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Popularity Prediction of Images and Videos on Instagram

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***Abstract*— We live in a world surrounded by numerous social media platforms, applications and websites which produce various texts, images and videos (posts) daily. People share their moments with their friends and families via these tools to keep in touch. This extensiveness of social media has led to an expansion of information in various forms. It is difficult to imagine someone totally unfamiliar with these concepts and not having posted any content on a platform. All users, ranging from individuals to large companies, want to get the most of their audiences' attention. Nevertheless, the problem is that not all these posts are admired and noticed by their audience. Therefore, it would be important to know what characteristics a post should have to become the most popular. Studying this enormous data will develop a knowledge from which we can understand the best way to publish our posts. To this end, we gathered images and videos from Instagram accounts and we used some image/video context features to predict the number of likes a post obtains as a meaning of popularity through some regression and classification methods. By the experiments with 10-fold cross-validation, we get the results of Popularity Score prediction with 0.002 in RMSE and Popularity Class prediction with 90.77% accuracy. As we know, this study is the first exploring of Iranian Instagram users for popularity prediction.**

Keywords—Popularity prediction; Social Network; Instagram; Regression; Classification;

I. Introduction

Social media and social networks have become an inevitable part of man's life. It is impossible to imagine a day without access to Facebook, Twitter, and Instagram etc. You rarely see any person, business, or organization who has not benefited from interesting advantages of posting in such media. They use these tools to connect with their audience, get close to them, sympathize with them, and many times advertise products and goods to increase their income. Making money is so common and simple using these platforms.

As we move on, the number of entities, using social media is increasing daily and the number of photos and videos uploaded on social platforms is growing astronomically. Millions of images are being uploaded around the world every day. Smartphones have made it easy to capture any incident immediately. Hence, in this explosion of data, it would be wise if one gathered this enormous information and did research on it to find useful patterns. Individuals can use this data to become more and more popular. Companies can understand which of their product has attracted more attention in order to target their advertisement more wisely. Organizations can make decisions more strategically and manage their resources more efficiently. Even governments can better understand the behavior of the masses.

Among all these photos and videos, some make a great impression and are noticed widely while some remain completely disregarded. Even two posts on the same page may have different feedbacks from their audience or maybe sometimes we need a recommender system to guide new members to pages and contents they like more. Therefore, the question are: what makes a post popular? What features, most affect the audiences' sentiments and result in achieving a lot of attention and admiration? What aspects should entities take into consideration in order to upload content that is more effective?'

One of the interesting approaches to this issue would be the prediction of the popularity that a post obtains. Popularity is mostly defined as the number of interactions on a platform (e.g. shares, likes, comments, clicks, views, etc.). Predicting such popularity is valuable for authors, content providers, advertisers, and even activists/politicians. No matter what platform they are using or how they define popularity, businesses and organizations can easily observe their uploaded data and examine how much their audience has admired their products or services. Understanding what your customers need, what they like, and what helps them meet their needs is a crucial matter. Therefore, predicting the popularity is an effective way to better understand your audience.

In this paper, we gathered images and videos from three Instagram pages for which we have been producing content. We extracted 25 features to predict the popularity (i.e. number of likes, comments, and video views). At first, the related works of our research area are studied. After that, we introduce our dataset and define its features in detail, then we will explain the experiment and the methods we applied to this dataset and finally we give the result of the experiment and see how much we were able to predict the popularity using those features we considered. The results of our experiments in our dataset for Popularity Score prediction and Popularity Class prediction, get the 0.002 RMSE and 90.77% accuracy in Popularity Class classification.

II. Related Work

Popularity prediction has become one of the topics that have received a lot of attention in the recent years. A lot of work is done in this area focusing on the textual materials. Some works have gone further and used image processing and classification methods on image content, image context, and user context features. Different strategies have been used to define popularity.

Some teams, groups, and companies have developed ways to build algorithms to make popularity prediction an easy task. They have managed websites and applications in which you can upload a photo and see how many likes your image is going to achieve.

