ConfLab: A Rich Multimodal Multisensor Dataset of Free-Standing Social Interactions in the Wild

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Abstract

Recording the dynamics of unscripted human interactions in the wild is challenging due to the delicate trade-offs between several factors: participant privacy, ecological validity, data fidelity, and logistical overheads. To address these, following a datasets for the community by the community ethos, we propose the Conference Living Lab (ConfLab): a new concept for multimodal multisensor data collection of in-the-wild free-standing social conversations. For the first instantiation of ConfLab described here, we organized a real-life professional networking event at a major international conference. Involving 48 conference attendees, the dataset captures a diverse mix of status, acquaintance, and networking motivations. Our capture setup improves upon the data fidelity of prior in-the-wild datasets while retaining privacy sensitivity: 8 videos (1920 × 1080, 60 fps) from a non-invasive overhead view, and custom wearable sensors with onboard recording of body motion (full 9-axis IMU), privacy-preserving low-frequency audio (1250 Hz), and Bluetooth-based proximity. Additionally, we developed custom solutions for distributed hardware synchronization at acquisition, and time-efficient continuous annotation of body keypoints and actions at high sampling rates. Our benchmarks showcase some of the open research tasks related to in-the-wild privacy-preserving social data analysis: keypoints detection from overhead camera views, skeleton-based no-audio speaker detection, and F-formation detection.

1 Introduction

A crucial challenge in the development of interactive social systems is recording and studying social human behavior in real-life situations. Social-science findings indeed show that the dynamics of human interactions vary significantly depending on the social situation [1–3]. Unfortunately, such dynamics are not adequately captured by many data collection setups where role-played or scripted scenarios are typical [4]. In this paper we address the problem of collecting a privacy-sensitive dataset of unscripted social dynamics of real-life relationships where encounters can influence someone’s daily life. We argue that doing so requires recording these exchanges in the natural ecology, requiring an approach different from the typical setup of locally-organized studies. Specifically, we focus on free-standing interactions within the setting of an international conference (see Figure 1).

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Recording an international community in its natural habitat is characterized by several logistical and ethical challenges. A non-invasive capture setup is needed to mitigate any influence on behavior naturalness and ecological validity [5–7]. For video, this is addressed by mounting cameras to use an aerial perspective [8, 9] that mitigates facial identification and expression analysis. However, this makes obtaining automatic pose annotations harder, since state-of-the-art (SOTA) body-keypoint estimation techniques perform poorly on top-down perspectives (Figure 3) [9, 10]. As such, the closest related datasets (see Table 1) suffer from several technical limitations precluding the analysis and modeling of fine-grained social behavior: (i) lack of articulated pose annotations; (ii) a limited number of people in the scene, preventing complex interactions such as group splitting/merging behaviors, and (iii) an inadequate data sampling-rate and synchronization-latency to study time-sensitive social phenomena [11, Sec. 3.3]. To address all these limitations, we propose the Conference Living Lab (ConfLab): a new concept for multimodal multisensor data collection of ecologically-valid social settings. From the first instantiation of ConfLab, we provide a high-fidelity dataset of 48 participants at a professional networking event.

Methodological Contributions: We describe a data collection design that captures a diverse mix of real levels of seniority, acquaintance, affiliation, and motivation to network (see Figure 2). This was achieved by organizing ConfLab as part of an international conference on multimodal machine learning. ConfLab had these goals: (i) a data collection effort following a by the community for the community ethos: the more volunteers, the more data, (ii) volunteers who potentially use the data can experience first-hand potential privacy and ethical considerations related to sharing their own data, (iii) in light of recent data sourcing issues [13], we incorporated privacy and invasiveness considerations directly into the decision-making process regarding sensor type, positioning, and sample-rates.

