Persona Identification based on Social Media Profile Images for Personification and Safety

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Abstract

Personification is important to ensure safety in social media. Images embedded in social media data is an important source intelligently ensure the personal safety. Paper proposes an applied machine learning on embedded image media to extract important feature traits and understand the semantics of correlation of feature space to understand the personification of given user. A strong belief is calculated using cascaded method and this inference is applied to different ml algorithms to derive the overlap of feature space. This algorithm validates the proposed objective that the user with more overlap and correlation among feature space are highly personified with each other. Using this personification-based method, better safety is ensured to mitigate possible social media attacks.

Keywords
Persona Identification, social media, Embedded Media.

Introduction

Social media is becoming the source of huge amount data needed for different types of analysis. These tasks are but not limited persona identification, churn analysis, social crisis understanding, sentiment analysis etc. One of the most important domains which gains increasing attention in recent years (Guellil, Azouaou, and Valitutti, 2019; Esuli, Sebastiani, and Moruzzi, 2006; Patra, Braja, Dipankar and Amitava, 2018) is persona identification. and (Wang and Xu. W., 2018) proposes demographic association extraction for the purpose.
of user trait understanding. Persona is an important trait which makes an individual in society different from others. It basically reflects your own way of thinking, speaking and behaviour.

Since long researchers are working on understanding the persona of an individual to understand social behaviour, social relationships quality, mental disorders etc. (Zarei, Farahbakhsh, and Crespi. 2019). The correlation between personality and behaviour can help in today’s social media-based ecosystem. During current time different types of social media platforms have seen humongous growth and are actively influencing people and their social life. The most important objective of such social media platforms is it acts as a place where people can share their opinions, personal stories, stay connected with friends, share their knowledge and achievements etc. The huge success of such social media platforms diverts their main intentions for example many a times social media influencers use social media platforms to manipulate masses, change their views or spreading wrong information which can reach to masses within no time. Persona understanding can be achieved using different types of data like user activities, events, information provided by user, natural language forms created by user on social media.

To provide the persona understanding these forms of input data can be easily available publicly and along with that is easy to process and understand. As the data is publicly available, different social media platforms are providing different type of information hiding techniques as well as GDPR (General Data Protection Rule) compliance-based techniques to restrict use of such information for the purpose of persona understanding. As a result, there will be possible scarcity of non-image-based data and also truthiness value of such type of embedded media data towards understanding the persona is at stake. Instead, by relying on image data like pictures uploaded on media wall solves most the issues described above. The reason is the single source truth nature of embedded images along with the nondisclosure of readable data from the embedded image inputs.

By looking at the scale of image-based data and the accuracy of different state of the art methods like CNN, R-CNN, YOLO-V4, SSD. (Everingham, Gool, et.al., 2010; He, Gkioxari, et.al., 2017; Liu, Anguelov, et.al., 2016; Stutzman, 2006). could help in understanding the user persona in better way if the embedded data is image. However, availability of social media embedded data for different purposes is an advantage and additionally useful to ensure better safety measures for the users. (Stutzman, Vitak, et al. 2012) analysed the behaviour of users of Facebook. It is observed that their social media users expect an increasing safety against unwanted malicious users. As this user sensitive data is available at finger tips, such data can be used and processed for malicious intent,
there is need of personification to ensure safety of user sensitive data. Proposed method aims at extracting personification from embedded media images and ensure proper safety measures against malicious behaviours.

For example, covid19 related information of a user and his social network data can be analysed and can be used to intrude the privacy of an individual with higher accuracy. This and many such issues should be taken into account while posting and exposing personal content over social media. To mitigate these issues, it is of great importance to understand the persona of users connected or wish to connect on social media platform and avoid possible access of sensitive data to those users whose persona is not matching with the self. In addition, a proposal is needed to ensure safety of user data from such malicious purposes. Proposed method addressing the first issue of understanding the persona of an individual present on social media using embedded data. Second using single source of information which is image type data as a validly parameter to allow access to the profile ensures every information present in the form of posts, comments, images and videos kept secure for only legitimate users.

**Literature Review**

There are different prior art studies available to demonstrate the personification of users in social media. There are different objectives for which personification can be used like intent prediction, marketing, emotion detection (Mageed and Ungar, 2017; Veiga and Eickhoff, 2016; Fitri, Andreswari, and Hasibuan, 2019). Traditional features-based techniques like extracting short term and long-term signals from user embedded media data for understanding the survival ratio of the user is proposed by (Mao. et.al., 2015) proposed Long Short-term Memory based method to understand the user persona for predicting the churn rate. One of the promising methods used by (Sermanet et al., 2014) analyses engagement and user actions using CNNLSTM model. The more interesting part of the work is they have used LSTM to capture temporal dynamics in user behaviour. Although these neural methods mostly used natural language data format, their method hinder single source of truth which results into poor summarization of reasons for their predictions.

