Factors for Social Media Content		
Factor	Description	Social-Media Context Factors
Correctness	Truthiness	Truth Inside a Post
Authority	Credibility of Author	Source of Text-Poster
Currency	Frequency of Verification	Number of Previously Correct Posts
Professionalism	Credible Post-Manner	Data Available with Post
Popularity	Expansion of Viewership	Number of Users Knowing Content
Quality	Popularity	How Many Users Rate the Content as Good
Impartiality	Unbiased	Unbiased Post Content

Table 2.1: Social Media Post Credibility Factors. [24] [25] [26]

age posts. Following are the various social-media posts credibility factors mapped over previously defined credibility factors [24] [25] [26].

2.2 Existing Research Over Finding Credible Location Source

There has been ample amount of researches regarding text-based information credibility which later on resulted in image-text credibility verification [27] [28].

Initially, researches mainly involved mapping databases of fetched Geo-locations from descriptions and metadata while mapping them for the exact images to filter out duplicates. The swift need of matching similarly looking images resulted with adding similarity measures [29] [30]. From the other spectrum, language processing techniques were being used to fetch location information from tweets for mapping purposes [31] [32]. This enabled variations of location contexts to be utilized to categorized similar posts.

The work revolving around image-text based location detection can be classified as follows.

2.2.1 Hierarchy-based Divide and Conquer Approach

Trevisiol, Jégou, Delhumeau and Gravier utilized user data, social information, and content based matching to estimate Geo-location within videos posted over social media in 2013 [33]. The proposed method worked well for finding locations within a video due to preference of user information over detailed frame matching.

2.2.2 Probabilistic Distribution Map Based

Hays, James and Efros, Alexei distributed collected geo-tagged images data over world-map to create density maps involving data-driven matching to find relevant locations data [34]. The clustering based approach allowed them to look for other information along with credibility-mapping such as rural/urban classification, density mapping etc. This research claimed to be 30 times faster than by-chance mapping.

2.2.3 Novel Multi-modal Location Based Mapping

Pascal and others devised a model to mapped untagged location images with tagged one by matching features at various levels within borders which are filtered by textual factors [35]. The allowed researchers to map similarly featured data at any scale with similarly typed content at the accuracy of 78.5 percent doubling the previous attempts the Ghent [36].

2.2.4 Two-steps Location Estimation

Olivier and others proposed a simple model to estimate location by clustering location following by finding most important keywords for each cluster leading to similarity match by deducting percentage of finding similar pictures in an area [37]. Its accuracy however was based on number of important features selection.

2.2.5 Salient Region Matching Based

Qian, Zhao and Han proposed a matching-based location verification technique which enabled limiting the feature matching of search by using similarity measure based one visual bag of words [38]. Its accuracy however was based on number of important features selection. The technique performed fairly well on OxBuild and GOLD data-sets [39].

2.2.6 Video-based Features Matching

Although finding credibility of video content is a different research domain, its simplistic and frame-independent models can be used to find still locations credibility. One such approach was purposed by Penatti and others which included matching bag-of-features involving low levels features of each frame [40].

2.3 Research Gap

Currently, researches being made in this domain are focused towards finding the location out of information rather than evaluating the currently mentioned location in description or Metadata. Such approach may work fine in conventional cases where plain matching of location words can end up with an accurate score, such approaches may not work within indirect or complex descriptions where direct evaluation of location may not be possible with a keyword or two.

While hierarchy based approached utilized some of user information while finding out location information, none of the approaches use the entire social media model and its associated information den to make better decision. Utilizing social media's information at hand can improve the score prediction of any proposed method more than a generic keyword based location suggesting techniques.

Current work is limited to isolated suggestion and exist. There is a need of introducing concept of propagation where the spread of false and correct information can be handled in an appropriate manner, which includes reduction of score if the content is found false later on despite being wide-spread.

Following is the placement of each work with regard to its contribution within credibility factors based on what factor each factor incorporates.

It can be seen that apart from correctness, almost entire discovered existing work is not capable of seeking-in remaining credibility factors, hence a system including remaining credibility factors is required.

Existing Work - Credibility Factors for Social Media Content						
Factor/Work	Div and Conq.	IM2GPS	FUSION	Lang Model	Salient	BoS Video Geo-coding
Correctness	Yes	Yes	Yes	Yes	Yes	Yes
Authority	Yes	No	No	No	No	No
Professionalism	No	No	No	No	No	No
Popularity	No	No	No	No	No	No
Quality	No	No	No	No	No	No
Impartiality	Yes	No	No	No	No	No

Table 2.2: Credibility Factors Within Existing Work.

Chapter 3

Proposed Methodology

This chapter contains the proposed methodology comprising of the previously-discovered gap within the existing work literature. This chapter will discuss the context behind the decision of coming up with the method and will be dissection various steps being used within.

