

# Multi-task Recurrent Neural Network for Immediacy Prediction

Xiao Chu Wanli Ouyang Wei Yang Xiaogang Wang

Department of Electronic Engineering, The Chinese University of Hong Kong

xchu@ee.cuhk.edu.hk wlouyang@ee.cuhk.edu.hk xgwang@ee.cuhk.edu.hk

## Abstract

In this paper, we propose to predict immediacy for interacting persons from still images. A complete immediacy set includes interactions, relative distance, body leaning direction and standing orientation. These measures are found to be related to the attitude, social relationship, social interaction, action, nationality, and religion of the communicators.<sup>1</sup> A large-scale dataset with 10,000 images is constructed, in which all the immediacy cues and the human poses are annotated. We propose a rich set of immediacy representations that help to predict immediacy from imperfect 1-person and 2-person pose estimation results. A multi-task deep recurrent neural network is constructed to take the proposed rich immediacy representations as the input and learn the complex relationship among immediacy predictions through multiple steps of refinement. The effectiveness of the proposed approach is proved through extensive experiments on the large-scale dataset.

## 1. Introduction

The concept of immediacy was first introduced by Mehrabian [18] to rate the nonverbal behaviors that have been found to be significant indicators of communicators' attitude toward addressees. In [18], several typical immediacy cues were defined: touching, relative distance, body leaning direction, eye contact and standing orientation (listed in the order of importance). A complete set of immediacy cues defined in this work are shown in Fig. 1. These cues are important attributes found to be related to the inter-person attitude, social relationship, and religion of the communicators [17, 36, 12]. Immediacy cues report the communicators' attitude which is useful in building up social networks. With vast data available from social networking sites, connections among people can be built up automatically by analyzing immediacy cues from visual data. Second, these immediacy cues are useful for existing vision tasks, such as human pose estimation [38, 32], social relationship, social role [27], and action recognition

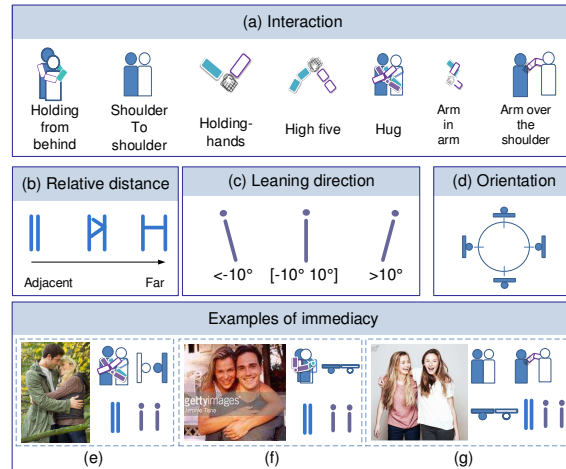


Figure 1. The tasks of immediacy prediction and three examples. Detailed definitions of immediacy cues can be found in Sec. 3

[16]. The immediacy cue “touch-code” is the same as interaction recognition and has been recognized by our society [37, 13, 23] for a long time. However, a complete dataset providing all the immediacy cues is absent. In addition, there is only little research on immediacy analysis from the computer vision point of view.

In order to predict immediacy, it is natural to use the information from 1-person pose estimation [38] and 2-person pose estimation, which was called touch-code in [37]. However, touch-code and single person pose estimation are imperfect. Especially, when people have interaction, inter-occlusion, limb ambiguities, and large pose variation inevitably occur. These cause the difficulty in immediacy prediction. On the other hand, interacting persons provide extra representations that motivate our work.

First, there are extra information sources unexplored when persons interact. Since both 1-person or 2-person pose estimation are imperfect, extra information sources, *i.e.*, overlap of body parts, body location relative to two persons' center, and consistency between 1-person and 2-person estimation, are helpful for immediacy prediction as well as addressing pose estimation errors. As an example for overlap of body parts, when all of person A and person

<sup>1</sup>The dataset can be found at [http://www.ee.cuhk.edu.hk/~xgwang/projectpage\\_immediacy.html](http://www.ee.cuhk.edu.hk/~xgwang/projectpage_immediacy.html)

B's body parts have large overlap, it is more likely that A is holding B from behind but less likely that A is shoulder-to-shoulder with B. Regarding relative location to two persons' center, if person A's right shoulder and persons B's left shoulder are close to the two persons' center, shoulder-to-shoulder is more likely to happen. As for consistency between 1-person and 2-person estimation, when 1-person and 2-person estimation results conform with each other, they are more reliable than results that do not. Therefore, we include these extra information sources and jointly consider both 1-person and 2-person pose information by integrating them with a deep model, so that these information sources validate each other's correctness in conforming with the global pattern of human interactions as well as other immediacy cues.