Contador et al analysed user preferences for around 50000 users across sixteen genres in different domains like music, books, etc. (Beer, David, and Taylor 2013) These different insights are useful to understand the prisonization better. Profiling of a user traits based on language-based understanding and psychology understanding is important takeaway from this work. The basic intuition followed is authors understood that people describe the user their words to explain their persona better that any other form. There are other studies based
on linguistic and psychological models to understand the persona traits of individual. These traits are explicitly analysed from the encoded form in the textual representation (Sermanet et al., 2014). Majority of the methods are initially based on linguistic studies based on the assumption explained in above paragraph. Over the past few years’ persona identification-based research is grown steadily and can be easily witnessed (Goldberg and L.R. 1982; Beer, David, and Taylor, 2013).

Many researchers are inspired to fetch useful information so that it can be explored and used for persona prediction. As it is well understood that there is strong correlation between online behaviour of a user and the persona traits. (Gosling and S. D. 2001; Graham and J. R. 2006) As there is enough prior art available, it helps to generate large corpus for inferring the persona traits. Tweeter is one of the most influential social media platforms. (Scott et.al, 2011) is one of the first who explored the different features of Tweeter like followers, following and count numbers to model the relationship between users and understand their underlying behaviour. On the same line, (Li R. et. al., 2012) used location information and online activities to infer the persona whereas (Oren et. al. 2020) build a hierarchical representation of words and sentences using state of the art deep learning methods to predict the persona identification for certain languages.

Niels et. al., 2017 analyses professional social network site and found that there is no strong correlation between personality trait and the profile of user. This in one way suggest a hypothesis that working experience does not provide better intuition to understand the personality traits of the user which mainly affects his or her social behaviour. Dineen et. al., 2002 proposes a theory which basically demonstrate the preference of computer-based analysis over manual analysis made by spouse, friends and society as a whole. It demonstrates a sound foundation to use social media like Facebook to understand the persona better along with that the proposal of using machine learning based method to predict the persona traits will prove better since computer-based analysis works well that the social factor-based analysis.

It is found that there is strong reason to select social media platform and then apply machine learning based method to understand the persona of every person on social media, so literature survey is conducted on selection of better machine learning method. One the first method used on personality prediction were mainly using SVM. Most early methods use lexical and semantic based method (Hughes et.al., 2011). From 2018 onwards researcher explored deep learning-based method to better approximate the nonlinearities to predict the persona trait as classification problem. (Majumder et. al. 2017; Mikolov et. al. 2013) used deep learning architecture. They created the features form social behaviour, syntactical
representation of user, explicitly designed features along with the grammatical annotations mapped to dictionary metadata collected from dialog data.

The aim behind using machine learning based method is to understand the statistical significance of the sentence and post data in different forms to annotate the relationship with personal traits. Researcher adopted value and sequential association-based method to achieve the same objective. Value based deep learning method tries to apply frequentist method to identify the signification and Association based method understand the temporal associations between the tokens. For example, (YouYou et. al. 2014) proposed Recurrent Neural Network based method to find the word embeddings and sentence embeddings to extend the word to vector based method proposed by (Argamon et. al. 2005; Majumder et. al. 2017). They proposed CNN based method to get the fixed length embeddings from the image embeddings, these embeddings are the repositories of feature traits which helps to identify the personification.

There are two main methods to extract the personification data from embedded data. The one is based on language data and the other is image data. It is understood that calculating word embeddings is slow task as it requires to create the metadata store if your use case is not matching with any existing use case. Also, for general purpose applications, most of the word embeddings are designed for deep learning (Manning, et.al., 2008; Collobert, et.al., 2011) Word embeddings can be helpful in improving the classification performance if proposed method trains them correctly by adopting the dynamic changes in megastore if new words arrive which are not seen at the training time. (Gao et. al., 2013) calculated learning specific word embeddings to adapt them for unknown scenarios. Based on this study, it is found that image embedding based persona analysis is more robust than language-based method. As it ensures less data drift and concept drift over longer period. So, embedded image media-based method is useful in leveraging personification and safety.