Technical Contributions: (i) aerial-view articulated pose: our annotations of 17 full-body keypoints enable improvements in (a) pose estimation and tracking, (b) pose-based recognition of social actions (under-explored in the top-down perspective), (c) pose-based F-formation estimation (has not been possible from prior work [8, 14–16]), and (d) the direct study of interaction dynamics using full body poses (previously limited to lab settings [17]). (ii) subtle body dynamics: we are the first to use a full 9-axis Inertial Measurement Unit (IMU) enabling a richer representation of behaviour at higher sample rates; previous rates were found to be insufficient for downstream tasks [18]. (iii) enabling finer temporal-scale research questions: a sub-second crossmodal latency of ~13 ms
Another approach exploited wearable-sensor data to allow for multimodal processing—sensors in wild social interaction settings. ConfLab is the first and only social interaction dataset that offers skeletal keypoint and speaking status at high annotation resolution, as well as hardware synchronized camera and multimodal wearable signals at high resolution.

| Dataset          | People/Scene | Video                  | Manual Annotations | Wearable Signals | Synchronization                          |
|------------------|--------------|------------------------|--------------------|------------------|------------------------------------------|
| Cocktail [19]†   | 7            | 512 × 384              | F-formations       | None             | Unknown                                  |
|                  |              |                        | (20 and 30 min, 1/5 Hz) |                  |                                          |
| CoffeeBreak [20]| 14           | 1440 × 1080            | F-formations       | None             | None                                     |
|                  |              |                        | (130 frames in two sequences) |                  |                                          |
| IDIAP [5]        | > 50         | 180 min; 654 × 439     | F-formations       | None             | None                                     |
|                  |              | 20 fps                 | (82 independent frames) |                  |                                          |
| SALSA [21]†      | 18           | 60 min; 1024 × 788     | Bounding boxes     | Audio MFCCs      | Post-hoc infra-red event-based (no-drift assumption) |
|                  |              | 15 fps                 | (30 min)           | (30 Hz)          |                                           |
|                  |              |                        | Head & body ori.   | Acceleration (20 Hz) |                                           |
|                  |              |                        | (30 min)           | (1 Hz)           |                                           |
|                  |              |                        | F-formations       | BR proximity (1 Hz) |                                           |
|                  |              |                        | (60 min)           |                  |                                          |
|                  |              |                        | (all 1/3 Hz)       |                  |                                          |
| MnM [9]†         | 32           | 30 min; 1920 × 1080     | Bounding boxes     | Accelerometer    | Intra-wearable sync via gossiping protocol; |
|                  |              | 30 fps                 | (30 min, 1 Hz)     | (20 Hz)          |                                           |
|                  |              |                        | F-formations       | Radio proximity (1 Hz) | Inter-modal sync using manual inspection @ 1 Hz |
|                  |              |                        | (10 min, 1 Hz)     |                  |                                           |
|                  |              |                        | Actions            |                  |                                          |
|                  |              |                        | (45 min, 1 Hz)     |                  |                                          |
| ConfLab          | ~ 45 min;   | 17 keypoints (16 min, 60 Hz) | Low-freq. audio     | Wireless hardware sync at acquisition, max latency of ~ 13 ms [11] |
|                  | 1920 × 1080 | 60 fps                 | (16 min, 60 Hz)    | (1250 Hz)        |                                          |
|                  |              |                        | Speaking status    | BT proximity (5 Hz) |                                           |
|                  |              |                        | (16 min, 60 Hz)    |                  |                                          |
|                  |              |                        |                     | 9-axis IMU (56 Hz) |                                           |

† Includes self-assessed personality ratings
‡ Upsampled to 20 Hz using Vatic [22]
BT: Bluetooth
IMU: Inertial Measurement

along with higher sampling rate of features (60 fps video, 56 Hz IMU) opens the gateway for the in-the-wild study of nuanced time-sensitive social behaviors like mimicry and synchrony.

2 Related Work

Early datasets of in-the-wild social events either spanned only a few minutes (e.g. Coffee Break [20]), or were recorded at such a large distance from the participants that performing robust, automated person detection or tracking with SOTA approaches was non-trivial (e.g. Idiap Poster Data [8]). More recently, two different strategies have emerged to circumvent such issues.