Second, immediacy cues are correlated. For instance, shoulder-to-shoulder only happens when two persons stand close to each other (distance) and side-by-side (standing orientation). Existing works treat interactions independently but do not explore the correlation mentioned above. We hence construct a multi-task recurrent neural network (RNN) to learn the correlations among immediacy as well as the deep representations shared by all the immediacy cues. RNN fits this problem because it can iteratively refine the coarse outputs from a deep model through multiple steps in the forward pass and pass estimation errors back to the deep model during training. Therefore, the whole model can be trained end-to-end with back propagation.

Our work contributes in the following three ways.

- Propose the immediacy prediction problem, and build a large-scale dataset that contains 10,000 images. It has rich annotations on all immediacy measures and human poses.
- Rich immediacy representations by taking extra information sources into consideration, *i.e.*, overlap of body parts, body location relative to two persons center, and consistency between 1-person and 2-person estimation. For predicting immediacy, a unified deep model is used for capturing the global interaction patterns from the proposed immediacy representations.
- Construct a multi-task deep RNN to model complex correlations among immediacy cues as well as 1-person and 2-person pose estimation. The recurrent neural network is used for refining coarse predictions through multiple steps. We prove that by jointly learning all tasks of predicting a complete set of immediacy cues with deep RNN, the performance of each task can be boosted dramatically, and pose estimation can be improved as well.

## 2. Related Work

Pose estimation is an input of our approach. Remarkable research progress in pose estimation has inspired our work and is the base of our work. Both holistic models

[28, 11, 19, 20, 33] and local models [31, 8, 39, 6, 9, 30, 24, 10, 26, 14, 29, 35, 25, 1, 21, 4] were used for estimating the pose of a single person. For multi-person pose estimation, some approaches used occlusion status [7] and spatial locations [37, 15, 3] of body parts as pairwise constraints. Existing works either considered only single person pose estimation [31, 34, 8, 39, 6, 9, 30, 24, 2, 26, 14, 29, 35, 25, 1, 21] or multi-person pose estimation [37, 13], while our model jointly takes 1-person and 2-person pose estimation as the input. Our work targets on predicting immediacy, although we do find prediction on immediacy can improve pose estimation.

Interaction pattern is called proxemics and was estimated using deformable part based models [13] and flexible mixtures of part models in [37]. It was estimated from videos using motion in [23]. Human distance was used in [3] for estimating social activities such as crowd and speaker-audience. 2-person pose estimation was used for interaction estimation in [37]. We differ in three aspects. First, existing works only consider single factors like interaction or distance, while our work is the first towards complete study on estimating all immediacy cues, including interaction, relative distance, body leaning direction and standing orientation, and learning them jointly. Second, extra information sources, *i.e.*, overlap, relative location to center, and consistency between 1-person and 2-person pose estimation, were not explored in these works. Third, existing works modeled the interaction types separately, while we construct a RNN to jointly learn their relationships.

Multi-task learning [40] have been used to directly model the relationships among correlated tasks. Immediacy prediction is a highly non-linear mapping function of the information from pose estimation, and therefore non-linear deep representation is desirable. The correlations among immediacy cues are also complex. In our work, such deep representation and immediacy relationship representation are jointly learned with an end-to-end deep multi-task RNN model. Razvan Pascanu *et al.* [22] provided many structures of deep RNN, which are usually used to model sequential data. Zheng *et al.* [41] showed that the iterative belief propagation in CRF can be approximated with RNN. These motivate us to use RNN to model the complex correlations among tasks. The predictions on multiple tasks at the previous step are used as the input for the network at the next step. They are coupled with the original input data through multi-layer nonlinear mapping to refine the prediction. As the refinement goes through more steps in RNN, higher nonlinearity can be modeled.

## 3. Immediacy Dataset

We construct a large-scale dataset for the proposed immediacy prediction problem. It consists of 10,000 images. Data are collected from four major sources: Getty Images website, photos of celebrities, movies and drama series.

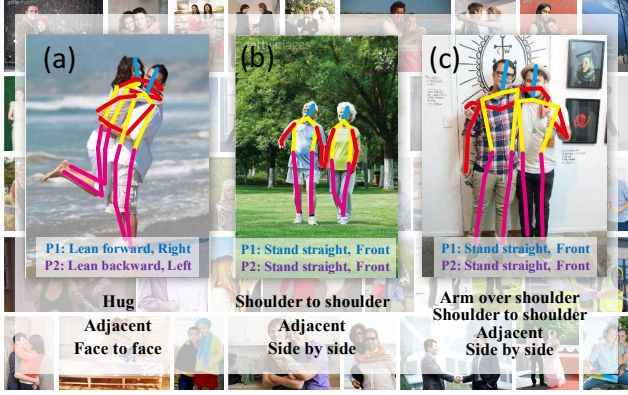


Figure 2. Examples of images in our dataset and their annotations. P1 represents the person on the left and P2 represents the person on the right.