One more challenge if natural language-based data is considered for persona identification and that is different languages used. So, to alleviate this issue, (Kanavos et. al., 2017) proposed novel bilingual word vectors to ensure the equivalence between language specific word vectors. Because of these challenges, the universal representation which is image is a uniform medium across all geographical locations. Proposed method uses image as data point so that provided solution can uniformly analyses the persona class of an individual.
Research Method

A person who is using social networking site is user. Before using any social media platform, every user registered with the platform to use the services offered by platform. Let’s denote user as $u$. Every user when registered on the platform will get connected to other users. Let’s denote those connections by friendship. This relationship will be an undirected edge which denotes bidirectional association of users with each other as this association is symmetric. Let $A$ and $B$ are friends of each other on social media. It implies a friendship relationship between them. This is defined using set theory as, relation $R$ between $A$, $B$ is said to be a symmetric relation iff $(A, B) \in R \Rightarrow (B, A) \in R$ for all $A, B \in$ User Set. i.e., $ARB \Rightarrow BRA$ for all $A, B \in$ User Set. Every user on the social media platform performs different activities like posting content, giving likes and dislikes, viewing the content posted by friends, chatting etc. One of the most important features is these associations are temporal in nature as users on social media may unfriend the other users based on some reason which that user finds difficult to continue the association. Now, in this model the user interaction is based on this interaction, which is tried to understand those user groups as “Social” and “Unsocial”. Here Social group contains those friends who retains similar types of persona and Unsocial group contains those friends who do not share any common and social persona with the friends in social group. Let’s define a persona graph for every user at time $t$,

$$G_t^p = (V_t^p, \varepsilon_t^p, X_t^p, E_t^p). \text{Here } V_t^p = \{p\} \cup N_t(p)$$  \hspace{1cm} (1)

Where $V_t^p$ denotes node in $G_t^p$. The set $N_t(p)$ denotes the set of persona related with $p$. $E_t^p$ is an association which represents the friendship association between persona $p$. The characteristics of persona which are extracted from image profile is represented using set $X_t^p$ and $E_t^p$ shows friendship association among persona characters. Using above characterization helped to cluster the persona based on the characteristics extracted from the user data. Let’s apply different clustering algorithms on feature data extracted.

A. Feature Extraction

As the method basically focusing on implementing persona recognition based embedded image form of data with intend to find the important features from the embedded data. Basically, to find spatial information from embedded data. Haar cascade classifier which internally contains series of stages. Each stage is basically a weak learning entity that will detect all the important features from embedding. This will help to understand the crucial features and then can able to extract the spatial parameters from the input data extracted.
The file is stored in xml format. Haar cascade is designed by OpenCV to detect important feature traits. It is available on github. Upon training, CNN classifier provides different spatial coordinates which have subsequently used to provide description.

![Cascaded method](image)

**Fig. 1 Cascaded method**

**B. Convolutional Neural Network**

Train used cascaded Convolutional Neural Network which takes cascaded inputs along with their spatial features. These all features are provided as cascaded input in terms of xml file. As different cascades are available using number of weak learners it easy to achieve optimization at low level which helps to boost the performance. Number of imaged trained are 500 images on quad core CPU. The search level optimization is also boosted when searching the social matching persona for the objective. The other achievement of adopting cascaded CNN is processed cascaded layers and not the whole piece of embedded data, it helps to achieve better accuracy across major variances and the processing time is reduced by factor of half as there is no need to process the whole pixel distribution with cascaded variant of CNN.

Proposed work is based on following key points. 1. Used small number of cascade stages. The shortest cascade of 4 stages is used with MCT descriptor as a boosting mechanism. This helps to extract the most important traits from the embedded data. 2. Parallel execution of third and fourth stage of cascade onto two different processing core units. This asynchronous way of implementation setup allows to reject majority of spatial features rejected in the first stage. Because of this setup, work on video data to process it is executed efficiently. 3. Compact design of CNN architecture to restrict the number of features lesser than 350. To ensure better generalization, training data setup is maintained with list of images with high variance. This small stage ensures better generalization and accuracy with compact and simple CNN architecture.

The cascaded network performs three tasks in sequence: Feature extraction from embedded data, Bounding Box Prediction, Spatial Localization and Persona Identification.
C. Embedded Data Feature Detection

It is basically a two-class classification method. From a given training set, each sample is feeded to the cascaded CNN architecture, there are couple of methods tried like Batch Processing Mode, Normal Mode and Stochastic method.

\[
L_i^{det} = -(y_i^{det} \log(p_i) + (1 - y_i^{det})(1 - \log(p_i)))
\]  \hspace{1cm} (2)

Where \(L_i^{det}\) is the probability that indicates inference provided by algorithm which subsequently equates with the ground truth using Cross entropy loss function mentioned in above equation and the notation is \(y_i^{det} \in \{0,1\}\).