One approach involved fully instrumented labs with a high-resolution multi-camera setup for video and audio data. Here automated pose estimation [17, 23, 24] could be applied to generate behavioral features. This circumvented the cost- and labor-intensive process of manually labeling head poses, at the cost of less portable sensing setups. Notable examples of such in-the-lab studies include both seated scenarios, such as the AMI meeting corpus [25], or the more recent standing scenarios of the Panoptic Dataset [17]. Both datasets enabled the learning of multimodal behavioral dynamics. However, the dynamics of seated, scripted, or role-playing scenarios are different from that of an unconstrained social setting such as ours. In contrast, ConfLab moves out of the lab with a more modular and portable multimodal, multisensor solution that scales easily in-the-wild, allowing data to be captured in less constrained physical settings.

Another approach exploited wearable-sensor data to allow for multimodal processing—sensors included 3 or 6 DOF inertial measurement units (IMU); infrared, bluetooth, or radio sensors to measure proximity; or microphones for speech behavior [9, 21]. While proximity has been used as a proxy of face-to-face interaction [21, 26–29], recent findings highlight significant problems with such an assumption [30]. Such errors can have a significant impact on the machine-perceived experience of an individual, precluding the development of personalized technology. Chalcedony badges used by [9] show more promising results with a radio-based proximity sensor and accelerometer [31], but such data remains insufficient for more downstream tasks due to the relatively low sample (20Hz) and annotation (1Hz) frequency [18]. In light of these challenges in wearable sensing, ConfLab features custom-developed Midge sensors that enable more flexible and fine-grained on-device recording. At the same time, ConfLab enables researchers in the wearable and ubiquitous computing communities
Figure 4: Screenshots from the Conflab: Meet the Chairs! event website

Figure 5: The Midge

to investigate the benefit of exploiting both visual and wearable modalities to improve upon purely wearable solutions.

Furthermore, while both SALSA [21] and MatchNMingle [9] capture a multimodal dataset of a large group of individuals involved in mingling behavior, the inter-modal synchronization is only guaranteed at 1/3 Hz and 1 Hz, respectively. Prior works coped with lower tolerances by computing summary statistics over input windows [18, 32, 33]. While 1 Hz is able to capture some conversation dynamics [34], it is insufficient to study fine-grained social phenomena such as back-channeling or mimicry that involve far lower latencies [11, Sec. 3.3]. Conflab provides data streams with higher sampling rates, synchronized at acquisition with our method shown to yield a 13 ms latency at worst [11] (see Sec. 3). Table 1 summarizes the differences between Conflab and other related datasets.

3 Data Acquisition

In this section we describe the considerations, design, and supporting community engagement activities for the first instantiation of Conflab at ACM Multimedia 2019 (MM’19), to serve as a template and case study for other similar efforts.

Ecological Validity and Recruitment  An often-overlooked but crucial aspect of in-the-wild data collection is the design and ecological validity of the interaction setting [5–7]. To capture natural interactions in a professional setting and encourage mixed levels of status, acquaintance, and motivations to network, we co-designed a networking event with the MM’19 organizers called Meet the Chairs! Our event website (https://conflab.ewi.tudelft.nl/) served to inform participants about the goals of a community created dataset, and transparently describe the data collection process (Figure 4). During the conference, participants were recruited via word-of-mouth marketing, social media, conference announcements, and the event website. As an additional incentive beyond interacting with the Chairs and participating in a community-driven data endeavor, we provided attendees with post-hoc insights into their networking behavior from the collected wearable-sensors data. See Supplementary material for a sample participant report.

Privacy and Ethics  The collection and sharing of Conflab is GDPR compliant. The dataset design and process was approved by both, the Human Research Ethics Committee at our institution (TUDelft) and the conference location’s national authorities (France). All participants gave consent for the recording and sharing of their data at registration. Given the involvement of private human data Conflab is only available for academic research purposes under an End User License Agreement. Such an as open as possible and as closed as necessary ethos for open science acknowledges the limitation that personal data places on open sharing [35, 36].