Previous related benchmark datasets: the WeAreFamily dataset [7] is used for multiple people pose estimation; The TVHI dataset (video) [23] and TVHI+ dataset (video) [13] are used for interaction classification. The proxemics dataset [37] provides labels for both human pose and interaction classes, but its scale is relatively small and the data are lack of diversity (only including persons in front view). Quantitative comparison is listed in Table 1. The comparison with TVHI is based on the frames used in [23].

Dataset	Annotation	Training	Test
Proxemics [37]	pose and interaction	300	289
WeAreFamily [7]	pose	350	171
TVHI [23]	interaction	599	714
TVHI+ [13]	interaction	1654	1566
Immediacy (ours)	interaction, pose and posture attributes	7500	2500

Table 1. Quantitative comparison of related datasets.

We provide multiple annotations for every image. Definitions of immediacy cues are shown in Fig. 1 and examples of annotated images are shown in Figure 2. Details about the annotations are listed as follows:

1. Pose: we annotate the pose of each person. For images containing lower body parts, we annotate the full pose. For the rest images, we only annotate the upper bodies. The visibility of each body joint is also annotated.
2. Interaction: we define 7 kinds of frequently appearing interactions as listed in Table 2. We annotate the interaction for each pair of persons. A pair of persons can be annotated with more than one kind of interactions. For instance, in Figure 2 (b), the man is “holding hands” and “shoulder to shoulder” with the woman.
3. Relative distance: the physical distance separating one person from another. It is quantified into three levels according to the scale of half arm. If two persons are

standing closely, *i.e.*, within the reach of half arm, we label this distance as “adjacent”. If they are farther than the reach of one arm, the distance is labeled as “far”. The rest is “near”.

4. Leaning direction: we annotate the leaning direction of each person as leaning forward to the other person, leaning backward or stand straight.
5. Orientation: whether a person is facing the camera (front view), facing left, facing right or facing back.
6. Relative orientation: relative body orientation of paired persons, *i.e.*, face to face, 90 degree or side by side.

1	Holding from behind	HB	869	Proxemics [37]
2	Hug	HG	2221	TVHI [23]
3	Holding hands	HH	1718	TVHI, Proxemics
4	High five	HF	613	TVHI
5	Arm over the shoulder	AS	3182	Proxemics
6	Shoulder to shoulder	SS	3453	Proxemics
7	Arm in arm	AA	1046	Proxemics

Table 2. Seven classes of interactions. The second column is the name for each class and the third column is its abbreviation we shall use in the following sections. The number of images under each kind of interactions is listed in the forth column. The fifth column shows which dataset previously defined such kind of interaction.

Our dataset is more challenging and more suitable for practical use in the following aspects: the age of characters varies from infancy to adulthood; the postures of human are diverse, including lying, sitting and standing; all kinds of viewpoints are included (front view, side view and back view); frames extracted from videos are not consecutive.

## 4. Overview

As shown in Figure 3, the overview of our approach for immediacy prediction is as follows:

1. 1-person pose estimation [38] is used for extracting the unary representation.
2. 2-person pose estimation approach [37] is used for obtaining pairwise feature representations. The unary representation and pairwise representation are basic representations that are extracted from existing approaches.
3. Based on the 1-person and 2-person pose estimation results, we proposed new representations. These new representations capture distinctness between a pair of poses, relative locations of a pair of poses and consistency between 1-persons pose estimation and 2-person pose estimation.
4. All representations mention before together called immediacy representations, which is used as the input of the multi-task deep RNN.
5. The multi-task deep RNN predicts the immediacy cues and poses. Since there are many candidates of  $\Psi$ , the prediction with the largest confidence in a local region is selected as the final results.