3.1 The Holistic View

Previously studied work was focused over finding location information by validating it through fetch data and image features. However, social media contains ample source of information which can be put to use for validating location credibility score [41]. Such approach can be helpful for not only evaluating better credibility scores but also for swiftly degrading previously credible posts with time

3.2 Social Media Network - Holistic View

Reflecting this approach over existing social media networks, one of the most commonly missed fact in recent researches regarding social media data is not realizing the fact that users are usually partially interconnected and most of the times the information shared would leave impact over the people linked-in with posting user [24]. The following block-diagram reflects the holistic view of social media users and their post association before moving on to proposed methodology 3.2.

3.3 Data Acquisition and Modification

Initially, Flickr8K dataset was expected to be used during initial stages [42]. Howetver, after realizing that Flickr8k data does not share elaborated user details of each image, Div150Cred dataset was used for primary testing [43]. Random network connections were entered to simulate the social network. Div150cred dataset consists of a images spanning upto 30 locations, a user annotation credibility set containing information for approximately 300 locations and more than 600 users and a test set containing more than 120 locations. Following information is provided with images:

- Location Name (mapped over id)
- Latitude and longitude GPS Coordinates
- Wikipedia web-page link of the location
- Up to 5 representative photos retrieved from Wikipedia
- A set of photos retrieved from Flickr (mapped according to unique flickr ID)
- Flickr XML Metadata
- Credibility descriptors
- Ground truth score for both relevance and diversity

Due to restricted time and resources available to process data, upto 10,000 images consisting of approximately 120 locations were kept for training and validation while additional 2000 images consisting of 25 locations were kept to test the method.

3.3.1 Data Modification

Since Div150Cred data consisted of user and post meta data along with credibility score, there was no major modification required other than normalizing the values for final-stage regression-based prediction.

Incorrect data was also generated by randomly exchanging the words from image description along with reducing their correction percentage.

Image Descriptions		
Completely correct	Partially Correct	Entirely Wrong
15305	14945	11750

Table 3.1: Dataset Summary [43]

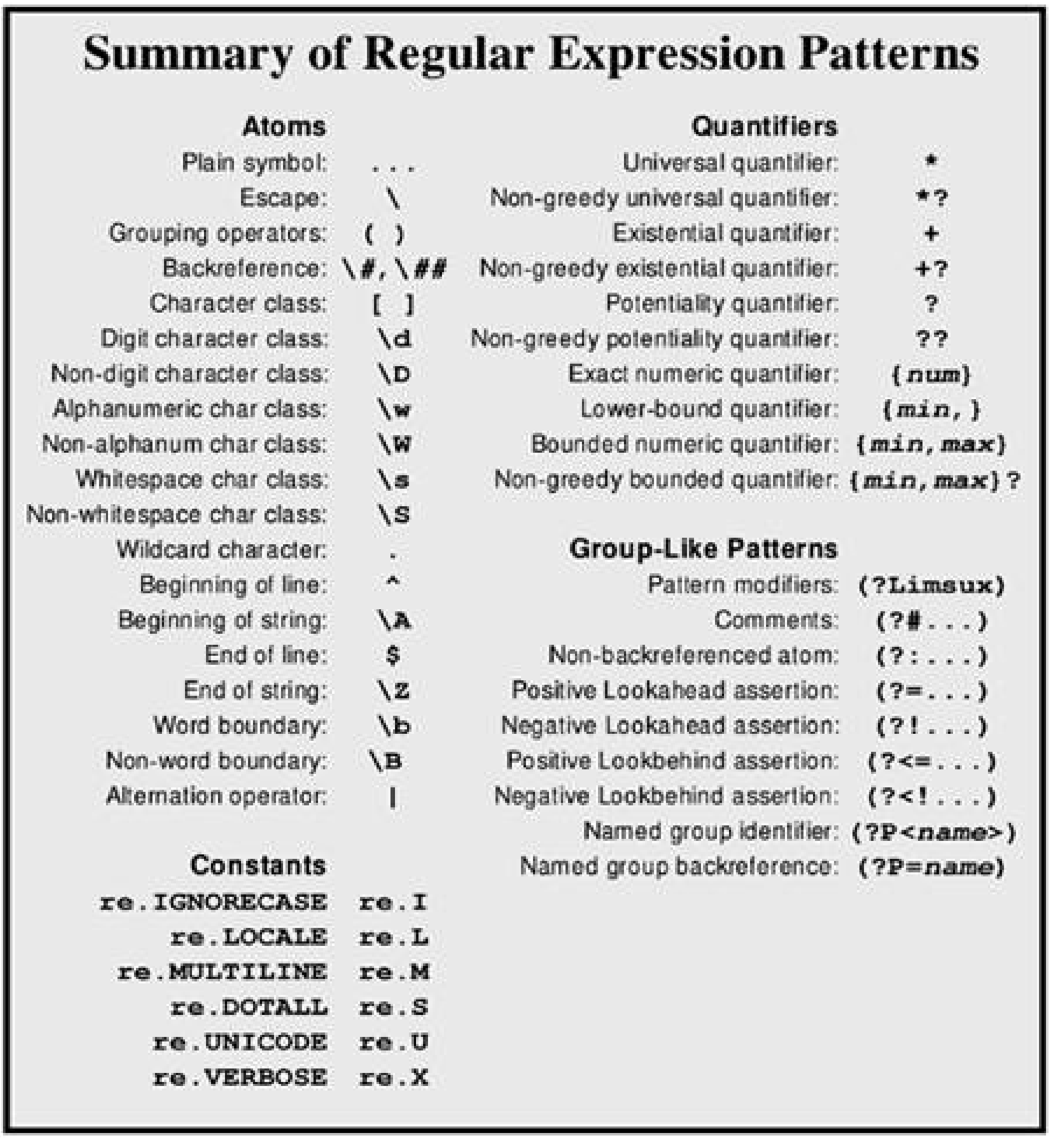
3.4 Keywords Extraction from Description

