PersonRank: Detecting Important People in Images

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Abstract—Always, some individuals in images are more important/attractive than others in some events such as presentation, basketball game or speech. However, it is challenging to find important people among all individuals in images directly based on their spatial or appearance information due to the existence of diverse variations of pose, action, appearance of persons and various changes of occasions. We overcome this difficulty by constructing a multiple Hyper-Interaction Graph to treat each individual in an image as a node and inferring the most active node referring to interactions estimated by various types of clews. We model pairwise interactions between persons as the edge message communicated between nodes, resulting in a bidirectional pairwise-interaction graph. To enrich the person-person interaction estimation, we further introduce a unidirectional hyper-interaction graph that models the consensus of interaction between a focal person and any person in a local region around. Finally, we modify the PageRank algorithm to infer the activeness of persons on the multiple Hybrid-Interaction Graph (HIG), the union of the pairwise-interaction and hyper-interaction graphs, and we call our algorithm the PersonRank. In order to provide publicable datasets for evaluation, we have contributed a new dataset called Multi-scene Important People Image Dataset and gathered a NCAA Basketball Image Dataset from sports game sequences. We have demonstrated that the proposed PersonRank outperforms related methods clearly and substantially. Our code and datasets are available at https://weihonglee.github.io/Projects/PersonRank.htm.

I. INTRODUCTION

In some social activities, not all of the people involved in an event act equally, and always there are important people among them. For example, people pay more attention to the speaker in a ceremony (Figure 3(b)), the interviewee (Figure 3) and the shooter in a basketball game (Figure 3(a)). In these examples, the important people in an image play a more important role than the others in the image and are more related to the event presented in the image [19], [22]. Detecting important people can potentially benefit event recognition and event detection [19]. In particular, analyzing the action of the important people enables intelligent system to better understand what has happened. For instance, a “shoot” in a game is closely related to the most important person, who shoots the ball (see Figure 3).

While person (face or pedestrian) detection is processed at an ever-faster rate, relatively little work has explored detecting important people against diverse changes of pose, action and appearance of persons and occasions. Existing work has attempted to use attention model [19] to predict the importance of people directly from their action and appearance or utilize regression model [22] on spatial and saliency information of face/body to infer relative importance between every two persons. However, these models ignore some semantic information such as interactions between persons, which are essentially useful for inferring the importance of persons.

Finding important people among individuals in images based on a large amount of visual or spatial cues is challenging, especially when diverse changes of pose, action, appearance of persons are observed at different occasions and identities of these persons are unknown. For example, the appearance of the most important people in two images shown in Figure 1 are totally distinct.

To address this problem, we cast the important people detection problem into ranking nodes in a graph from interactions. Specifically, we propose to consider each person in an image as a node in a graph. Between nodes, we model four types of edge message functions to mimic interactions between any pairwise persons, such as how a person attracts another, how a person is located relative to another, how a person’s action would affect another and what the appearance difference is between them. This would result in a pairwise-interaction graph which is bidirectional. We also infer the relation between the local consensus of a group of persons and any focal person, which results in a unidirectional hyper-interaction graph. The hyper-interaction graph is unidirectional because the consensus is not physical and thus there is no message forward from focal person. The use of hyper-interaction graph can take advantage of local pooling as suggested in other tasks [6], [26], [28] so as to enrich person-person interaction estimation. Finally, we modify the PageRank algorithm [15] to make it suitable for inferring the activeness of nodes on the union of pairwise-interaction and hyper-interaction graphs, termed the Hybrid-Interaction Graph.

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Graph (HIG), and the most active person is selected as the most important person in an image. We thus call our model the PersonRank.

Since there is a lack of publicable image-based dataset on inferring important people, we also contribute a new dataset, called Multi-scene Important People dataset. This new dataset consists of a large number of images illustrating several events involving multiple persons in different scenes. There are 2310 images mainly from six types of scene. The ground-truth most important person in each image is annotated. We also formed another dataset consisting of images of basketball games by extracting event-starting frame from the NCAA Basketball Dataset [19]. This dataset contains more than 10,000 images and annotations are provided. Although, there is only one dataset named Image-Level Dataset collected for important person detection before by Solomon et al. [22], unfortunately, this Image-Level Dataset is not publically available, and it contains only 200 images, much smaller than the ones we collected and formed in this work.

In summary, we make the following contributions. First, we have proposed a PersonRank (PR) that first casts the important people detection problem into ranking nodes in a graph from interactions, which is efficient and effective; Second, we have collected a large images dataset which consists of different events and formed a large basketball games images dataset with massive annotations for important people detection. Experimental results show that our PersonRank (PR) model has obtained the state-of-the-art performance on the two datasets.