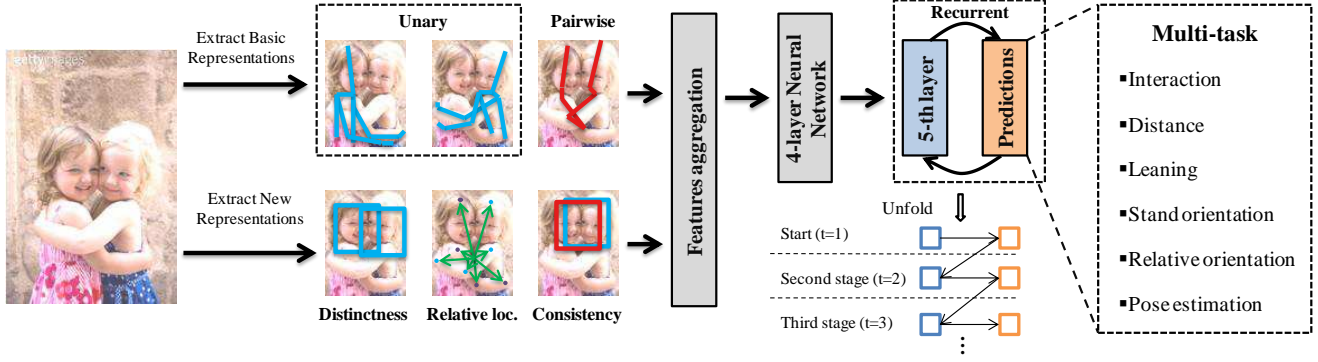


Figure 3. Overview of our approach for immediacy prediction and pose estimation.

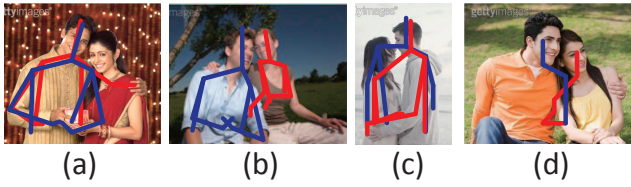


Figure 4. Failure cases of 1-person pose estimation and 2-person pose estimation. For pose estimation, the double counting (a), missing body joints (b) and miss alignment of body joints (c) are major problems, especially when multiple persons interact. For 2-persons pose estimation, false positive on wrong class frequently occurred.

## 5. Rich immediacy representations

### 5.1. Basic representations

**Unary representation**  $\Psi_u$  describes the features of a single person's pose. A classical pose estimation approach [39] is used for feature extraction. In this approach, the pose of a person is modeled by a tree-structured graph, with each node in the graph representing a body joint.  $\Psi_u$  can be expanded into the following components:  $\Psi_u = [\Psi_u^a, \Psi_u^d, \Psi_u^m]$ .  $\Psi_u^a$  is the appearance score for each body joint, which indicates the correctness of part appearance.  $\Psi_u^d$  is the relative location between one part, e.g. hand, and another part, e.g. elbow.  $\Psi_u^m$  is normalized by the human head's scale. This term describes the articulation of a pose.  $\Psi_u^m$  is the mixture type of each body joint.

**Pairwise representation**  $\Psi_p$  mainly captures information when two persons interact. Previous work on recognizing proxemics [37] restricted the way of describing interactions to touch-codes. Inspired by their work, we train multiple models to capture the touch-codes in 7 kinds of interactions.  $\Psi_p$  is composed of  $\Psi_p^a, \Psi_p^m$  and  $\Psi_p^d$ . The meaning of each term is same with the corresponding terms in  $\Psi_u$ .  $\Psi_p^a$  is the appearance score of each body joint,  $\Psi_p^m$  is the mixture type and  $\Psi_p^d$  is the relative location.

The models employed to extract pose features from im-

ages are imperfect. The examples in Figure 4 show the major problems existing in current approach. These problems lead to the unreliability of the basic feature representations  $\Psi_u$  and  $\Psi_p$ . Therefore, extra representations shall be introduced in the following section to assist immediacy estimation.

### 5.2. New representations

**Distinct pose representation**  $\Psi_{ov}$  measures the similarity between a pair of poses from single person pose estimation. In pose estimation, a bounding box is defined for each body joint to extract its visual cue. The bounding box for the  $p$ th body joint is called the  $p$ th part-box and denoted by  $box_p$ . The overlap of each part  $ov_p$  is defined by the intersection over the union as follows:

$$ov_p = \frac{\cap(box_p^1, box_p^2)}{\cup(box_p^1, box_p^2)}, \quad (1)$$

where  $box_p^1$  and  $box_p^2$  are the  $p$ -th part-box for the first person and the second person respectively. Only the part-boxes for the same body joint of paired persons are considered in this representation. In our framework, large amount of overlaps for many body parts can be accepted by interaction classes such as “holding from behind” and “hug”, and rejected by interaction classes such as “holding hands”.  $\Psi_{ov} = [ov_1, \dots, ov_P]$  also implicitly improves non-maximum suppression (NMS). One body part could generate two part-boxes during pose estimation, and they could be wrongly interpreted as coming from two persons when modeling interaction, instead being merged into one by NMS. The representation  $\Psi_{ov}$  can identify such potential cases and help to address pose estimation errors in the higher layers of the neural network.