Pre-processing over post description is performed to extract useful keywords within data. Pre-processing often done to text for quantifying meaningful data into usable feature setsc[44]. This includes removing NON-alphanumeric characters leading to tokenization - which is creating useful word-embedding pair. Such tokens are usable as features for any classification or clustering inputs. This is performed using Python's builtin library named Tokenizer [45]. NLTK library along with regular expressions are used to remove stop-words, and other irrelevant characters and information. Word2Vec model are utilized to create pairs-of-words based features from truth-table of such keywords [46].

3.5 Methodology Overview

The proposed method works with the principle of matching features of previously fed similar images through clustering of words-bag fetched from image description. If a cluster contains large amount of images but is unable to find similar images within the corpus then it would be allotted a negative score accordingly. However the score is also expected to degrade the entire user credibility score along with its connected neighbours. Such method will help setting up a predictable default credibility user-score for each post. It must be noted that the methodology assumes that users are partially connected with other uses in the network. Following is the flow diagram of purposed methodology 3.3.

For each user U, there's an initial (previous score) stored along with other credibility factors. *User Location, Age, Popularity (Normalized Number of Incoming connections)* are the factors being used as features for prediction of post-credibility. Following are the sub-modules of proposed methodology



Summary of Regular Expression Patterns

Atoms

Plain symbol:	...
Escape:	\
Grouping operators:	( )
Backreference:	\#, \##
Character class:	[ ]
Digit character class:	\d
Non-digit character class:	\D
Alphanumeric char class:	\w
Non-alphanum char class:	\W
Whitespace char class:	\s
Non-whitespace char class:	\S
Wildcard character:	.
Beginning of line:	^
Beginning of string:	\A
End of line:	$
End of string:	\Z
Word boundary:	\b
Non-word boundary:	\B
Alternation operator:	|

Constants

re.IGNORECASE	re.I
re.LOCALE	re.L
re.MULTILINE	re.M
re.DOTALL	re.S
re.UNICODE	re.U
re.VERBOSE	re.X

Quantifiers

Universal quantifier:	*
Non-greedy universal quantifier:	*?
Existential quantifier:	+
Non-greedy existential quantifier:	+?
Potentiality quantifier:	?
Non-greedy potentiality quantifier:	??
Exact numeric quantifier:	{*num*}
Lower-bound quantifier:	{*min*,}
Bounded numeric quantifier:	{*min*,*max*}
Non-greedy bounded quantifier:	{*min*,*max*}?

Group-Like Patterns

Pattern modifiers:	(?Limsux)
Comments:	(?#...)
Non-backreferenced atom:	(?:...)
Positive Lookahead assertion:	(?=...)
Negative Lookahead assertion:	(?!...)
Positive Lookbehind assertion:	(?<=...)
Negative Lookbehind assertion:	(?<!...)
Named group identifier:	(?P<*name*>)
Named group backreference:	(?P=*name*)

Figure 3.1: Summary of Regular Expression Patterns [47]