Data Capture Setup  The 10 m × 5 m interaction area was recorded by 14 GoPro Hero 7 Black video cameras (60fps, 1080p, Linear, NTSC) [37]. 10 of these were placed directly overhead at a height of ~ 3.5 m at 1 m intervals, with 4 cameras (not shared to preserve privacy) at the corners providing an elevated-side-view perspective. For capturing multimodal data streams, we designed a custom wearable multi-sensor pack called the Midge (see Figure 5 for a design render), based on the open-source Rhythm Badge designed for office environments [38]. We improved upon the Rhythm Badge to achieve more fine-grained and flexible data capture (see Appendix D). We designed the Midge in a conference badge form-factor for seamless integration. Unlike smartphones, wearable

2Documentation and schematics: https://github.com/TUDelft-SPC-Lab/spcl_midge_hardware
badges allow for a simple grab-and-go setup and do not suffer from sensor/firmware differences across models. Popular human behavior datasets are synchronized by maximizing similarity scores around manually identified common events, such as infrared camera detections [21], or speech plosives [39]. While recordings in lab settings can allow for fully wired recording setups, recording in-the-wild requires a distributed wireless solution. We developed a solution to synchronize the cameras and wearable sensors directly at acquisition while significantly lowering the cost of the recording setup [11], making it easier for others to replicate our capture setup. See Appendix D for additional synchronization and calibration details, and Appendix B for images of the setup.

**Data Association and Participant Protocol** One consideration for multimodal data recording is the data association problem—how can pixels corresponding to an individual be linked to their other data streams? To this end, we designed a participant registration protocol. Arriving participants were greeted and fitted with a Midge. The ID of the Midge acted as the participant’s identifier. One team member took a picture of the participant while ensuring both the face of the participant and the ID on the Midge were visible. In practice, it is preferable to avoid this step by using a fully automated multimodal association approach. However this remains an open research challenge [40, 41]. During the event, participants mingled freely—they were allowed to carry bags or use mobile phones. Conference volunteers helped to fetch drinks for participants. Participants could leave before the end of the one hour session.

**Replicating Data Collection Setup and Community Engagement** After the event, we gave a tutorial at MM’19 [42] to demonstrate how our collection setup could be replicated, and to invite conference attendees and event participants to reflect on the broader considerations surrounding privacy-preserving data capture, sharing, and future directions such initiatives could take.

### 4 Data Annotation

**Continuous Keypoints Annotation** Existing datasets of in-the-wild social interactions have mainly focused on localizing subjects via bounding boxes [9, 21]. However, richer information about the social dynamics such as gestures and changes in orientation cannot be retrieved from bounding boxes alone, and necessitates the labeling of multiple skeletal keypoints. The typical approach to keypoint annotation involves using tools such as Vatic [22] or CVAT [43] to manually label every $N$ frames followed by interpolating over the rest of the frames. This one-frame-at-a-time annotation procedure makes obtaining keypoint annotations a labor- and cost-intensive process. Moreover, interpolation fails to capture the finer temporal dynamics of the underlying behavior, and reduces the benefits of higher-framerate video capture. Limited by existing tools, no related dataset of in-the-wild human behavior has included time-continuous pose or speaking status annotations.

In contrast, to overcome these issues we collected fine-grained time-continuous annotations of keypoints via a web-based interface implemented as part of the Covfee framework [45]. Here, annotators follow individual joints using their mouse or trackpad while playing the video in their web browser. The playback speed of the video is automatically adjusted using an optical-flow-based technique to enable annotators to follow keypoint trajectories continuously without pausing the
video. This design enables easy keypoint labeling in every frame of the video (60 Hz). Annotators simultaneously controlled a binary occlusion flag (per body joint) to indicate when a body joint was not directly visible. A pilot study on the efficacy of Covfee compared to non-continuous annotation via CVAT [43] is presented in [45].

Keypoints for ConfLab were annotated per camera (so the same subject could be annotated in multiple cameras due to view overlap) for 5 of the overhead cameras (see Fig. 1). Videos were split into two-minute segments to ease the annotation procedure. Each segment was annotated by one annotator by tracking the joints of all the people in the scene.