II. RELATED WORK

Persons and General Object Importance. Recently, several works [4], [11], [12], [13], [24], [14], [22] were proposed to study the importance of generic object categories and persons. Solomon et al. [22] studied relative importance between persons and developed regression model for predicting the importance of persons in an image. In contrast to using regression model in [22], we develop a graph-based model to predict the importance of persons, where not only interactions but also importance scores of others are taken into account. In addition, only spatial information was explored in [22], and in comparison more significant context information such as attention, action and appearance information are explored and fused effectively in this work. Ramanathan et al. [19] trained “attention” model with event recognition labels to detect key actors in basketball games videos. Compared to [19], our model does not rely on temporal information and event annotations, but deeply explores the pairwise-interaction and the hyper-interaction between persons directly on images. Some researches also studied detecting important people and objects in egocentric videos and learned a regressor to predict important regions with which the camera wearer has interaction based on cues such as the nearness to hands, gaze, and frequency of occurrence [13], [14]. However, these approaches are not suitable for detecting important people in still images.

Social Interaction. Since we model the interaction between persons in an image, detecting or modeling social interactions [8], [3], [2] is related to ours. Fathi et al. [8] proposed a method for detection and recognition of social interactions in the first-person video of social events. Amer et al. [3] presented an approach to model social interactions on a “Tower Game” video dataset which is also an egocentric videos dataset. However, these works did not develop for further identifying important people, while we use edge message functions to model the interaction between persons and develop PersonRank model to select the most active person.

Saliency Detection. Related to important people/objects detection, saliency detection tells where an image draws attention of viewers. It gains huge benefit from the recent large-scale datasets, and a variety of models [18], [7], [29], [5] have been developed. However, the saliency detection approach may not work well for detecting the most important person if multiple people exist in an image, due to the lack of analysis on the relationship between persons. This will be verified by our experiments.

III. APPROACH

We propose a Hybrid-Interaction Graph (HIG) based PersonRank (PR) to infer the importance of each person in this section. In the following, we first present four types of message functions used for modeling the interaction between any pairwise persons, then detail the construction of the HIG, and finally describe the technique to find important people. An illustration of our method is shown in Figure 2.

A. Modeling Interactions by Message Functions

We treat people in an image as nodes in a graph and model the interaction between any pairwise persons as the edge message communicated between them via message functions. We form four types of edge message functions, including spatial and action message functions, appearance message function, and attention message function in order to describe how a person attracts another, how a person is located relative to another, how a person’s action would affect another and what the appearance difference is between them. Based on each type of message function between nodes (persons), a bidirectional pairwise-interaction graph is generated in the next section.

Spatial and Action Message Functions. Given the relative spatial feature $\phi^s_{pi}$ and action feature $\phi^{ac}_{pi}$ for any person $p_i$, the message function $\Phi^s(\phi^s_{pi}, \phi^s_{pj})$ and $\Phi^{ac}(\phi^{ac}_{pi}, \phi^{ac}_{pj})$ are used to measure how $p_j$ locates relative to $p_i$ and how the action of $p_j$ would affect $p_i$. For this purpose, the spatial and action message functions $\Phi^s(\phi^s_{pi}, \phi^s_{pj})$ and $\Phi^{ac}(\phi^{ac}_{pi}, \phi^{ac}_{pj})$ are denoted below, respectively:

$$\Phi^s(\phi^s_{pi}, \phi^s_{pj}) = w^s T \exp(\phi^s_{pi} - \phi^s_{pj}),$$
$$\Phi^{ac}(\phi^{ac}_{pi}, \phi^{ac}_{pj}) = w^{ac} T \exp(\phi^{ac}_{pi} - \phi^{ac}_{pj}),$$

where $w^s$ and $w^{ac}$ are learned by a two-class support vector machine in order to identify the difference between an important person and any non-important person from the difference between any two non-important people.
Appearance Message Function. The appearance message function is to model the difference between the appearance of pairwise persons, and this is the fact that the appearance of the important people in images could differ from the others (see Figure 3). To this end, given the appearance feature of the person \( p_i \) and \( p_j \):

\[
\Phi^{\text{ap}}(\phi^\text{ap}_{p_i}, \phi^\text{ap}_{p_j}) = w^{\text{ap}T}(\phi^\text{ap}_{p_j} - \phi^\text{ap}_{p_i}),
\]

where \( w^{\text{ap}} \) is also learned by a two-class SVM so that the appearance difference between an important person and any non-important person is larger than the one between any two non-important people.