**Relative location representation**, denoted by  $\Psi_l$ , captures the relative locations of poses from 1-person pose estimation to their center.

$$l_p^k = ([x_p^k, y_p^k] - \frac{1}{KP} \sum_k \sum_p [x_p^k, y_p^k]) / p_{scale}, \quad (2)$$





step  $t - 1$ . The predicted immediacy  $\mathbf{p}_t$  in (6) is obtained from the updated hidden variables in  $\mathbf{h}_{5,t}$ .

There are other choices of RNN structures, such as 1) directly connecting  $\mathbf{p}_{t-1}$  with  $\mathbf{p}_t$  instead of  $\mathbf{h}_{5,t}$ ; or 2) connecting  $\mathbf{h}_{5,t-1}$  (instead of  $\mathbf{p}_{t-1}$ ) to  $\mathbf{h}_{5,t}$ . Experiments show that the structure in Figure 6 is most suitable for our problem and dataset. In option 1), there is only one-layer nonlinear mapping between  $\mathbf{p}_{t-1}$  and  $\mathbf{p}_t$  and hence, it cannot well model complex relationships. In option 2), the influence from the previous predictions to the current predictions is transmitted by hidden variables  $\mathbf{h}_{5,t-1}$ , which is more indirect and hard to learn given a limited dataset.

## 6.2. Learning

The  $i$ -th sample for the  $c$ -th immediacy cue is denoted as  $(\Psi_{(i)}, y_{(i)}^c)$ , where  $y_{(i)}^c$  is the label for  $c$ -th immediacy cue. The parameter set  $\Theta = \{\mathbf{W}_*, \mathbf{b}_*\}$  in (3)-(6) is learned by back propagation using the following loss function:

$$\arg \min_{\Theta} \sum_i \sum_c \lambda^c y_{(i)}^c \log p(y_{(i)}^c | \Psi_{(i)}; \Theta) + \sum_c \|\mathbf{w}\|_2^2, \quad (7)$$

where  $\mathbf{w}$  is the concatenation of all elements in  $\mathbf{W}_*$  into a vector.

## 6.3. Analysis

The hidden variables at higher layers (with larger  $l$ ) progressively extract more abstract feature representations. The hidden variables in  $\mathbf{h}_{5,t}$  summarize the correlations of immediacy cues. The immediacy cues can be mutually consistent or exclusive.

When two immediacy cues are mutually consistent, the existence of one cue reinforces the confidence on the existence of another cue. For example, “shoulder to shoulder” often happens together with “arm in arm”. Once “arm in arm” appears, the “shoulder to shoulder” has its prediction confidence raised.

If two immediacy cues are mutually exclusive but confident prediction scores are assigned to both of them in the preliminary prediction stage, then there is a conflict between the predictions. The hidden variables in  $\mathbf{h}_{5,t}$  have access to the information of the lower layer  $\mathbf{h}_{4,t}$  as well as the prediction results  $\mathbf{p}_{t-1}$  in the previous step.  $\mathbf{h}_{5,t}$  notices this conflict by using information from both  $\mathbf{h}_{4,t}$  and  $\mathbf{p}_{t-1}$  in order to make a decision on which conflicted prediction is wrong. For example, “holding hands” is mutually exclusive to “high five”. In Figure 7, the preliminary prediction  $\mathbf{p}_{t-1}$  has unreasonably high responses to both “holding hands” and “high five”.  $\mathbf{h}_{5,t}$  finds this conflict from  $\mathbf{p}_{t-1}$ . Then it is able to figure out that “high five” is correct but “holding hands” is wrong through nonlinear reasoning from  $\mathbf{h}_{4,t}$  and  $\mathbf{p}_{t-1}$ . The response of “holding hands” is finally suppressed.

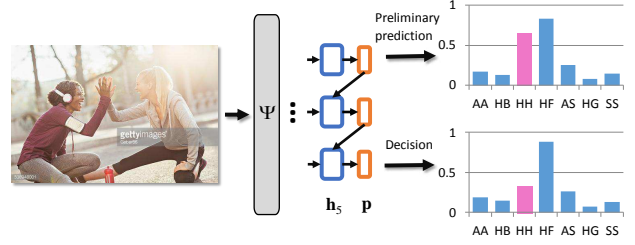


Figure 7. Illustration of our proposed multi-task RNN. The image on the left is the input. Predictions are on the right. The horizontal axis shows six classes of interactions, and the vertical axis is the true positive rate of specified interaction. The preliminary predictions on 7 classes of interaction are reported on the top, while the refined predictions are reported at the bottom.