**Continuous Speaking Status Annotations** Speaking status is a key non-verbal cue for many social interaction analysis tasks [46]. We annotated the binary speaking status of every subject due to its importance as a key feature of social interaction [47–51] and to contribute the existing community who are working on this task [18, 52, 53]. Action annotations have traditionally been carried out using frame-wise techniques [9], where annotators find the start and end frame of the action of interest using a graphical interface. Given the speed enhancement from Covfee, we also annotated speaking status time-continuously. A binary annotation interface, where annotators were asked to press a keyboard key when they perceived speaking starting or ending, was implemented in Covfee [45]. Similar to [9] the annotations were made by watching the video. All overhead views were provided to the annotators to enable the best view from the peoples’ visual behavior.

**F-formation Annotations** Identifying who is likely to have social influence on whom is another important feature for analyzing social behavior. This is operationalised via the theory of F-formations, which are groups of people arranging themselves to converse or socially interact. Similar to prior datasets [9, 19, 21], F-formations group membership were annotated using an approximation of Kendon’s definition [54]. Annotations were labeled by one annotator at 1 Hz. The member(s) that used mobile phones are available as part of the annotations of F-formations. The best camera view was chosen for each F-formation to mitigate ambiguities in dealing with truncated formations that span across two neighboring camera views.

**5 Dataset Statistics**

**Individual-Level Statistics** Figure 6c shows the average occlusion values we obtained from annotators for each of the 17 keypoints. In Figure 7a we show the distribution of turn lengths in our speaking status annotations, for both newcomers and veterans, as per their self-reported newcomer status to the conference. We defined a turn to be a contiguous segment of positively-labeled speaking status, which resulted in a total of 4096 turns annotated.

**Group-Level Statistics** We found 119 distinct F-formations of size greater than or equal to two, and 38 instances of singletons. Of these, there are 14 F-formations and 2 singletons that include member(s) using the mobile phone. The group size and duration per group size distribution are shown in Figures 7b and 7c, respectively. Mean group duration doesn’t seem to be influenced by group size although higher variations are seen at smaller group sizes. The fraction of community newcomers (first-time attending the conference) in groups is summarized in histogram in Figure 7d. This figure clearly demonstrates two peaks on both sides of the spectrum (i.e., no newcomers vs. all newcomers in the same group). This spread over mixed and non-mixed seniority presents opportunities to study how acquaintance and seniority influence conversation dynamics.
6 Research Tasks

We report experimental results on three baseline benchmark tasks: person and keypoints detection, speaking status detection, and F-formation detection. The first task is a fundamental building block for automatically analyzing human social behaviors. The other two demonstrate how learned body keypoints can be used in the behavior analysis pipeline. We chose these benchmarking tasks since they have been studied on other in-the-wild behavior datasets. Code for all benchmark tasks is available at: https://github.com/TUDelft-SPC-Lab/conflab.

6.1 Person and Keypoints Detection

This benchmark involves the tasks of person detection (identifying bounding boxes) and pose estimation (localizing skeletal keypoints). Since pre-trained SOTA methods struggle with a privacy-sensitive top-down perspective [10] (also see Figure 3 and Appendix F.1 for ConfLab results), we finetune COCO-pretrained models on our dataset. We used Mask-RCNN [55] (Detectron2 framework [56] implementation) with a ResNet-50 backbone for both tasks for benchmarking. Since keypoint annotations were made per camera, we used four of the overhead cameras for training (Cameras 2, 4, 8, 10) and one for testing (Camera 6). Implementation details are available in Appendix E.1.

Evaluation Metrics. We evaluated object detection performance using the standard metrics in the MS-COCO dataset paper [57]. We report average precision (AP) for intersection over union (IoU) thresholds of 0.50 and 0.75, and the mean AP from an IoU range from 0.50 to 0.95 in 0.05 increments. For keypoint detection, we use object keypoint similarity (OKS) [57]. $A_{OKS}$ is a mean average precision for different OKS thresholds from 0.5 to 0.95.