Attention Message Function. Since the person who attracts others (persons in the image) mostly is more likely to be the most important person, we form an attention-message function \( \Phi^\text{at}(\phi^\text{at}_{p_i}, \phi^\text{at}_{p_j}) \) where \( \phi^\text{at}_{p_i} \) is the attention feature of the \( i \)th person in order to describe the likelihood of the person \( p_i \) looking at person \( p_j \) as follow (similar to [8]):

\[
\Phi^\text{at}(\phi^\text{at}_{p_i}, \phi^\text{at}_{p_j}) = \exp(\mathbf{v}_{p_i} \cdot g(w^\text{at} \odot (f_{p_j} - f_{p_i})) - 1),
\]

where \( \odot \) is the element-wise product, \( g(\cdot) \) is used for normalizing the input vector. As shown in Figure 4, in Eq. (3), \( \mathbf{v}_{p_i} \) is the direction of the attention of \( p_i \), \( g(w^\text{at} \odot (f_{p_j} - f_{p_i})) \) is computed to approximate the unit orientation from \( p_i \) to \( p_j \), and \( w^\text{at} = [1, c]^T \) is tuned on validation data. Hence the inner product between \( \mathbf{v}_{p_i} \) and \( g(w^\text{at} \odot (f_{p_j} - f_{p_i})) \) can describe the strength of attention between \( p_i \) and \( p_j \).

B. Inferring Importance of Persons from Hybrid-Interaction Graph

Suppose that a set of \( N \) persons \( \{p_i\}_{i=1}^N \) are detected in a still image. In order to find important people, we form a Hybrid-Interaction Graph (HIG), denoted as \( H = (V, E, G) \), where \( V = V^p \cup V^r \) is a set of nodes, \( E = E^p \cup E^r \) is a set of edges and \( G \) is an interaction matrix.

Constructing Pairwise-Interaction Graph \( H^\text{pig} \): First of all, as shown in Figure 2(b), we construct a bidirectional graph \( H^\text{pig} \), where \( V = \{p_i\}_{i=1}^N \) are nodes representing persons \( \{p_i\}_{i=1}^N \), and \( E^p = \{e_i^1, \ldots, e_i^\text{ac}, e_i^\text{ap}, e_i^\text{at}, \ldots, e_k^N\} \) are edges. Here, each directed edge \( e_i^s_j = (V_{p_i}, V_{p_j}) \) is used to model the interaction between pairwise persons. For each type of edge \( 1 \phi^\text{pig}_{p_i} (z \in \{s, \text{ac, ap, at}\}) \), we design four types of edge message functions \( \Phi^s(\phi^z_{p_i}, \phi^z_{p_j}) \) (\( z \in \{s, \text{ac, ap, at}\} \)) formulated in the last section and assign \( G_{i,j}^p = \Phi(e^s_{i,j}) = \Phi^s(\phi^z_{p_i}, \phi^z_{p_j}) \) to each edge in order to capture how a person is interacting with another. Therefore, for each type of edge message function, the person-person interactions among \( V^p \) can be expressed as a \( N \times N \) bidirectional interaction matrix \( G^p \).

Constructing Hyper-Interaction Graph \( H^\text{hig} \): In order to utilize the local spatial consensus of person attractions on a focal person for identifying whether that focal person is important, we explore a higher level interaction graph for each focal person. As shown in Figure 2(c), for each focal person \( p_i \), we divide the area around him/her into \( Q \) block regions and denote each local region as \( r_{i,k} \) corresponding to node \( V_{r_{i,k}} \in V^r \) in graph \( H^\text{hig} \). Then we compute the maximum of the

1The feature is mentioned in Sec. III-A and to be elaborated in Sec. III-C.
person-person interaction between any person in each block region and focal person. Specifically, for each type of feature $\phi_k^p(z \in \{s, ac, ap, at\})$, we denote the consensus of persons on the focal person $p_i$ in the local region $r_k$ as $\gamma^p_{k,i} = \max(\phi^s_{k,i}, \phi^ac_{k,i}, \phi^ap_{k,i})$, where $p^k$ is the person in region $r^k$ and $\gamma^p_{k,i}$ is the feature representation of $V_{r^k}$. Then, as shown in Figure 2(d), the unidirectional hyper-edge $e^p_k = (V_{r^1}, \ldots, V_{r^l}, V_{p_i}) \in E^r$ between $Q$ consensus and focal person is formed by message function as similarly described in the last section. So that we use a $Q \times N$ unidirectional interaction matrix $G^r$, with $G^r_{k,i} = \Gamma(\gamma^p_{k,i}, \phi^p_{k,i}) = \delta^T(\phi^p_{k,i} - \gamma^p_{k,i})$, $(k = 1, \ldots, Q)$, to model such a region-person hyper-interaction and assign $\sum_{k=1}^Q G^r_{k,i}$ to $e^p_i$. Note that we form the unidirectional edge rather than the bidirectional one because each consensus is not physical person and thus there is no backward message sent from the focal person. We empirically set $Q = 4$ and the vector $\delta$ is learned by a two-class SVM to separate the most important and non-important person.