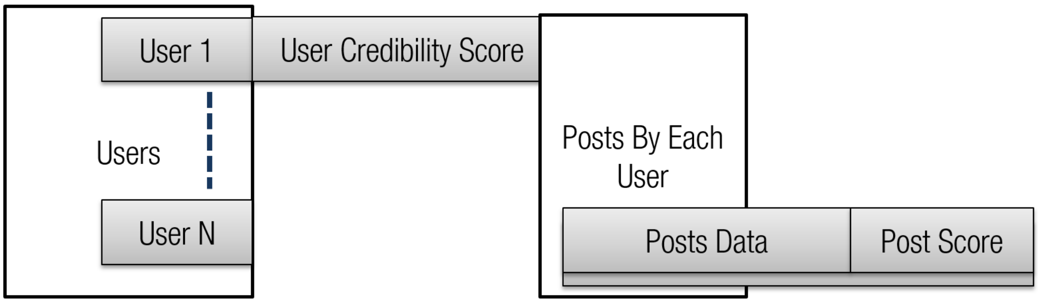


Figure 3.2: Block Diagram of the Proposed Holistic View

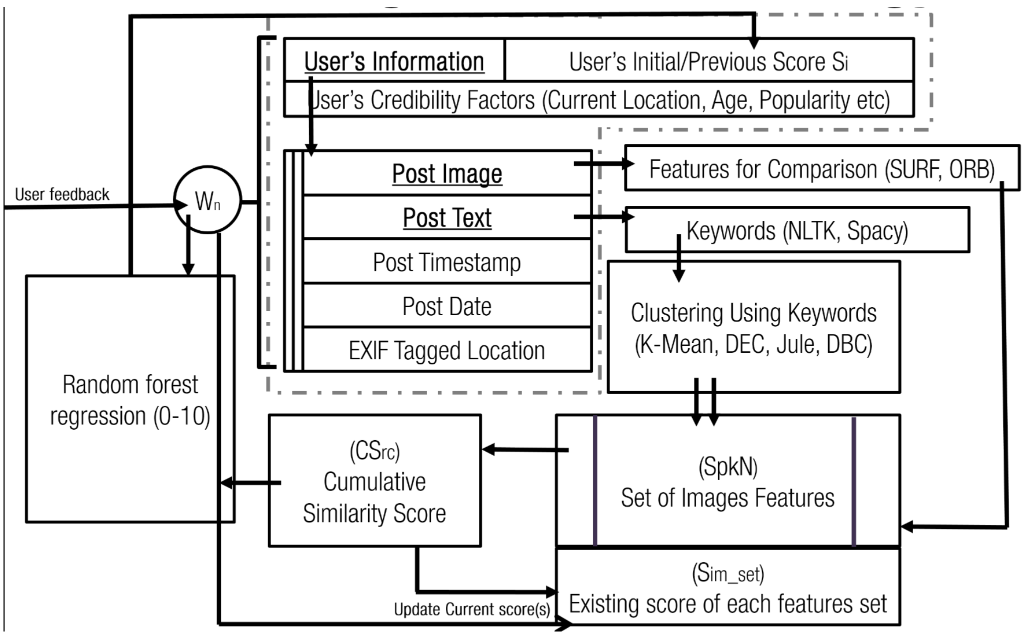


Figure 3.3: Flow Diagram of the Proposed Methodology

3.5.1 Initialization of Users in Network

Assuming that all users have equal probability of sharing a false or correct information, all the users in the network are initialized with middle-number initial score value. While any initial post (if not scored already) is also scored at middle-value.Any new users would have an average sum of its incoming user connections as default User-Credibility score.

3.5.2 Fetching Information From New Post

Once a user generates an image post with description, nouns, adjectives and verbs are extracted from keywords, which are then used as features for clustering algorithm. Also, any previous score mentioned is also used for further score adjustment.

3.5.3 Setting up Keywords-Based Cluster

Once keywords are fetched from post, they will be used to form a cluster consisting of similarly keywords of images. The comparison of few clustering techniques for optimal results will be discussed ahead in chapter. The clustering will enable of mapping images with similar keywords into specific clusters which would reduce the space-complexity of comparable images. Following are the results of few high-dimensional clustering algorithms placed to run at Div150cred data-set. The clustering accuracy is found with the sample set up to 10,000 trained and 1,000 testing keywords set for each trained model.

Div150Cred	3,000	5,000	10,000
K-Mean [48]	54.7	47.4	47.1
VaDE [49]	78.3	84.8	82.6
DEN [50]	77.4	74.8	80.5
DKM [51]	79.2	76.3	78.8

Table 3.2: Clustering Accuracy of Clustering Algorithms

Since Variational Deep Embedding (VaDE) has yielded the most accuracy for small and large data-sets, it is used for clustering of keywords [49]. VaDe is a type of Variational Auto-Encoder (VAE) consisting of a Gaussian Mixture Model (GMM) and deep neural network (DNN) where GMM picks the cluster for latent embedding while DNN generates observables using GMM's latent embeddings.

3.5.4 Matching Similar Images Within Cluster

For clustering, the most primitive way was expected to be utilizing k-means cluster. However, since expected feature-set is of high-dimensional along with undefined range of features,various high-dimensional clustering algorithms were tested to find the one with optimal percentage between over-fitting and under-fitting. Since time-complexity was of more importance in this stage of matching due to possibility of having large data-set, following are the comparative time-measurements of various commonly used image matching techniques for finding 10 similar images within various number of data-sets.

It must be observed that DeepMatch has the most versatile image matching, that is ability to match between much image variations such as rotation, skewing, partial

Div150Cred	2,000	5,000	10,000
SURF [52]	2	4	9
ORB [52]	<1	2	4
DeepMatch [53]	4	5	11*

Table 3.3: Time-Complexity of Image-Matching Algorithms with Div150Cred Data-set

cover etc. However due to its training time cost and other complications, ORB was preferred choice of image matching technique.

3.5.5 Calculation of Post Credibility Score from Similar Images

If the image is unable to find any relevant cluster, it will be added into the system with its own cluster having user's previously existing credibility score. However, if there's an existing cluster where features are being placed then the system is expected to calculate image credibility score with number of similarly matching images within that specific cluster using following equation.