Results and Analyses. Table 2 summarizes our person detection and joint estimation results. Our baseline achieves 73.9 $A_{50}$ in detection and 45.3 $A_{OKS}$ in keypoint estimation. Figure 8 shows qualitative results from our fine-tuned network for top-view images. For further insight performed several analyses and ablations. In Appendix Table 5, we depict the effect of varying the number of training samples on performance. Here we use the same four cameras for training, and only vary the number of frames for each camera. We evaluate on the same testing images from camera 6. We find that performance saturates at 16% training samples. While we used all four cameras for training here, we next investigated the effect of increasing training data size by adding specific cameras. We report results in Appendix Table 6. There is a 260% performance gain when first doubling the training samples to 69 k with the addition of camera 4, and a 46% gain when adding another 43 k samples from camera 8. Overall ConLab features a higher person density compared to prior similar datasets (15 on average per camera view) which is a useful resource for developing overhead keypoint estimation. Finally, since the lower body regions suffer from higher occlusion, we experiment with different sections of body for further insight and report results in Appendix Table 7.

6.2 Speaking Status Detection

In data collected from real-life social settings, individual audio recordings can be hard to obtain due to privacy concerns [58]. This has led to the exploration of other modalities to capture some of the motion characteristics of speaking-related gestures [32, 33]. In this task we explore the use of body pose and wearable acceleration data for detecting the speaking status of a person in the scene.

Setup. We use the SOTA MS-G3D graph neural network for skeleton action recognition [59], pre-trained on Kinetics Skeleton 400. For the acceleration modality, we evaluated three time series classifiers, each of which we trained from scratch: 1D Resnet [60], InceptionTime [61], and

Table 2: Mask-RCNN results for person bounding box detection and keypoint estimation.

| Model      | Person Detection | Keypoint Estimation |
|------------|------------------|---------------------|
|            | $A_{50}$ | $A_{75}$ | $A_{OKS}$ | $A_{OKS}$ |
| R50-FPN    | 73.9    | 38.9    | 38.4    | 45.3    | 13.5    | 3.3    |

Figure 8: Predictions from the Mask-RCNN model; COCO pretrained (left), and ConfLab finetuned (right).
Table 3: ROC AUC and accuracy of skeleton-based, acceleration-based and multimodal speaking status detection (10-fold cross-validation).

| Modality      | Model      | AUC  | Acc. |
|---------------|------------|------|------|
| Pose          | MS-G3D [64]| 0.676| 0.677|
|               | InceptionTime [61]| 0.798| 0.768|
| Acceleration  | Resnet 1D [60]| 0.801| 0.767|
|               | Minirocket [62]| 0.813| 0.768|
| Multimodal    | MS-G3D + Minirocket | 0.823| 0.775|

Table 4: Average F1 scores for F-formation detection comparing GTCG [16] and GCFF [65] with the effect of different threshold and orientations (standard deviation in parenthesis).

|          | GTCG | GCFF |
|----------|------|------|
|          | T=2/3 | T=1  | T=2/3 | T=1  |
| Head     | 0.51 (0.09) | 0.40 (0.12) | 0.47 (0.07) | 0.31 (0.23) |
| Shoulder | 0.46 (0.11) | 0.38 (0.11) | 0.56 (0.25) | 0.36 (0.16) |
| Hip      | 0.45 (0.10) | 0.37 (0.12) | 0.39 (0.06) | 0.25 (0.11) |

Minirocket [62]. We performed late fusion by averaging the scores from both modalities. Like prior work [18, 33], the task was set up as a binary classification problem. We divided our pose (skeleton) tracks into 3-second windows with 1.5 s overlap. A window was labeled positive if more than 50% of the continuous speaking status labels within it are positive. This resulted in an imbalanced dataset of 42882 windows with 29.2% positive labels. Poses were pre-processed for training following [59]. Three of the keypoints (head, and feet tips) were discarded due to not being present in Kinetics. We adapted the network by freezing all layers except for the last fully connected layer and training for five extra epochs. Acceleration readings were not pre-processed, other than by interpolating the original variable-sampling-rate signals to a fixed 50 Hz.

Evaluation Evaluation was carried out via 10-fold cross-validation at the subject level, ensuring that no examples from the test subjects were used in training. We used the area under the ROC curve (AUC) as main evaluation metric to account for the imbalance in the labels.