**Constructing Hybrid-Interaction Graph $H$:** With the unidirectional Hyper-interaction graph $H^{(hi)}$, the Hybrid-Interaction Graph (Figure 2(e)) is finally formed as $H = H^{(hi)} \cup H^{(hi)} = (V, E, G)$, and the full interaction matrix $G$ that describes pairwise and hyper person-person interactions is defined as:

$$G = \begin{bmatrix} G^s & 0 \\ G^c & G^p \end{bmatrix},$$

(4)

where 0 denotes a zero matrix and $G$ is a $(N+Q) \times (N+Q)$ square matrix.

**Inferring Importance.** We model the activeness of each person in the graph as the accumulated interactions with the others, because active people in a scene are always likely to interact with other active people more. Let the importance score of person $p_i$ be denoted by $\lambda_{p_i}$. Hence, in a graph, we can compute the importance score of a node by the accumulation of message function values from other nodes, i.e.:

$$\lambda_{p_i} = \frac{(1-\alpha)}{N} + \alpha \sum_{k=1}^Q G^r_{k,i} + \alpha \sum_{j=1}^N G^p_{j,i} \frac{\lambda_{p_j}}{C_{p_j}},$$

(5)

where $\alpha = \frac{(1-\alpha)}{N} + \sum_{k=1}^Q G^r_{k,i}$ is the prior importance score inferred from hyper-person-person interaction, $\alpha$ is a damping factor that can be set within the range $0 < \alpha < 1$, and $C_{p_j} = \sum_{n=1}^N G^p_{j,n}$ is the total number of outbound links from node $V_{p_j}$. The interaction $G^p_{j,i}$ is weighted by the important score of another person $p_j$, because the more interaction between two persons the more they would communicate and thus the message input from more active people would be more important to estimate the importance (activeness) of a person.

We actually modify the PageRank algorithm by adding $\sum_{k=1}^Q G^r_{k,i}$ in Eq. (5) to rank the nodes in a graph. The term $\sum_{k=1}^Q G^r_{k,i}$ is a specific bias to person $p_i$. In conventional PageRank, the prior score is fixed as $\frac{(1-\alpha)}{N}$ for each person, while in our modification, the prior score is $\frac{(1-\alpha)}{N}$ + $\frac{\alpha \sum_{k=1}^Q G^r_{k,i}}{\sum_{k=1}^Q G^r_{k,i}}$ and this score differs for different persons $p_i$. Our experiments have shown that such an asymmetric formulation would gain benefit.

For computation, we infer the importance of each person in an image by applying eigen-analysis [15] on the Hybrid-Interaction Graph, since computing the important score vector $\Lambda = [\lambda_{p_1}, \lambda_{p_2}, \ldots, \lambda_{p_N}]^T$ can be viewed as an eigenvector problem, $\Lambda = G \Lambda$, where $G = \alpha G^p + \alpha G^r + \frac{1}{N} I$. Here, $G^p_{i,j} = G^r_{i,j} / \sum_{n=1}^N G^p_{i,n}$ is the element of $G^p$ and 1 is an all-ones vector.

**Inferring Importance on Multiple Interaction Graphs.** Since we have designed four types of edge message functions, four Hybrid-Interaction Graphs $H^r, (z \in \{s, ac, ap, at\})$ are formed, and we resort to fuse the importance scores $\phi^p_{z,i} = [\lambda^s_{p_i}, \lambda^ac_{p_i}, \lambda^ap_{p_i}, \lambda^at_{p_i}]^T$ generated by the four graphs for each person. For this purpose, we compute the fused importance score $R_{p_i}$ for each person $p_i$ by

$$R_{p_i} = \prod_{z \in \{s,ac,ap,at\}} (\lambda^z_{p_i})^{q_z},$$

(6)

where $q_z = [q_s, q_ac, q_ap, q_at]^T$ is a weight vector consists of weight for each graph. Therefore, the fused message function $\phi^f(R_{p_i}, R_{p_j})$ is denoted as:

$$\phi^f(R_{p_i}, R_{p_j}) = \log \frac{R_{p_i}}{R_{p_j}} = q^T [\log(\phi^s_{p_i}) - \log(\phi^s_{p_j})].$$

(7)

So eigen-analysis is used again to infer the importance score of each node, and finally the node corresponding to the largest score is selected as the most important person.