## 7. Experiment

We mainly use the immediacy dataset introduced in Section 3 for training and testing. In training stage, negative images from INRIA [5] are used. In the training and testing stage, it is assumed that the bounding boxes of the two interacting persons are given, so that the algorithm knows which persons are targets of interest among people in an image. On our dataset, we compare the results on 7 classes of interactions and the other immediacy cues, *i.e.*, relative distance, body leaning direction and standing orientation. We also briefly evaluate pose estimation results. Immediacy factors are measured between two specified persons. The overlap between the provided person bounding boxes and prediction candidates is calculated. If the overlap is smaller than 0.3, the candidate will be ignored at the evaluation stage.

### 7.1. Predictions on interactions

Method	HB	AA	HH	HF	AS	SS	HG	mAP
svm+ $\Psi_u$	24.8	18.6	32.5	37.6	51.0	70.4	50.5	40.7
proxemics [37]	45.5	59.6	52.4	83.7	59.9	80.1	61.1	63.2
deep+ $\Psi_p$	43.5	60.0	64.0	82.7	67.7	74.9	68.4	65.9
deep+ $\Psi_u$ + $\Psi_p$	46.6	62.3	66.8	82.2	69.6	86.3	66.6	68.6
deep+ $\Psi$	47.5	68.6	73.0	83.7	77.6	89.8	78.1	74.0
d+ $\Psi$ +joint	56.8	70.2	73.8	86.8	79.0	89.0	79.8	76.7
d+ $\Psi$ +j+RNN	<b>64.3</b>	<b>73.6</b>	<b>74.5</b>	<b>88.4</b>	<b>82.3</b>	<b>90.2</b>	<b>82.3</b>	<b>79.8</b>

Table 3. Interaction prediction results. The second row shows the results on the existing method in [37].

In the implementation of our approach for interaction prediction, we use the bounding box covering both persons to reject interaction candidates. For prediction of other immediacy measures and pose, the bounding boxes of two persons are used to reject pose candidates. The evaluation criteria we use is mean average precision (mAP), the same as [37]. Experiment results are shown in Table 3.

**Investigation on using single representation.** The  $svm+\Psi_u$  in Table 3 denotes the results of only using unary representation  $\Psi_u$  from 1-person pose estimation. SVM is used as the classifier. Because of inter-occlusion and limb

ambiguities, it only has mAP of 40.7%. The *proxemics* in Table 3 denotes results of using the approach in [37]. We retrain their models on our dataset with their released code. This approach also provides us the pairwise representation  $\Psi_p$ . Proxemics estimation is better than directly using the unary representation for paired persons.

**Investigation on using multiple representations.** In this set of experiments, we use multi-layer deep models for evaluation. Each task is treated separately, aiming at evaluating the effectiveness of our proposed immediacy representations  $\Psi = [\Psi_u, \Psi_p, \Psi_{ov}, \Psi_l, \Psi_m]$ .  $\text{deep}+\Psi_p$  denotes the result that only uses  $\Psi_p$  (pairwise representation in Sec. 5) as the input to the deep model, with mAP 65.9%.  $\text{deep}+\Psi_u+\Psi_p$  denotes the result that only uses the basic representations  $\Psi_u$  (unary representation) and  $\Psi_p$  (pairwise representation) as the input to the deep model. The mAP for this combination is 68.6%. Simply adding the single poses to  $\Psi_p$  could not gain obvious improvement.  $\text{deep}+\Psi$  denotes uses our proposed representations  $\Psi_{ov}, \Psi_l$  and  $\Psi_m$  as input, modeling the input features with deep model. Compared to the result in  $\text{deep}+\Psi_u+\Psi_p$ , large improvement (6.6%) is gained by employing the new representations  $\Psi_{ov}, \Psi_l, \Psi_m$ . Therefore, the effectiveness of the newly proposed representations are proved. All the results above are learned independently by using only single interaction class for supervision.