A team of scientists from MIT's Computer Science and Artificial Intelligence Lab, eBay Research Labs and DigitalGlobe, led by MIT doctoral candidate Aditya Khosla, came up with the algorithm that predicts how popular your photo will become on a scale from 1 to 10. To build such algorithm, they gathered data from 2.3 million pictures from Flickr and eventually they concluded that they could predict the popularity of an image based on images content and social context. The algorithm considers everything from colors, textures, and objects present in the image to predict the popularity score.

Another company called Beautiful Destinations has developed an algorithm that will tell you how many likes and comments your image will get, the nature of those comments and how many people will click a link on it before you post. They created the algorithm by gathering many pictures from Instagram, Flicker, and Pinterest that had reactions to them and telling the computer to make correlations. They also ran the analysis on pictures their photographers took before and after editing them to figure out how those changes influenced audience reaction as well.

Khosla et al. [1], investigate simple image features such as color and intensity variance, low-level vision features such as Gist, texture, color patches and gradient and high-level image features such as the presence of various objects on a dataset of images from Flickr to predict the number of views an image acquires implementing Linear Support Vector Regression (LinearSVR).

Gelli et al. [2], propose to use visual sentiment features, object features, context features and user features were used to predict the number of views of social images on a dataset of images on Flickr implementing Support Vector Machine (SVM) and Convolutional Neural Networks (CNN).

McParlane et al. [3], use a combination of image contents, image context, user context, and tags as features to predict the number of views and comments on images from MIR-Flickr 1M. They applied Support Vector Machine (SVM) using a radial-basis function (RBF) kernel for classification.

Hu et al. [4], implement Caffe [16] deep learning framework on Yahoo Flickr Creative Commons 100M (YFCC100M) to extract visual features for each image and compare several multimodal and unary learning approaches to predict the number of views as a meaning of popularity prediction. In their experiment, they use tag features along with visual features of 10,000 images selected from the dataset. Finally, they conclude that tag features outperform all other unimodal and multimodal learning models.

Aloufi et al. [6], consider three factors, which are important in predicting the popularity of a medium: visual content, social context and textual information. They use 1.5 million images uploaded from 90,532 users through Flickr API. They define the popularity score to be the number of views an image has got. They modeled the dataset using Ranking SVM methods and implement it under different circumstances.

Wu et al. [7], propose a novel prediction framework called Deep Temporal Context Networks (DTCN) to investigate the sequential prediction of popularity. They use the TPIC17 dataset which contains 680K photos shared over 3 years on Flickr. They show that their DTCN method outperforms all methods used in this dataset previously.

Mazloom et al. [8], present an approach for predicting the popularity of user posts by considering the preferences of individual users to the items. They evaluate their approach on an Instagram user posts dataset with over 600K posts in total related to different tourist places in the Netherlands. Their idea relies on the information on how popular a post is in its visual and textual context, which is shared by a user related to an item.

Fernandes et al. [9], collected data of 39000 articles from the Mashable website which took two years and they extract a total of 49 features to predict the number of shares an online news article gets. They used five classification methods for this reason, which include Random Forest, Adaptive Boosting, Support Vector Machine with a Radial Basis Function, K-Nearest Neighbor, and Naive Bayes by which they reached to an accuracy of more than 60%.

Keneshloo et al. [10], propose a method to predict the number of page views that a news article will receive within the first day since its publication. They consider metadata features, contextual features, temporal features and social features on news articles from The Washington Post and use regression methods to predict the popularity.

Nwana et al. [11], predict the popularity distribution of YouTube videos within a campus network. They explore two broad approaches for this sake: consensus approaches and social approaches. They measure the performance under a simple caching framework.

Jheng et al. [12], develop a concept drift-based popularity predictor, by ensemble multiple trained classifiers from social multimedia instances of different time intervals. Their goal aims to predict the popularity of social multimedia in a microblog.