D. Bounding Box Prediction

Bounding Box prediction is considered as a regression problem. A standard pretrained model parameters to predict the coordinate points \(x, y, w, h\) where \((x, y)\) is centre coordinates of bounding box and \(w\) being width and \(h\) being height of the bounding box. The pretrained model allows to achieve the best Region of Interest (ROI). Region of Interest is considered as one the most intuitive metric for evaluating the performance of bounding box regression problem. To ensure further improvements in Region of Interest (ROI) Euclidian Distance is used as a metric which is invariant to low lever features changes. This decision helped to achieve robust performance in bounding box prediction. The Euclidian distance is formulated as,
\[ L_i^{box} = \| \hat{y}_i^{box} - y_i^{box} \|_2^2 \]  

(3)

Where \( \hat{y}_i^{box} \) is prediction variable provide by cascaded CNN and \( y_i^{box} \) is the ground-truth coordinate which is annotated from existing dataset. Four coordinates, including left top which is represented with \((x, y)\), height \( h \) and width \( w \), It is formulated as, \( (y_i^{box} \in \mathbb{R}^4) \).

E. Shape Coordinate Localization

Similar to above task, shape coordinate localization can be formulated as a regression problem. This further optimized using Euclidian distance as metric to evaluate the distance metric. It is formulating as,

\[ L_i^{landmark} = \| \hat{y}_i^{landmark} - y_i^{landmark} \|_2^2 \]  

(4)

Where \( \hat{y}_i^{landmark} \) are the landmark’s coordinate obtained from the network and \( y_i^{landmark} \) is the ground-truth coordinate. Five shape coordinates are selected for the purpose of persona Identification, left mouth corner, and right mouth corner, left eye, right eye, nose. This setup is formulated as, \( y_i^{landmark} \in \mathbb{R}^{10} \).

F. Persona Identification

As the traits are available, the next task is to understand the persona from these traits. To fix this objective by relying on Turning Test method. A structured method to understand persona based on all traits collected in previous step.

<table>
<thead>
<tr>
<th>Feature Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trait-1</td>
<td>Great perseverance, Courage, strong willed, courageous, stern, clever, talented and shrewd.</td>
</tr>
<tr>
<td>Trait-2</td>
<td>Kind, compassionate, friends, talk movie, arts lovers, emotional.</td>
</tr>
<tr>
<td>Trait-3</td>
<td>thoughtful, sensitive, peaceful, hesitate, less ambition, flat emotions in middle age, Men work harder, Women married late.</td>
</tr>
<tr>
<td>Trait-4</td>
<td>careerists, spend more money, quality of life.</td>
</tr>
</tbody>
</table>

G. Clustering

All persona descriptions are trained on different clustering algorithms like K-means, DBSCAN and PCA. Using these clustering algorithms, each persona description is feeded to understand their contextual similarity. This Contextual similarity helped to understand
the persona which is socially similar. The persona descriptions belong to one cluster ensure good behaviour and not lead to any unlawful activity. This null hypothesis is tested under Bayesian setup and it validates the observation.

As, cascaded CNN is designed to perform different tasks such that training different types of training images in the learning process, such as embedding data, regression of bounding box coordinates and regression of shape traits. This method slightly changed the loss function and incorporated these three traits. For example, compute \( L^i_{\text{det}} \) and the remaining regression losses are initialised to 0. The reason being for both regression problems utilised pretrained weights. So, the final objective function is formulated as,

\[
\min \sum_{i=1}^{N} \sum_{j} \alpha_j \beta_j L^j_i \quad (5)
\]

where \( N \) is the number of training examples. \( \alpha_j \) defined task priority. Use \( \alpha_{\text{det}} = 1, \alpha_{\text{box}} = 0.5 \), \( \alpha_{\text{landmark}} = 0.5 \) to process the forward propagation for all samples and pick top 70 percent hard samples. Once forward propagation is outputted at the output layer, compute the gradient and propagate it in backward propagation phase. This setup to prioritize the difficult samples set the inference logic in CNN so that it generalizes well and helped to achieve better accuracy in recognition and regression task at the time of training.