*For each image having credibility score >= 0.4 CSrc = (MSim_set1+MSim_Set2+_SetM) / M) * (M/T)*(Su/Norm(NPu))*

Where *CSrc* is the new calculated image-post-credibility score, *MSim_Set* is the existing score of each matched image's credibility score, *M* is total number of matched images, *T* is total number of images in a cluster, *Su* is user's current credibility score while *Norm(NPu)* is normalized Number of posts previously made by user. The equation predicts the estimated score of newly fed image-keyword pair by averaging out currently allotted score.

3.5.6 Regression For Optimal Score

Once the Cumulative Image-Post credibility score is generated, an intelligent method is used to factor in existing parameters along with current score to evaluate final post credibility score. For that. Such task can be performed using either a classifier mapping into smaller scores or a regression algorithm regressing towards an optimal score. Random Forest Regressor was selected due to the entropy-value nature of remaining features [54]. Following features were use within features set as input while training, testing and other executions.

Features	Input Range	Normalized Input
TimeStamp	Timestamp	Timestamp
Longitude	Float value	Numerical
Latitude	Float value	Numerical
Age	Numeric	Numeric
Country/City from EXIF	Name of City/Country	Numerical Mapping
Popularity	Numeric	Numeric
Past Credibility Score	Numeric	Numeric

Table 3.4: Input Features for Random Forest Regression

With fine-tuning, it was observed that the ideal parameter for maximum number of trees were 12 while maximum depth parameter was 6. Following are the various training and validation scores with various ranges of data-sets with 1000 at validation sample set.

Training Sample Size	Training Score	Validation Score
10,000	0.69	0.65
20,000	0.79	0.87
40,000	0.83	0.84

Table 3.5: Training and Validation Rates of RandomForest Regressor

3.5.7 Placing Final Post-Image Credibility Score

Once the prediction score *Sp* is generated, it can be blended with previously detected Cumulative Score *CSrc* in multiple ways in order to evaluate the best possible prediction. Following are the various ways to blend the prediction results with their resulting accuracy matched to dataset.

Method	Difference from Ground Truth		
Methods/Range of Dataset	2,000	5,000	10,000
Average	0.03	0.15	0.21
Weighted Multiplication	0.04	0.12	0.16
Cumulative Score as Parameter	0.13	0.24	0.55

Table 3.6: Comparison Between Predictive and Cumulatively Calculated Scores Summarizing Methods

From results, it can be seen that weighted multiplication of predicted score *Sp* (without having Cumulative score within as parameter) with cumulative score *CSrc* yields closer to accurate output hence is preferred as the default way of blending both scores. This will result in final image-post credibility Score Sim_setNew for the given image.

3.5.8 Updating User-Credibility and Current Images Score

Since the user posting this holds the generic user-credibility score for the data *Su*, the new user credibility score*Sun* is expected to be the average between existing user credibility score *Su* and newly calculated final Image-Post Credibility Score Sim_setNew. Hence, it can be said that Final user credibility score will be following.

$$Sun = Su + Sim\_setNew/N \quad \text{Where is total number of posts by user.}$$

For image-set score update, the newly calculated score will be averaging the entire image-keywords cluster set using following equation.

$$MSim\_setUpdated = (MSim\_setNew + MSim\_Set) \ / \ 2)$$

3.5.9 User-Feedback based credibility degrade

Once user rates the image-description as not-credible, it can have a reduced score depending on the voter's credibility score. This will ensure gradual or swift decline in post-score depending on number of credible users down-voting it. The updated image score is calculated by following equation.

MSim_setUpdated = (MSim_setSuggested(((1-Si)*UserCount))))*

where *MSim_*setSuggested is the user suggested score while *UserCount* is number of users devoting the credibility

This completes the proposal of system, including its credibility growth and deduction while incorporating the user feedback.

Chapter 4

Results and Evaluation

This chapter consists of accuracy-measurement results and evaluation of those results of the proposed system while being placed with various existing methods. The chapter will begin by mentioning the evaluation measurements being used. These evaluation measures are Accuracy, F1 score, Precision, Recall, and two different cross-validation techniques. After discussing evaluation measures, the system is then executed for various ranges of data-set to find the evaluation metrices before their comparison with existing work with similar baseline. After comparison, various credibility factors are discussed and their coverage is checked for the proposed system.

4.1 Evaluation Metrics

Since this work is based on the function of its sub-components along with few learning algorithms, few evaluation metrics are used to measure various parameters of this work [55]. Those metrices are mentioned below.

4.1.1 Precision

Precision primarily answers the question that among all results classified as positive by a proposed model, how many positives were actually correctly measured by the system. Generally, highest precision reflects that system has performed well and has come up with more results specially in a system where more result are important even if it adds more false outcomes [55].

4.1.2 Recall

Recall is a performance measure which is used to reflect the number of correctly measured positives (that are points labelled as positive) which were found by the system. Higher recall reflects better performance of the system. [56].

4.1.3 Accuracy

Accuracy is defined as the combination between true and false detected data to find closeness with actual ground-truth. Accuracy can be defined as ratio of correctly predicted measurements to the total records. It can be stated in an equation as follows [56].