Chu et al. [13], propose a real-time popularity prediction system based on user feedback. They develop effective algorithms, which utilize the temporal growth of user feedbacks. This dataset contains about 500 target bloggers, 100,000 posts, and 100,000,000 updates collected from Instagram.

Mazloom et al. [14], propose category specific post popularity prediction using visual and textual content for action, scene, people, and animal categories. They conducted their experiment on a collection of 65K posts crawled from Instagram. They considered concept features, low-level features, visual sentiment features, word-to-vec features, bag-of-words feature and textual sentiment features to present their model.

Shaunak et al. [15], use a Deep Neural Network (DNN) trained on data collected from the visual media-sharing social platform Instagram account of a popular Indian lifestyle magazine to predict the popularity of future posts. Mini-batch gradient descent method is used to learn the weights in DNN and the objective function is a cross-entropy. They report an accuracy of more than 70% of their model.

Tracinski et al. [16], propose a regression method to predict the popularity of an online video measured by its number of views. Our method uses Support Vector Regression with Gaussian Radial Basis Functions. Their dataset contains 24,000 videos from YouTube and Facebook on which they analyzed social features and visual features and show that social features represent a much stronger signal in terms of video popularity prediction than the visual ones.

As we observe here, a lot of research is done in this area, various features have been taken into consideration, and different approaches have been done to predict the popularity of social network contents. There are many other important items that could be taken into consideration for predicting the popularity of a post, which we will shortly introduce.

III. Proposed Method

Fig. 1 shows the overall process of our proposed method for popularity prediction. We first, aggregate data of what people shared on Instagram, then extract features from the posts and then, pre-process the extracted features. After that, it is time to predict the Popularity Score by regression methods and Popularity Class prediction by classification methods. In the following, if this part, we introduce our dataset and explain its features and target attributes. Then we propose the preprocessing methods and apply regression and classification methods on our dataset.

A. Data Collection

We collected our data from three different Iranians Instagram business accounts. We named these datasets PFC, PLDM and RDZO after their account's username, consisting of 117, 96, and 58 instances, respectively, each of which includes 22 features. The usernames are @palladium_fitness_club, @palladiummallfan, and @rodizioiran, respectively. These accounts are business pages of three sections in a department store.

As the uploaded media were mainly images and videos, we divided the features into five main categories including Time features, Common Features, Text Features, Video Exclusive Features, and Visual Features. Finally, we considered three items for Popularity Score including the number of likes, comments and video views. The details of the features are as follow:

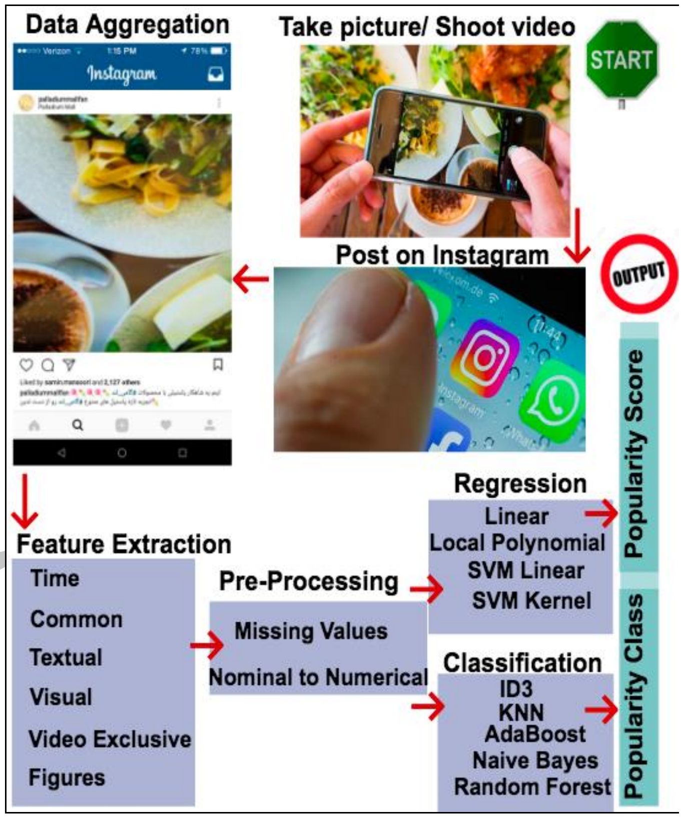

Fig. 1. The overall process of our proposed method for popularity prediction

1- Time Features: All different faces of time that we considered:

1.1- Season: The season in which the medium was posted

1.2- Month: The month in which the medium was posted

1.3- Weekday: The weekday in which the medium was posted

1.4- Day Time: Time of the day the medium was posted including morning, afternoon and night

1.5- Holiday: Whether the day that the medium was posted was a holiday or not

1.6- Event: Whether there was an event (social, cultural, etc.) on the posting day

2- Common Features: Features that are common to images and videos:

2.1- Type: File type of the post which is an image or video

2.2- Topic: The topic that the post is about (food, health, sport, motivational, social, cultural, commercial, news, political)

2.3- Width: The width of the post

2.4- Height: The height of the post

2.5- Orientation: Orientation of the post, which can be landscape, portrait, or square

2.6- Production: Whether we have produced the post or we copied it from somewhere else

2.7- Situation: The feeling that the post gives you about whether you are indoor or outdoor or none

3- Text Features: Features related to any text about the post

3.1- Caption: The caption under the post

3.2- Hashtag Count: The number of hashtags used in the caption

3.3- Media Text: Whether the post has some text inside it or not

4- Video Exclusive Features:

4.1- Music: Whether the video has a global music, local music or none

4.2- Narration: Whether the video has a male narrator or a male narrator or none

4.3- Video Cover: The cover of the video can be a frame, a logo, any text or a black frame

5- Visual Features:

5.1- R: Mean of values of Red in image/video/slideshow RGB

5.2- G: Mean of values of Green in image/video/slideshow RGB

5.3- B: Mean of values of Blue in image/video/slideshow RGB

6- Figures:

6.1- Followers: The number of followers when the post was being uploaded

6.2- Like: Number of likes

6.3- Comment: Number of comments

6.4- View: Number of video views

One issue that needs to be taken into consideration is as follows: Imagine you have 1000 followers when you are posting an image. A week later, you have 2000 followers and you post another image. Of course, this difference between the number of followers has a great impact on the likes these images get. Therefore, we recorded the feature "Followers" and we normalized the number of likes with respect to this attribute. As a result, the attribute "Popularity Score" was created which will be introduced later.

The attribute "caption" is recorded in order if somebody wants to do sentiment analysis experiments on texts.

B. *Preprocessing*

Preprocessing has become an inevitable part of modeling data and helps get results that are more accurate. Therefore, we first replaced missing values with the mode of the related feature and then normalized the data and removed useless attributes. Finally, we replaced nominal data with numerical data as shown in Fig. 1.

Topic		Place		Situation		Orientation	
food	0	RDZO	0	indoor	0	landscape	0
health	1	PLDM	1	none	1	square	1
sport	2	PFC	2	outdoor	2	portrate	2
motivational	3	Type		Day Time		Holiday/Event	
social	4	image	0	morning	0	no	0
cultural	5	slideshow	1	afternoon	1	yes	1
commercial	6	video	2	night	2	Production	
news	7					original	0
political	8					copy	1

Fig. 2. Changing nominal features to numerical features

Other attributes that are not included in Fig .1, are replaced in increasing order starting from 0.

We merged all three datasets to increase the number of records. However, one can conduct experiments on each dataset individually. To apply the effect of being from a certain dataset we added another column to the dataset and considered the page that a record belongs to.