**Algorithm**

**Algorithm 1: Persona Identification from embedded media.**

Require: social media Pictures  
Ensure: Persona Identification For each social media Picture  
1. Perform Feature Extraction:  
   a. Cascaded CNN:  
      \( P^{k+1} = P^k + Net^k(Fea(l, P^k)) \)  
   b. Regression Loss:  
      \( L^i_{\text{det}} = -(y^i_{\text{det}} \log(p_i) + (1 - y^i_{\text{det}})(1 - \log(p_i))) \)

2. Perform Bounding Box Detection:  
   \( L^i_{\text{box}} = \| \hat{y}^i_{\text{box}} - y^i_{\text{box}} \|^2 \)

3. Perform Spatial Annotations:  
   \( L^i_{\text{features}} = \| \hat{y}^i_{\text{features}} - y^i_{\text{features}} \|^2 \)

\( Y \leftarrow Train \ Accuracy \)

4. Calculate Cumulative Cost Function:  
   \( \text{loss} \leftarrow \min \sum_{i=1}^{N} \sum_{j} \alpha_j \beta_j L^j_i \)

5.  
   \( \text{loss} \leftarrow L(\beta) = \sum_{i=1}^{n}((y_i \log(p_i) + (1 - y_i)\log(1 - p_i)) \)

6. if \( \text{loss} > \text{threshold} \) then  
   \( \text{loss} \leftarrow -\sum_{i=1}^{n}((y_i \log(p_i) + (1 - y_i)\log(1 - p_i)) + \lambda_\beta \| \beta \|^2 \)

   \( \text{loss} \leftarrow -\text{loss} \)

endif
Experiments

Strategy on being more considerate on difficult samples used for training purpose. Then compared method with different methods like WF, FDDB and AFLW. WF and FDDB are datasets which is into 70, 30 distributions. AFLW is annotation dataset used for bounding box alignment. The setup which was used in the experiment is then used to evaluate the computational efficiency of the Algorithm.

Result and Discussion

The section demonstrates and evaluate the performance of method. All machine learning models are implemented in Python 3.7.1. All experiments were executed on Jupyter Notebook IDE. It is most popular IDE used for model development and supported machine and deep learning libraries and packages in scikit-learn, TensorFlow and Keras. This Data science work bench is installed on a Ubuntu system with an Intel Corei7 CPU at 2.4GHz, 12 GB of RAM used Spyder IDE for experimentation.

A. Feature Extraction

As shown in Fig.3, set of features are extracted for each embedded media using stagewise cascading. This method iteratively increments the weighted filtering method from weak feature extraction to strong feature extraction. Strong features are dominant features which are more useful in personification of provided embedded media. The evaluation about whether the feature is weak or strong at each cascaded stage is done with the help of correlation and covariance metrics. Mostly it is observed that at latter stages of cascading more stronger features with higher covariance are extracted which defines stronger association. This stagewise feature extraction from embedded media localizes the important spatial feature objects in the given feature space.
B. Feature Space Analysis

As shown in Fig. 4a, there’s a large correlation between features per persona and the Persona types per feature distribution. It is based on person correlation factor there is a note of 69 percent correlation between features per persona and Persona types per feature distribution. This basically demonstrates that the people connected on social media with each other have on an average 70 percent features which are matching to ensure better personification and safety.

Now, from this figure it is evident that under 0.3 probability feature distribution the notion of personification and safety is crucial to predict and understand. These feature sets mainly attributed from the ecosystem, environment, location and different about each persona. Now, 69 percent features correlating with persona. This is an interesting first step to explore
into the data and features. This further is extended to predict the personality types and based on that the personification-based safety analysis of users is predicted based on their social media based embedded media postings using machine learning.

C. Effect of Similarity on Personification

![Fig. 5 Correlation Coefficient](image)

As shown in Fig. 5., it is clearly indicated that there is Homoscedasticity, that the variances along the line of best fit remain similar as you move along the line. This hypothesis implies that person correlation is more relevant to calculate the correlation among the features to understand the impact analysis towards personification of class variable. Pearson correlation is calculated using,

\[ r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \] (6)

D. Performance Analysis

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forest</td>
<td>93 %</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>92 %</td>
</tr>
<tr>
<td>K-mean Clustering</td>
<td>96 %</td>
</tr>
<tr>
<td>CNN</td>
<td>98 %</td>
</tr>
<tr>
<td>DBSCAN</td>
<td>91 %</td>
</tr>
</tbody>
</table>