$Accuracy = TruePositives + TrueNegatives \ / \ (TruePositives + TrueNegatives + FalsePositives + FalseNegatives)$

4.1.4 F-Measure

For any model or system, high-accuracy does not always mean that the system or model is accurate, there are times when asymmetrical data-sets may not reflect a true accuracy rate due to unusually high difference in false positives and false negatives. In order to estimate a fair score in which both precision and recall are balanced through having a mean of both precision and recall. The higher F1 score can possibly reflect better overall performance of the system[56].

$$F\text{-}Score = (1+\beta^2) * (Recall * Precision) \ / \ (Recall + (\beta^2 \ . \ Precision))$$

Where β is importance value of precision over recall.

4.1.5 Hold-Out Validation

Hold-out validation is among the simplest of validation techniques which can quickly yield a validation score by training and testing through a single-time splitted data ratio. This can be less accurate but can give a fair estimate of system's validity for most of the times. For the proposed method [57]. Data sets of 1,000, 2,000 and 2,000 samples are held for testing of a trained data-set spanning over 10,000, 20,000 and 40,000 sample ranges respectively.

4.1.6 Data Specification

This work has been carried out by utilizing the ranges of Div150Cred data-set. Data-set is split into 11000, 22,000 and 42,000 ranges for validation of variance in growing data up to limited extend 3.1. Since proposed methodology consisted of connection data, data-sets were randomly connected during execution of training and testing simulating up to 50, 100 and 150 users for each data-set range respectively. "locationSimilarity" score-field is assumed as the ground truth field from data-set. While tags are fetched from list provided with each image.

4.2 Evaluation of Random Forest Regressor

Random Forest Regression was suggested due to its similar nature of matching features based on their importance. Following is the accuracy again. Following is the training versus testing accuracy score for Random Forest Regressor with respect to output "locationScore" in data-set 4.1.

Training/Testing Range	Training Score	Testing Score
10,000/1,000	0.51	0.64
20,000/2,000	0.76	0.87
40,000/2,000	0.86	0.88

Table 4.1: Random Forest Regression - testing vs training scores

4.3 Evaluation of System

In order to find the accuracy and f-measurement of the system, the system is executed with 3 different data ranges. Following are the results of executions with each range's measurements within difference of ± 0.5 to avoid noise-based errors 4.2.

From the calculated data, F-Score is calculated and the results are in following table 4.3.

Training/Testing Range	TP	FN	TN	FP	Precision	Recall	Accuracy
10,000/1,000	458	102	319	121	0.7910	0.8179	0.7770
20,000/2,000	1103	195	476	226	0.6985	0.8498	0.6645
40,000/2,000	1373	78	493	56	0.7358	0.9462	0.7145

Table 4.2: Results of Various Div150Cred Training and Testing Run

Training/Testing Range	F-Score
10,000/1,000	0.8042
20,000/2,000	0.7668
40,000/2,000	0.8279

Table 4.3: F1-Score of Proposed System Under Various Div150Cred Test Ranges

From the results, it can be observed that the while accuracy of the system is between 66% to 77%. F-Score of 76%-82% reflects that the system is also able to negate falsely classified news regardless of size of data sample. Upon inspection, the fall of 20,000 data-set was partially due to the fact that there were more more clusters being formed while having lesser data resulting in poor matches.

4.4 Placing with Existing Systems

Other works related to image description credibility were limited to isolated approach to each sample without factoring in the entire network. Divide and Conquer approach incorporates user home location, upload history and social information as features of model but fails to recognize the importance of inter-connected user graph. This leads to limited success with conventional training and testing. In order to maintain a fair baseline, existing methods were executed with Div150Cred data-set having similar testing ranges as the proposed method and were compared to the estimated score in data-set with a difference of 0.5. Doing this would bring all methods over a single baseline to start with. Table 4.4 states the accuracy scores and F-Scores of existing work when executed using Div150Cred data-set chunks.

Method	Training Data	Testing Data	Accuracy	F-Score
Divide & Conquer (D&C)	10,000	1,000	0.7370	0.7207
	20,000	2,000	0.7213	0.7263
	40,000	2,000	0.7177	0.7049
IM2GPS	10,000	1,000	0.5270	0.4952
	20,000	2,000	0.5239	0.5383
	40,000	2,000	0.5027	0.5214
Fusion	10,000	1,000	0.6230	0.6476
	20,000	2,000	0.6440	0.6536
	40,000	2,000	0.6035	0.6388
Lang Similarity	10,000	1,000	0.6673	0.6717
	20,000	2,000	0.6420	0.6516
	40,000	2,000	0.6675	0.6452
Salient Region Matching	10,000	1,000	0.6855	0.6845
	20,000	2,000	0.7067	0.7172
	40,000	2,000	0.7025	0.7046
BoS Geo-location Encoding	10,000	1,000	0.6161	0.6249
	20,000	2,000	0.6865	0.7011
	40,000	2,000	0.6912	0.7037