Finally, we discuss how to learn $q$ in the above model. Suppose we are given a set of persons $p = \{p_i\}_{i=1}^N$ detected in an image, and we denote $p^* \in p$ as the most important person in the image. For convenience, we rewrite the fusion message function $\phi^f(\phi^s_{p_i}, \phi^s_{p_j}) = q^T x_{i,j}$, where $x_{i,j} = \log(\phi^s_{p_i}) - \log(\phi^s_{p_j})$ is a logarithm difference between $p_i$ and $p_j$. The weight vector $q$ is learned such that for any non-important person $p_i \in p$, $p_i \neq p^*$, the distance between an important person and any non-important person is larger than the one between any two non-important people, that is to learn the projection $q$ such that

$$q^T x_{i,j} > q^T x_{i*,j},$$

(8)

where $x_{i*,j} = \log(\phi^s_{p_i}) - \log(\phi^s_{p_j})$.

We optimize the above constraint in a two-class SVM framework implemented by the toolbox in [1]. The parameter $\alpha$ in Eq. (5) is set to 0.85 as a default value. All of hyper-parameters of SVM were chosen by cross-validation on the validation set of datasets.

**C. Implementation Details: Importance Feature.**

For convenience of description, we denote the bounding box of a person as $[x_{p_i}, y_{p_i}, w_{p_i}, h_{p_i}]$, where $[x_{p_i}, y_{p_i}]$ is the location of $p_i$ in the image and $[w_{p_i}, h_{p_i}]$ is the scale of $p_i$. Afterwards, for describing different complicated interactions among persons $\{p_i\}_{i=1}^N$, four types of importance features are extracted for each person $p_i$: 1) spatial feature ($\phi^s_{p_i}$), 2) attention feature ($\phi^a_{p_i}$), 3) action feature ($\phi^p_{p_i}$), and 4) appearance feature ($\phi^d_{p_i}$).

**Spatial Feature.** From the perspective of the photographers, they often use a narrow depth-of-field to keep the important
people in focus (see Figure 3(c)) so that the important people in photos are likely to be larger, clearer, or closer to image center. Also, the density of persons is also useful; for instance, in the basketball games shown in Figure 3(a), the players (especially the one holding the basketball) are more important than audiences, and thus the density helps distinguish the players from audiences. These spatial information is then represented by a 7-dimensional spatial feature vector \( \phi_{pi}^{sp} = [s_{pi}, \ell_{pi}, d_{pi}] \) for each person \( p_i \), including three parts: saliency features \( s_{pi} \), location \( \ell_{pi} \), and density \( d_{pi} \).

The saliency feature \( s_{pi} \) is a four dimensional vector consists of the area of face/body bounding box, face sharpness by applying a Sobel filter [21] and computing the sum of the gradient energy in a face bounding box, face aspect ratio [22] and detection confidence computed by [27]. On the location feature \( \ell_{pi} \), we compute the distance between the bounding box center and the image center and compute the distance between each person and the group centroid, the averaged centers of bounding boxes. These distances are normalized by the scale of image. The density of persons \( d_{pi} \) is computed within a \( m \times m \) support area centered around person \( p_i \), where \( m \) is one tenth of the width of the image.

**Attention Feature.** Based on the location, scale and orientation \( \theta_{pi} \), the attention feature of person \( p_i \) is a four dimensional feature denoted as \( \phi_{pi}^{at} = [f_{pi}, r_{pi}, \ell_{pi}, \theta_{pi}] \), where \( f_{pi} = [x_{pi}, \frac{1}{h_{pi}}] \) and \( r_{pi} = [\sin(\theta_{pi}), \cos(\theta_{pi})] \). In \( f_{pi} \), \( x_{pi} \) estimates the horizontal coordinate of \( p_i \) in 3D, and \( \frac{1}{h_{pi}} \), the inverse of the height of face bounding box can reflect the depth of \( p_i \) from the camera; in \( r_{pi} \), \( \theta_{pi} \) is the yaw angle of person \( p_i \) extracted by the face detector [27], so \( \sin(\theta_{pi}) \) is the horizontal component and \( \cos(\theta_{pi}) \) is the depth component of yaw (Figure 4).

**Action Feature.** As shown in Figure 3, identifying action information of each person helps detect important people in images. For instance, the most important person of ceremony is the speaker who raised his left hand (see Figure 3(b)). Thus, for each person \( p_i \) in an image, a 2048 dimensional vector \( \phi_{pi}^{ac} \) extracted by a ResNet [9] on the support region centered at the face of \( p_i \) which is 6 times larger than the scale of the face bounding box or 3 times larger than the body bounding box, where the network was trained on UCF-101 dataset [23].