**Investigation on learning correlations among interactions.** The methods evaluated in this set of experiments are all based on the full set of immediacy representations  $\Psi$  and deep models. The  $d+\Psi+\text{joint}$  in Table 3 shows the results when all immediacy cues are jointly predicted without RNN for refining predictions. With joint learning of all the cues, the mAP of  $d+\Psi+\text{joint}$  gets 2.7% improvement than single task learning, *i.e.*,  $\text{deep}+\Psi$ . Among all the tasks, the performance of interaction “holding from behind” is dramatically improved from 47.5% to 56.8%. With extra supervision provided by other immediacy tasks, better deep representations can be learned for “holding from behind”. However, the overall gain of  $d+\Psi+\text{joint}$  compared with  $d+\Psi$  is not obvious. Our proposed RNN in Figure 6, denoted by  $d+\Psi+j+\text{rnn}$ , propagates the prediction  $\mathbf{p}_{t-1}$  at step  $t-1$  to  $\mathbf{h}_{5,t}$  at the next step. Experimental results show that it outperforms all the previous methods by 3% in overall mAP. Directly utilizing the predictions at previous step, which are more summarized information and more directly influenced by supervision, could better assist the predictions in the next time step.

## 7.2. Predictions on relative distance, body leaning direction and orientation

Table 4 shows the results on predicting relative distance, body leaning direction and orientation. The denotations are the same as those in Table 3. The first row  $\text{svm}+\Psi_u$  is the result using only  $\Psi_u$  (the representations from 1-person pose estimation) as the input to train SVM, and the mean accu-

method	dist	ori	lean	rel ori	mean
$\text{svm}+\Psi_u$	78.6	62.1	74.3	49.6	66.1
$\text{svm}+\Psi$	76.1	61.9	74.2	48.8	66.2
$\text{deep}+\Psi$	80.6	68.9	74.8	50.9	68.8
$d+\Psi+j$	81.2	63.8	75.7	55.0	68.9
$d+\Psi+j+\text{rnn}$	<b>82.7</b>	<b>72.3</b>	<b>76.5</b>	<b>64.9</b>	<b>74.1</b>

Table 4. Accuracies on other immediacy prediction tasks. All these tasks are multi-class classification problem. We use accuracy of each task as evaluation criteria.

racy is 66.1%. The second row  $\text{svm}+\Psi$  shows the results using the full set of proposed immediacy representations  $\Psi$  as the input of SVM. No improvement is achieved because the limitation of SVM in processing such nonlinear relationship. Replacing SVM with the deep model, using the full set of the immediacy representations  $\Psi$ , and learning each task independently, the predictions have a mean accuracy of 68.8%, denoted by  $\text{deep}+\Psi$  in Table 3. When jointly learning all the tasks, we find that 3/4 tasks get better results but the task of learning human body absolute orientation fails. This is consistent with our assumption that simply using deep model without stage by stage refinement is not reliable. Our proposed multi-task RNN beats all the previous results on all the tasks, with the highest mean accuracy being 74.1%.

## 7.3. Pose estimation

Pose estimation is the basic task in our framework. It assists learning immediacy cues. In the process of pursuing better performance of immediacy prediction, we find that the pose estimation result is improved as well. For pose estimation, the percentage of correct keypoints (PCK) proposed in [38] is used as the evaluation criteria. An estimation of body part is defined as correct if it falls within  $\alpha \max(h, w)$  pixels of the ground-truth body part location. Here,  $h$  and  $w$  are the height and width of the bounding box of the upper body respectively.  $\alpha$  is the threshold controlling how close the part location to its ground truth location should be. In our experiment,  $\alpha = 0.2$ . We also use ground truth upper body bounding box to select candidates. All the settings are exactly the same as [39].

Experimental results are reported in Table 5. The *single* in the table is the result of directly applying 1-person pose estimation. The previous approach in [21] used deep model for single person pose estimation, denoted by  $\text{deep}+1P[21]$  in Table 5. Their approach has mean PCK 48.70 on our dataset. The performance is slightly improved compared with single person pose estimation[39]. The result in  $\text{deep}+\Psi_u$  denotes the result of paring two single pose estimates as input and train a deep model to learn the relationship between a pair of poses. The performance is largely boosted by this implementation. The mean PCK of this approach is 51.66. Under the frame work of  $\text{deep}+\Psi_u$ , this improvement is mainly from the idea of checking consis-

tence of two related poses. If one persons is reaching out his hand, another person tends to hold his hands. Based on the  $deep + \Psi_u$ , the addition of  $\Psi_p$ , denoted by  $deep + \Psi_u + \Psi_p$ , has mean PCK 51.72. Simple addition of interaction feature does not provide much improvement. But with the newly proposed feature  $\Psi_{ov}$ , which calculate the consistence between  $\Psi_u$  and  $\Psi_p$ , denoted by  $deep + \Psi$ , the mean PCK is further improved to 53.33.