C. *Regression*

As a first approach, we applied four different regression methods on our dataset in order to predict the Popularity Score calculated as shown in (1).

$$Popularity\ Score = \frac{Number\ of\ Likes}{Number\ of\ Followers} \quad (1)$$

The methods are as follow:

- Linear Regression [17]
- Local Polynomial Regression [18]
- Support Vector Machine [19]
- Support Vector Machine (Linear) [19]

In Linear Regression there are four feature selection methods including M5 Prime, Greedy, T-Test and Inductive T-Test. there are two more parameters called min tolerance and ridge, which were tuned.

The factors engaging in Local Polynomial Regression are degree, ridge factor, numerical measure, and neighborhood type.

Using Support Vector Machine, we face kernel type (including dot, radial, polynomial, neural, anova, epachnenikov, gaussian_combination and multiquadric). The parameter C (SVM Complexity) is tuned for better results.

Support Vector Machine (Linear) is the same as SVM but with a linear kernel.

D. Classification

As we wanted to perform classification methods on our data, we needed to discretize the labels. We did this by categorizing the "*Popularity Score*" into three labels: High, Medium, and Low.

The methods we used are as follow:

- K-Nearest Neighbor [20]
- Random Forest [21]
- Naive Bayes (Kernel) [22]
- C4.5 [23]
- Decision Tree [24]

In K-Nearest Neighbor method, we tuned number k and the parameter measure types to get the best result.

The number of trees, criterion (gain_ratio, information_gain, gini_index, and accuracy), and maximal depth are changed to get results.

Using Naive Bayes (Kernel) method, we can choose the number of kernels to get various results.

We imported Weka's W-J48 as the C4.5 algorithm.

Decision Tree method has the same criterion parameter as Random Forest has and is used to get the best results.

In order to define the labels for data examples, as that illustrated in Fig. 2, we first sorted Popularity Score in increasing order and plotted its diagram to figure out how we should label the data. If the Popularity Score is below *0.02* it is labeled "*Low*". If it is between *0.02* and 0.15, it is labeled "*Medium*". If it is more than *0.15*, it is labeled *"High"*.

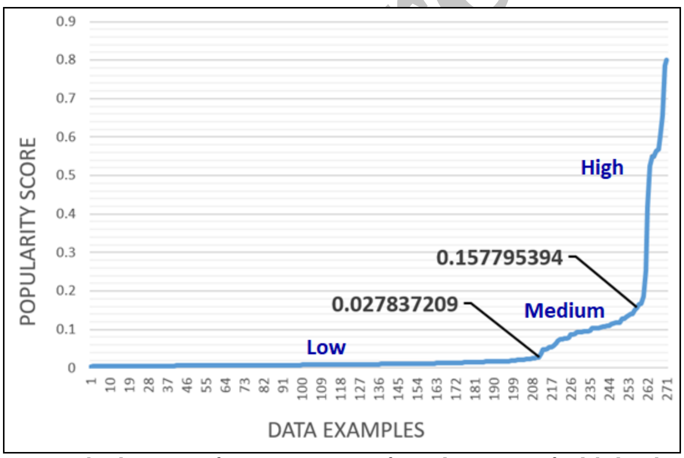

Fig. 3. The diagram to figure out a range of Popularity Score for labels. The two annotated points show the Popularity Score values to specify label of Popularity Class.

IV. EXPERIMENT

We did the experiment using Rapidminer Studio Free 7.4.000 on a computer with the following specifications. The processor is i5-2430M CPU @ 2.40GHz, 2.40 and Installed Memory (RAM) is 4.00 GB. In all experiments by the shuffled data, 10-fold cross-validation was performed to get results that are more realistic. The accuracy computed here is the number of instances that have been predicted correctly divided by the number of all instances. Plus/minus denotes the variance of the results, like as accuracy or other measures. RMSE is Root Mean Squared Error.

We included the results of using regression and classification methods on our merged dataset in Table I and Table II respectively. In these two tables, best-derived results are shown in bold text.