**Appearance Feature.** Sometimes, the appearance of important people in images, such as the color of clothes, the object he/she operates (e.g. a ball, a microphone), is likely to differ from the others. As shown in Figure 3, the most important person in Figure 3 (c) is the torchbearer who holds a torch and wears clothes different from the others. We use a ResNet to extract a 2048 dimensional vector around the location of person \( p_i \), denoted as \( \phi_{pi}^{ap} \), where the network is pre-trained on ImageNet [10].

**IV. NEW IMPORTANT PEOPLE DETECTION IMAGE DATASETS**

We have collected/generated two large datasets: 1) Multi-scene Important People Image Dataset 2) NCAA Basketball
Image Dataset. The multi-scene important people image dataset contains 2310 images from more than six types of scenes. These images were mined from Internet using search queries such as “graduation ceremony”, “people+events”, and etc. We manually identified mainly 6 key scene types listed in Table I. This dataset includes three subsets: a training set consists of 924 images, a validation set consists of 232 images, and a testing set consists of 1154 images. Since faces of most persons are detectable, a robust and stable face detector [27] was used to detect persons in all images in our dataset, and the detector has a fairly low false positive rate. In order to label the most important person in an image, ten annotators were asked to vote and the person who is with the largest number of votes is then annotated as the ground-truth most important person in an image.

2) NCAA Basketball Image Dataset. Another natural choice for collecting important people detection images dataset is team sports. In this work, we gathered an image dataset for important people detection by extracting frames which contain ball location annotations from a multi-person event detection video dataset [19], covering 10 different types of events. The bounding box annotations for NCAA basketball dataset are the same as the ones in [19], where both annotated the shooter as the most important person in a basketball game image. Since faces of the sportsmen are always very small, the whole person body was detected by a Multibox detector [25], [19].

V. EXPERIMENT

In this section, we conducted evaluations of important people detection on the two new datasets.

A. Compared Methods

Baseline. We compared our model with several baselines: “Most-Center”, “Max-Scale”, “Max-Face”, “Max-Pedestrian” [17] and “SVR-Person”, where “Most-Center” means selecting the person who is closest to the center of an image, “Max-Scale” means selecting the person of whom the face/body size is the largest one in an image, “Max-Face” means selecting the person of whom the detected face is most confident in an image by using [27], “Max-Pedestrian” means selecting the person of whom the pedestrian detection score is the most confident using [17], and “SVR-Person” means using ν-SVR [1], [22] to predict relative importance between persons and select the most important person based on the concatenation of the four types of features we used.

“Max-Saliency”. In order to measure how well a saliency detector performs on important people detection, a recently proposed saliency detector [18] was also compared. In particular, we implemented the saliency detector to produce saliency map and computed the fraction of saliency intensities inside each face bounding box as a measure of its importance. We denote this compared model as “Max-Saliency”.

VIP. We compared the VIP model a recent important people detection model proposed by Solomon et al. [22].

B. Evaluation Criterion

For quantifying the performance of different methods on important people detection, the mean Average Precision (mAP) [16], [20], a criterion which is widely used in object detection, is utilized for judging the correctness of detected important people and reported in the table. In addition, the cumulative matching characteristics (CMC) curve is plotted to show the results of top k-rank important people.

C. Experiments on Multi-scene Important People Image Dataset

All methods were conducted on Multi-scene Important People Dataset and the mean Average Precision for important people detection were shown in Table II. The best baseline achieved 75.9% mAP and VIP obtained 76.1%, and our approach achieved 88.6%. Overall, we achieved improvement 14.2% and 14.0% over the “SVR-Person” baseline and VIP, respectively. The result shows the advantages and effectiveness of our approach.

In addition, we report the CMC curve in Figure 5(a). As shown in Table I, there are more than 8 persons in an image on average in our Multi-scene Image Dataset. Our approach obtained 85.6% rank-1 matching rate and 94.2% rank-2 matching rate. This shows that our proposed method is capable of clearly better inferring the importance of persons and localizing the most important one in an image.

D. Experiments on NCAA Basketball Image Dataset

The NCAA Basketball Image dataset has its special characteristic that it was captured at a distance so that images are low-resolution and people in images are small. Therefore, the person body bounding box is used to locate a person. In addition, the detail of attention feature and some facial characteristics that it was captured at a distance so that images are low-resolution and people in images are small. Therefore, the person body bounding box is used to locate a person. In addition, the detail of attention feature and some facial information which are hard to capture due to the small size of persons are not estimated. So the attention message-based