Table 4.4: Accuracy and F1-Score of Existing Work Using Div150Cred Data-set

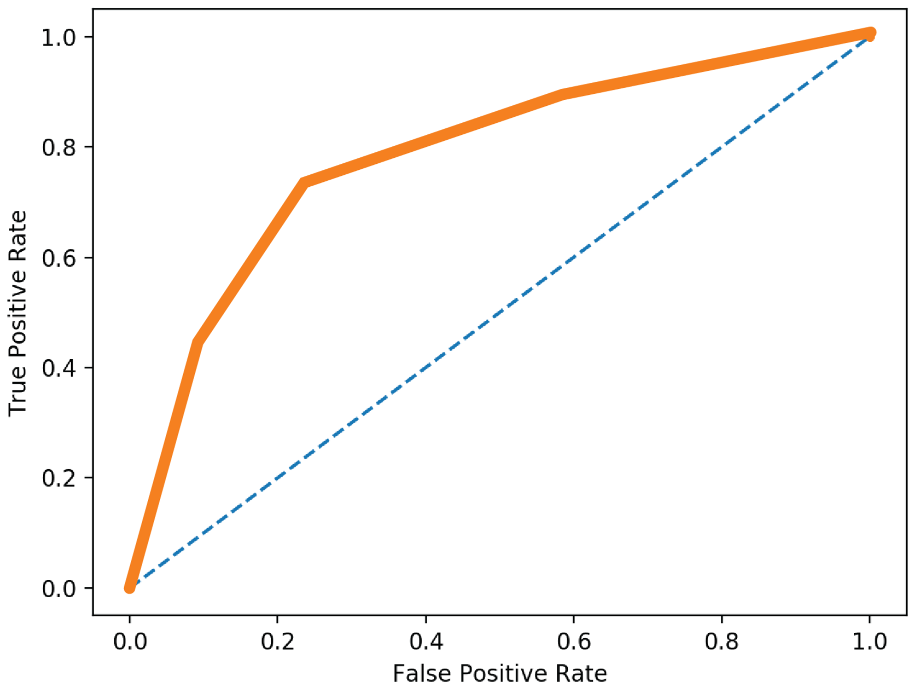


Figure 4.1: ROC Curve of predictive data classification using Div150Cred data-set (within 10% as positive)

Table 4.4 reflects that the proposed method has general 5% more accuracy and 5%-8% higher f-score depending on the data-range and type. This reflects that system is capable to match and outperform existing systems within its current structural capacity.

Other than looking for placement accuracy, it is also important to consider if system encompasses credibility factors.

4.5 Credibility Factors

In chapter two, few credibility factors for an authentic media post were discovered, making them useful parameters to calculate the authenticity score of a media post. The proposed methods covers following parameters of a credibility.

Proposed Contribution - Credibility Factors for Social Media Content							
Factor	D&C.	IM2GPS	FUSION	LangMod	Salient	BoSG	Proposed
C1	✓	✓	✓	✓	✓	✓	✓
A1	✓	✗	✗	✗	✗	✗	✓
P1	✓	✗	✗	✗	✗	✗	✓
P2	✗	✗	✗	✗	✗	✗	✓
Q1	✓	✗	✗	✗	✗	✗	✓
I1	✓	✗	✗	✓	✓	✗	✓

Table 4.5: Credibility Factors Comparison of Proposed System.

Where C1 is Completeness, A1 is Authority, P1 is Professionalism, P2 is Popularity, Q1 is Quality and I1 is Impartiality.

4.5.1 Correctness

Correctness reflects the accuracy of information being posted, which happens to be among primary task of current work. Proposed system validates correctness by matching important keywords with their respective images. Not founding images within a cluster would mean that the system is unable to find correctness within a post.

4.5.2 Authority

Authority points towards the experience and popularity of the posting user. The propose system calculates this by estimating the credibility score of user using its incoming connections and previous credibility score.

4.5.3 Professionalism

Professionalism indicates the set of features and tools to help maintaining quality of posts. The proposed method incorporates user-feedback based degradation of poor quality or less credible content which enhances the professional aspect of media post.

4.5.4 Popularity

Unlike authority, popularity points towards quality content being shared which ads to poster's popularity. The gradual enhancement of user and image-keyword pair score enables popularity-rise within the network.

4.5.5 Quality

Verification of post from various sources can add to post's quality. This can be useful for scoring authentic post content. The system uses previous quality scores from each cluster to set the new score so that quality post may get more score and coverage.

4.5.6 Impartiality

Missing or incomplete information of post can be misguiding. Hence the need of discouraging incomplete posts can be useful for any credibility scoring system. The propose system initiates the clustering based on pairs of important grammatical constructs. Missing keywords would lead to a difference cluster where there will be little to none matching features to gain score. It can be said that the proposed system encompasses following credibility factors in the table below.

Hence it can be concluded that the proposed method utilizes most of the media credibility factors available at hand.

4.6 Summary

Upon the execution of system over 11,000, 22,000 and 42,000 sample sets having 1,00, 2,000 and 2,000 testing samples separated, the system was able to score 77%, 66%, 71% accuracy with 0.80, 0.76, 0.82 F-Scores for respective data-set ranges.On average, the system is able to improve 5% of F-Score when placed against existing location verification or credibility methods and techniques. The system achieved the target by incorporating correctness, authority, professionalism, popularity, quality and impartiality within the system.