TABLE I. RESULTS OF REGRESSION METHODS ON OUR DATASET

Regression Methods	Evaluation Metrics		
	RMSE	*Relative Error*	*Relative Error Lenient*
Linear Regression	0.086+/-0.028	353.24%+/-115.13%	82.68%+/10.43%
Local Polynomial Regression	**0.002+/-0.000**	**20.20%+/-8.35%**	**17.89%+/6.28%**
Support Vector Machine	0.087+/-0.099	424.35%+/-686.20%	77.85%+/21.53%
Support Vector Machine (Linear)	0.087+/-0.050	100.29%+/-28.74%	53.44%+/5.26%

TABLE II. RESULTS OF CLASSIFICATION METHODS ON OUR DATASET

Classification Methods	Evaluation Metrics		
	Accuracy	*Classification Error*	*Relative Error*
K-Nearest neighbor	88.92%+/-4.71%	11.08%+/-4.71%	21.66%+/4.42%
Random Forest	85.62%+/-6.68%	14.38%+/-6.68%	30.42%+/4.00%
Naive Bayes	89.66%+/-4.34%	10.34%+/-4.34%	11.35%+/3.97%
C4.5	89.66%+/-4.93%	10.34%+/-4.93%	14.86%+/3.96%
Decision Tree	**90.77%+/-5.05%**	**9.23%+/-5.05%**	**13.84%+/4.76%**

The regulated parameters, which are set up in trial and error over available parameters of methods, are as follow:

1- Regression parameter specifications:

- Linear Regression:

  Feature selection = None, ridge = 10^{-8}

- Local Polynomial Regression:

  Neighborhood type = fixed distance, k = 0.4

- Support Vector Machine:

  Kernel type = anova, C = 0

- Support Vector Machine (Linear):

  Default parameters.

2- Classification parameters specifications:

- K-Nearest Neighbor:
  K = 14.
- Random Forest:
  Number of trees = 16
- Naive Bayes (Kernel):
  Estimation mode = full, bandwidth selection = fix
- C4.5:
  Default parameters.
- Decision Tree:
  Criterion = gain ratio

The parameter regularizations just explained lead us to best results in each regression and classification accuracy/error.

As Tables I and II show we got the best results for Popularity Score prediction using a Local Polynomial Regression method with the RMSE of 0.002 and Popularity Class prediction, with Decision Tree acquiring an accuracy of 90.77%.

V. Discussion

We tested our method on our dataset, which led us to the following results according to tables I and II. We predicted the Popularity Score in a regression task using Local Polynomial Regression in which RMSE was 0.002 and its variance was 0 (Table I). The fact that variance equals zero shows that this method has descent stability. The good result of this method is caused by the polynomial-looking shape and distribution of data shown in Fig. 3.

On the other hand, we predicted the Popularity Class in a classification task using Decision Tree with the accuracy of 90.77% and variance of 5.05% (Table II) which is a sign of a good classifier for our dataset. As it is obvious, our dataset is unbalanced according to the classes. Consequently, applying methods that handle unbalanced data would be a good idea to reach greater accuracies.

VI. Conclusion and Future Works

In this paper, we introduced our dataset of Instagram images/videos on which we implemented different regression and classification methods to predict the popularity of posts. In addition, as we know, this study is the first exploring of Iranian Instagram users for popularity prediction of posts.

Comparing the results achieved for Popularity Score prediction and Popularity Class classification, from our experiments we conclude that Local Polynomial Regression and Decision Tree algorithms outperform the other methods tested. These results show that with 10-fold cross-validation we get the results of popularity score prediction with *0.002* in RMSE and Popularity Class prediction with *90.77%* accuracy.

In the future, we can define Popularity Score with the number of times a post has been seen instead of using the number of followers, which is a more realistic measure. In addition, by adding new data between the range of Popularity Score which was visualized in Fig. 3, we can balance the classes so we have more accurate class popularity predictions. Furthermore, in order to improve our method, we can test our method on the daily popular posts announced by Instagram.

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