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**TABLE I**

MULTI-SCENE IMPORTANT PEOPLE IMAGE DATASET

| Scene          | Training (Testing) Images | Avg. # persons |
|----------------|---------------------------|----------------|
| Lecture / Speech | 360 (360)                 | 9.45           |
| Demonstration   | 200 (200)                 | 10.57          |
| Interview      | 208 (207)                 | 6.40           |
| Sports         | 121 (122)                 | 8.35           |
| Military       | 153 (152)                 | 8.45           |
| Meeting        | 38 (45)                   | 5.48           |
| Others         | 78 (68)                   | 7.57           |
| Total          | 1156 (1154)               | 8.39           |

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**TABLE II**

MEAN AVERAGE PRECISION (% FOR EVALUATION OF DIFFERENT METHODS ON MULTI-SCENE IMPORTANT PEOPLE IMAGE DATASET

| Method     | Max-Face | Max-Pedestrian | Max-Saliency | Most-Center | Max-Scale | SVR-Person | VIP P% | Ours P% | Ours R% |
|------------|----------|----------------|--------------|-------------|-----------|------------|--------|---------|---------|
| Lecture/Speech | 36.4 | 28.2 | 38.3 | 39.4 | 77.8 | 59.9 | 69.6 | 89.5 | 90.2 |
| Demonstration | 29.9 | 27.2 | 45.4 | 59.0 | 75.3 | 77.5 | 94.3 | 90.8 | 92.0 |
| Interview   | 36.9 | 36.6 | 36.8 | 59.6 | 78.5 | 77.7 | 85.0 | 89.5 | 90.2 |
| Sports      | 35.8 | 33.8 | 40.1 | 60.9 | 67.4 | 69.0 | 79.5 | 80.5 | 83.6 |
| military    | 37.9 | 28.5 | 43.3 | 42.3 | 62.6 | 75.4 | 87.7 | 87.1 | 86.5 |
| Meeting     | 43.2 | 36.2 | 45.1 | 58.6 | 69.0 | 57.5 | 67.9 | 75.2 | 76.5 |
| Other       | 35.3 | 31.4 | 37.5 | 57.9 | 74.5 | 69.6 | 76.8 | 86.7 | 86.7 |
| Total       | 35.7 | 30.7 | 40.3 | 50.9 | 71.9 | 75.9 | 80.1 | 87.5 | 88.6 |

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3These two datasets will be publically available.
graph will not be used and the spatial graph will be built on feature of person body bounding.

We report the comparison on CMC curve in Figure 5(b).

In particular, our approach achieved 68.0% rank-1 matching rate and 84.7% rank-2 matching rate, which indicates that our method can clearly better identify the important people (shooter) in the basketball games, whereas the rank-2 matching rate of “Max-Saliency”, “Most-Center”, “Max-Scale”, “SVR-Person” and VIP is 30.4%, 35.2%, 35.8%, 73.9% and 65.8%, respectively.

In addition, we compared a state-of-the-art method reported by Ramanathan et al. [19], and we call it the Ramanathan’s model. Ramanathan’s model is not compared in our Multi-scene Important People Image dataset because it can only run on video-based data and trained with event labels rather than importance annotations. Although NCAA is a still image-based dataset, it is a subsampling of the original video-based dataset, namely multi-person event detection video dataset [19]. Hence we compared our method learned on still images with the Ramanathan’s model leaned on the full video sequences. Ramanathan’s model using temporal information for important people detection obtained 61.8 % mAP, and in comparison, our approach achieved 74.1%. In particular, our approach is a graph-based model and further analyzes hyper-interaction between persons rather than just the pairwise ones, and in addition exploits some features (such as action features) which are significant but not estimated in Ramanathan’s model. Also, from the mAP comparison aspect, our proposed method outperformed notably the baseline methods, VIP and “Max-Saliency” model again. Our approach outperformed these methods in almost every category and especially performed very well on picking the shooter which is the most important person in the cases like “free-throw succ./fail” and “3-point succ./fail”.

E. Visual Comparison

Figure 6 shows some qualitative visual results of the baseline (“Max-Scale”), VIP and our approach on the two datasets. We can see that VIP and “Max-Scale” often picked the person whose bounding box is closest to the image center or the largest one as the most important person. In comparison, as some results shown in Figure 6 (a) and (d), our approach can detect the important people in images more precisely, although the bounding box of the most important person in an image is not closest to the image center or the largest one. In addition, we show some failure cases (Figure 6 (c) and (f)). In Figure 6 (c), the interviewee in the image is the most important person while our method picked the reporter who is interviewing as the most important person. In Figure 6 (f), our method detected the defender that is closest to the shooter as the most important person, while the shooter is the groundtruth. Interestingly, we examined the results and found that the ground-truth most important person annotated was the second most important person output by our model in each of the two images.