Different machine learning algorithms are used to calculate the accuracy of method of the three K-mean clustering perform well than the others. In this, the clusters 0, 4 and 6 accounts to more percentage of persona, understanding differences between these 3 clusters is key. The cluster 4 which consists of Career and Professionalism, which are top centroid features and can say this cluster consists of persona which is more related with
professionalism, few persona of each cluster and try to understand the differences. By reading the cluster 2 and 9 which contains courageous and kind people, which is clearly indicates that courageous people are not kind people and hence each persona belongs to separate cluster and is concluded that persona from these cluster tend to opposite behaviour point of view. By reading persona traits from cluster 0, this explains that these persona are extremely positive and are very happy. So, mostly people belong to cluster 0 tend to behave socially and can have better friendship relationship with all types of persona. By reading cluster 5, it is seen that the key persona is overachiever and ambitious people. It indicates some kind of people agree with least of the things related to the social persona traits and there is something which is slightly disagree with common expectation. So, tend to match with persona of the same cluster.

E. Feature Space for Achieving Safety

Cluster 0: emotion, good, moving, tend, overwhelming, heart, flair, eye, sleeve, express.
Cluster 1: word, like, people, quality, improv, comfort, complete, prevent, need.
Cluster 2: think, often, logic, straight, courage, eyebrow, people, clever, shrewd, stern.
Cluster 3: sensory, stimuli, resent, emphasis, use, trick, less, passion, like, practice.
Cluster 4: base, quick, make, their, tri, stronger, circle, idealist.
Cluster 5: popular, luck, wealth, other, relationship, kind, career, good, honest, improv
Cluster 6: work, little, power, effort, specul, spare, pursuit, hard, energetic, broad.
Cluster 7: base, quick, make, tri, stronger, circle, necessarily
Cluster 8: base, quick, make, their, tri, stronger, idealist
Cluster 9: base, quick, make, tri, stronger, circle, necessarily, idealist

Number of all the cluster 4 accounts to more percentage of persona understanding i.e., above 4000. If the top terms per cluster are observed, the clusters based on the behavioural traits and behaviour wise social and non-social behaviour. For example, the investigation of cluster 8 presents the reviews which talk more about emotion, quick, stronger, circle, idealist behaviour. In these, it’s better to understand the cluster centre top features rather than individual traits. By using Elbow method, generated optimal 10 clusters for both the bag of words and TFIDF techniques in both the cases, one cluster accounts around 100+ traits which is large chunk from the dataset and rest are distributed unevenly. Ignore 2 clusters or keep 2 clusters depending upon the business goal for bag of words generation as both contain only 1 personal traits.
F. Final Observations

Cascaded CNN architecture performs embedded media detection with 98.6 accuracy. These embeddings are forwarded onto extracting more embedding vector which basically provide the spatial annotations for different component of the image embedding. This data then described with textual descriptions which is extracted form. It is then forwarded to three algorithms. Among clustering method performs best to identify the persona. For TFIDF K means is best for identification than K MEANS for BOW, all the clusters are clearly reflecting they were grouped based on the social and non-social behaviour. However, K means did best on the cluster centres top terms but however when reviews are compared, few places it is not correlating. DBSCAN is very poorly performing on the 10+ columns as it is grouping all behaviours in one cluster. Hierarchical, for BOW and TFIDF, we cannot identify the clusters and not divided unevenly, but for average word to vectors all are grouped and divided evenly. It is very difficult to identify the type of persona based on Hierarchical formation.

G. Possible Use Case

Social Media platform like Facebook needs verified connections. These connections can be verified using proposed persona identification and safety method. Existing system recommends connections based on existing friendliest. This is not an accurate mechanism as there is high probability of untrustworthy recommendations which in turn are not verified using persona verification as well as safety assurance. Proposed method can replace existing connection recommendation in following way. 1. Input set embedded images recommended at connection request to next step. 2. Extract Important feature embeddings using cascaded convolutional neural network. 3. Align each embedding with predefined feature map in text description format. 4. Cluster the textual features extracted in previous steps. 5. Allow the connection requests to only those persona which belongs to same cluster as it ensure better safety.

Conclusion

The method of identifying the persona based on features extracted from embedded image frame is designed. This design needs an annotation method to understand the features in each image with the help of psychological embedding provided by subject matter expert. The Novel method proves with higher accuracy when evaluated the performance using Bayesian benchmark and Turing Test based Assessment. At the outset, the solution ensures better personification to ensure lesser risk on social media.
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