Chapter 5

Conclusion and Future Work

The following chapter concludes the work with summarizing the contribution made within the domain of image-description credibility while and whether the research objectives were achieved in a satisfactory manner. Then a brief summary of the significance of work-done is explained. The chapter ends with discussing limitations and possible future work which can lead to significant improvements.

5.1 Conclusion

Finding information credibility has been an important problem for all sorts of medium due to the ability of false news to manipulate the thoughts and perception of masses. People use social media largely for seeking information which can be non-credible for most of the times. Hence the need of finding credibility scores for such posts is of much importance, specially for images and videos which can create far bigger impact. There has been ample research focused over finding image description credibility using text, keywords and meta-data. However, there was a need of having an social-media-only approach where maximum information can be utilized for prediction of such description score. We proposed a holistic view which based over the fact that the probability of information being shared is directly proportional to the number of users one is in connection with. This led to a method proposal where one can factor in user credibility factors such as age, posts, previous credibility score along with the description (keyword) based clustering and matching with similar images to find estimated score. By merging features from two different approaches, we are able to produce better accuracy rates when compared to conventional methods. results as compared to baseline models. For evaluation and verification, hold-out-validation approach is used. Evaluation metrics including accuracy, and F1 measures have been used for finding accuracy percentage. In this work, 77%, 66%, 71% accuracy has been achieved for 11000, 22000 and 42000 images within Div150Cred data-set while pushing up the F-Score by 5-7% when compared to existing methods.

5.2 Contribution of Research

By doing this work, we're able to add following contributions within the field of image description credibility within social media.

5.2.1 RO1: Discovery of Existing Factors of Credibility

This work has highlighted few important social media credibility factors which previously existed in information credibility research literature. correctness, authority, currency, professionalism, popularity, quality and Impartiality are few of the factors which can attributed with the credibility of social media shared information, including the location within post text.

5.2.2 RO2: Discovery of Existing Credibility Systems

After extensive literature review, few of the possibly prominent approaches to verify or learn location within the social media image-description posts were state, analyzed and their domain of improvements were evaluated. With the existing systems can efficiently approximate the matching locations within image description text, they were designed to run within isolation of data set without having the notion of evaluation of data within socially connected data sets. Hence, the need for proposing such system was acknowledged.

5.2.3 RO3: Incorporating Social Media Credibility Factors

After discovering the credibility factors of social media information from literature, along with the discovered need of using such factors for evaluation of image's stated location accuracy within its provided description, a method was proposed and designed evaluate social media image post credibility by factoring in the interconnectivity of users within a social media network, and their associated credibility factors. For that, image comparison to match image with cluster of keywords. Then those keywords were traversed for finding similar images within the network. Having a new cluster-image pair means the information was newly fed into the system, while having a poor cluster-image comparison score means the information is most likely to be fabricated, which eventual resulted in negative scoring of the user and post. Each new post had its initial score using the cumulative interconnect users and posts score along with user's own details. This enabled separation of cluster-image pair making, cluster-image pair matching and data evaluation using a regular classification mode while incorporating social media credibility factors.

This research work is an important path forward in the exciting journey of works and researches related to social media post credibility measurement. New way perceive social media credibility problem is proposed were used to address shortcoming of previous work. The major contribution was the use of additional contextual information and the information added by the user-graph which helped in getting better performance. In conclusion, a better system has been developed that can predict credibility score with improved accuracy as compared to previous frameworks.

5.3 Limitations and Future work

While the system is yielding better results, it can still be considered as a groundwork for upcoming researches. Following areas are identified while working over various aspects.

5.3.1 Improvement of Image-Keyword Cluster Matching

Better and optimal image matching techniques can be used to improve the matching rates while including variances. The current system is designed by evaluating few of the most commonly used image comparison methods to have an optimal comparison module. However, the recent advancements in computer vision and artificial intelligence means there can be a better comparison method to fit within the requirements.

5.3.2 Improvement in Score Calculation

Weights of Cumulative Scores and Predicted Scores can be adjusted in a better manner, probably an intelligent one. This can be trained and tested over larger data sample collected during the real-time execution.

5.3.3 Adding Intelligence-Based Value of User Feedback Data

User feedback can be incorporated in an improved manner by evaluating better rates of change. User weight-age can be managed in an efficient manner that way

5.3.4 Testing by Real-Time Social-Media Expansion

Rigorous testing of method over larger data-set involving complex or real-time descriptions to see if any of the models being used within the proposed system can exponentially increase the system's complexity. If yes, then what can be the measurements to reduce the complexity in such cases.

5.3.5 Enhanced Textual Understanding

Incorporation of multi-lingual, informal and sarcasm language support for system can be useful. It might be essential for an effective credibility system to understand and process sarcastic,informal and bilingual image descriptions in order to evaluate the credibility in an efficient manner. Since this is a vast area of research, the work can be moved into the direction of understand more data rather than working over the core-analysis and comparison.

There can be more directions of each segment within the proposed method since it adds a new dimension of connection social media data into the credibility measurement equation.

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