F. More Evaluation of the Proposed PR

Effect of $h^{\text{pig}}$. For evaluating the effect of forming $h^{\text{pig}}$, the mean average precision of PR (PR$^\text{pig}$) inferring the importance of persons on the pairwise-interaction graph $H^{\text{pig}}$ only and the our full model PR inferring on Hybrid-Interaction Graph which is constituted as the union of $H^{\text{pig}}$ and $H^{\text{pig}}$ are reported in Table II and Table III. It is evident that PR makes improvement of 1.1% (88.6% - 87.5%) on Multi-scene Important People Image Dataset and 3.0% (74.1%-71.1%) on NCAA Basketball Image Dataset by PR$^\text{pig}$. These results indicate that important people detection can be benefited from exploiting hyper interaction between persons.

### Evaluation of different components in PR

We now report the mAP of PR using each type of feature, where PR$^\text{ap}$, PR$^\text{sp}$, PR$^\text{ac}$, PR$^\text{at}$ are our approaches using only spatial, appearance, action and attention feature, respectively, and the full one (PR) that fuses all message graphs in Table IV. Compared to the results of other methods listed in Table II, on Multi-scene Important People Image Dataset, our approach using just single type of feature achieved comparable performance in general. Especially, our approach using spatial feature (PR$^\text{sp}$) still outperformed VIP and the best baseline “Max-Scale”. On NCAA Basketball dataset, by comparing the results in Table III with the ones in Table IV, our approach using single feature outperformed most of other methods. When fusing all message graphs, the results in Table IV also show that PR makes great improvement on the two datasets, and this suggests all the message graphs are effective and the combination of them yields the best.

### Table IV

| Method | NCAA Basketball Image Dataset | Multi-scene Important People Image Dataset |
|--------|-------------------------------|------------------------------------------|
| PR$^\text{ap}$ | 77.5% | 78.7% |
| PR$^\text{sp}$ | 80.7% | 81.3% |
| PR$^\text{ac}$ | 82.0% | 82.4% |
| PR$^\text{at}$ | 85.2% | 85.5% |
| PR | 86.0% | 86.5% |

### Table III

| Events | Max-Scale | Max-Saliency | Most-Center | Max-Scale | VIP | PR | Ramanathan model | Ours | PR$^\text{pig}$ | PR$^\text{at}$ |
|--------|-----------|-------------|-------------|-----------|-----|----|-----------------|------|-----------------|-------------|
| Top-pick | 32.5 | 27.4 | 15.9 | 12.8 | 24.8 | 31.8 | 54.2 | 35.8 | 35.7 | 71.6 |
| Free-throw | 30.9 | 24.1 | 9.6 | 8.1 | 7.1 | 5.8 | 5.4 | 5.8 | 5.4 | 72.7 |
| Layup | 32.5 | 23.1 | 17.0 | 14.4 | 11.4 | 8.4 | 5.9 | 5.9 | 5.9 | 68.5 |
| 2-point | 25.6 | 21.1 | 19.9 | 17.1 | 15.4 | 13.8 | 13.8 | 13.8 | 13.8 | 54.2 |
| Slam dunk | 41.8 | 36.6 | 35.2 | 32.2 | 30.7 | 29.1 | 29.1 | 29.1 | 29.1 | 92.8 |
| Total | 33.4 | 28.5 | 18.4 | 16.0 | 14.0 | 12.0 | 12.0 | 12.0 | 12.0 | 78.6 |

### Table E.1

| Event | NCAA Basketball Image Dataset | Multi-scene Important People Image Dataset |
|-------|-------------------------------|------------------------------------------|
| PR$^\text{ap}$ | | | |
| PR$^\text{sp}$ | | | |
| PR$^\text{ac}$ | | | |
| PR$^\text{at}$ | | | |
Parameter Evaluation. We evaluate $\alpha$ from 0.01 to 1 with interval 0.01. The mAP of our method ranged from 88.5 % to 88.8 % on the Multi-scene Important Person Image Dataset, where it is 88.6 % at $\alpha = 0.85$; the mAP ranged from 73.8% to 74.1% on NCAA Basketball Image Dataset, where it is 74.1% at $\alpha = 0.85$. The results indicate that the parameter $\alpha$ is not sensitive in our modeling. Since $\alpha$ is not sensitive, we empirically set $\alpha = 0.85$ on both datasets.

VI. CONCLUSION

The main contribution is to first cast the important people detection problem as node ranking problem in a graph. We form two types of graphs, namely the bidirectional pairwise-interaction graph and the unidirectional hyper-interaction graph, and design four edge message functions to mimic the interactions between persons. A modified pagerank algorithm is applied to rank the nodes (i.e., persons) in the graph. This all forms the proposed PersonRank. Extensive evaluations reported on two new datasets have shown the clearly better performance of PersonRank.

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