The result in  $svm + \Psi$  utilizes all the proposed immediacy representations  $\Psi$  to train a svm. Mean PCKs get a slightly improvement by 1.5%. In the joint learning process, the pose estimation result is reported in  $d + \Psi + joint$ . An improvement in the mean PCK by 1% is observed, comparing to only learn the pose estimation task, *i.e.*,  $deep + \Psi$ . Finally, joint learning with our proposed RNN further improves the mean PCK by 1.9% compared with deep model without RNN, *i.e.*,  $deep + \Psi$ .

method	head	shd.	elbow	wrt.	hand	tor.	mean
single[39]	69.5	63.0	42.6	31.8	29.0	43.9	46.96
deep+IP[21]	67.7	61.3	46.4	35.4	32.5	48.9	48.70
deep+ $\Psi_u$	68.2	71.4	48.5	37.2	34.0	50.3	51.66
deep+ $\Psi_u + \Psi_p$	68.5	71.5	48.4	37.2	34.4	50.3	51.72
svm+ $\Psi$	70.8	62.0	44.9	33.8	32.0	48.5	48.36
deep+ $\Psi$	78.0	71.4	48.2	37.1	34.5	50.8	53.33
d+ $\Psi$ +joint	82.4	72.6	48.9	35.5	32.0	<b>55.6</b>	54.50
d+ $\Psi$ +j+rnn	<b>82.5</b>	<b>74.6</b>	<b>50.1</b>	<b>38.8</b>	<b>37.1</b>	55.4	<b>56.42</b>

Table 5. Pose Estimation Results. PCK is used as evaluation criteria. “shd.” for shoulder, “wrt.” for wrist and “tor.” for torso.

## 7.4. Results on the proxemics dataset

We also compare our method on the publicly available proxemics dataset [37] with their method. Since only five classes of interactions defined in the proxemics dataset are the same as our dataset, we only compare the performance on these five classes. The class named ES in proxemics dataset is the same as the class “holding from back”. We retrain our model on the proxemics dataset.

In [37], there are two settings for evaluation: one is given ground truth face bounding boxes and the other is given the detection results of face bounding boxes. Considering that the face ground truth is a too strong prior, we choose to compare with their results based on face detection. The experimental results are shown in Table 6.

	HH	AS	SS	AA	ES	mean
proxe[37]	36.7	28.0	50.0	35.9	33.5	37.5
ours	<b>41.2</b>	<b>35.4</b>	<b>62.2</b>	<b>43.9</b>	<b>55.0</b>	<b>46.68</b>

Table 6. Experiment results on the proxemics dataset.

## 7.5. Social relationship

Here we target on an simple example to show predictions on immediacy can reveal social relationships. We select

five people, *i.e.*, Michelle Obama, Malia Obama, Hillary Clinton, Vladimir Putin, and Barack Obama to form four pairs of celebrities. They have different social relationships, which could be revealed from immediacy. We obtain images from the top ranked images of the Bing image search engine<sup>2</sup> with the queries such as “Barack Obama and Michelle Obama Photos”. Unrelated images are removed. It can be seen from Figure 8 that Barack Obama has many intimate interactions with his wife Michelle Obama and his daughter Malia Obama like arm over shoulder. And we also find that Obama hugs his daughter less than his wife. The histogram for Obama and his family is very different from the histogram for Obama and other politicians. Obama mainly show shoulder-to-shoulder interaction with Hillary and Putin. The other immediacy cues also help. We find that the average standing distance between Hillary and Obama is closer than Putin and Obama. The standing distance between Obama and his family is closer than the distance between Obama and other politicians.

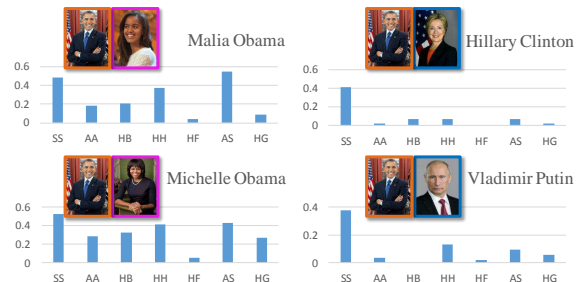


Figure 8. Application. Pink outline indicates family relationship, while blue outline indicates working relationship.

## 8. Conclusion and Discussion

In this paper, we target on immediacy prediction and construct a dataset, in which annotations of the full set of immediacy cues as well as human poses are provided to facilitate further applications. We propose rich immediacy representations from extra information sources to help immediacy prediction from imperfect 1-person and 2-person pose estimation. A multi-task RNN is proposed to refine coarse predictions through multiple steps and model the complex correlations among immediacy cues. For pose estimation, we observe failure cases when many body parts are occluded or outside the image boundary. Besides, when unusual interaction happens, human pose estimation benefits little from interaction detector.

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<sup>2</sup><http://www.bing.com/images>



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