Results The results in Table 3 indicate a better performance from the acceleration-based methods. One possible reason for the lower performance of the pose-based methods is the significant domain shift between Kinetics and ConfLab, especially in camera viewpoint (frontal vs top-down). The acceleration performance is in line with previous work [18]. Multimodal results were slightly higher than acceleration-only results, despite our naive fusion approach, a possible point to improve in future work [63]. Experiments with the rest of the IMU modalities are presented in Appendix F.2.

6.3 F-formation Detection

Setup Like prior work [8, 14–16], we operationalize interaction groups using the framework of F-formations [54]. We provide performance results for F-formation detection using GTCG [16] and GCFF [65] as a baseline. Recent deep learning methods such as DANTE [15] are not directly applicable since they depend on knowing the number of people in the scene, which is variable for ConfLab. We use pre-trained model parameters (reported in the original GTCG and GCFF papers on the Cocktail Party dataset [19]) and tuned a subset of parameters more relevant to ConfLab attributes on camera 6. More details can be found in Appendix E.2. We derive three different sets of orientation features from (i) head, (ii) shoulder and (iii) hip keypoints.

Evaluation Metrics We use the standard F1 score as evaluation metric for group detection [16, 65]. A group is correctly estimated (true positive) if at least $|T \star |G|_i$ of the members of group $G$ are correctly identified, and no more than $1 - |T \star |G|_i$ is incorrectly identified, where $T$ is the tolerance threshold. We report results for $T = \frac{2}{3}$ and $T = 1$ (more strict threshold) in Table 4.

Results We show that different results are obtained using different sources of orientations. Different occlusion levels in keypoints due to camera viewpoint may have affected performance. Another factor influencing model performance with different choice of orientation feature is that F-formations (which are driven by lower-body orientations [54]) may have confounding conceptual overlap with conversation floors [49], which are more relevant to head orientations.
7 Conclusion and Discussion

ConfLab contributes a new concept for multimodal real-life data collection in-the-wild and captures a rich and high-fidelity multisensor and multimodal dataset of mixed levels of acquaintance, seniority, and personal motivations.

ConfLab: the Dataset We improved upon prior work by providing higher-resolution and framerate data and also carefully designed our social interaction setup to enable a diverse mix of seniority, ac-

quaintanceship, and motivations for mingling. The result is a rich set of 17 body-keypoint annotations of 48 people at 60 Hz from overhead cameras for developing more robust estimation of keypoints, speaking status and F-formations for further analyses of more complex socio-relational phenomena. Our Baseline results for these tasks highlight how ConfLab can assist in the development of more robust methods for these key tasks. We hope that future ConfLab pre-trained body keypoint models would eventually fill the gap in the cue extraction pipeline, enabling past datasets [8, 9] to be reinvigorated; this would open the floodgates for more robust fully-automated analysis of social phenomena that are already labeled in other datasets. Finally, our baseline social tasks form the basis for further explorations into downstream prediction tasks of socially-related constructs such as conversation quality [66], dominance [51], rapport [47], influence [67] etc.

ConfLab: the Data-Collection Concept Since ConfLab captures social relationships, if we want to relate an individual’s behaviors to longer-term behavioral trends within the social network (e.g. across coffee breaks in one day, days at a conference, or multiple conferences), more instantiations similar to this first edition of ConfLab are needed. This paper serves as a record for how to run such a data collection, providing a template for future ventures. Regarding maximizing data fidelity while preserving participants’ privacy, we designed the choices of overhead camera perspective, low audio recording frequency, and non-intrusive wearable sensors matching a conference badge form-factor. However, richer information about participants’ social networks is also necessary for a more in-depth study of technologies to help people’s social decision-making. We argue this is an key step towards a long-term goal for developing personalized socially aware technologies that can enhance and foster positive social experiences and assist in social decisions.

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ConfLab: A Rich Multimodal Multisensor Dataset of Free-Standing Social Interactions in the Wild

Appendices

The Appendices are organized as follows:

- **Section A:** Hosting, licensing, and organization information for ConfLab
- **Section B:** Documentation for ConfLab, following Datasheets for Datasets [68]
- **Section C:** Sample post-hoc behavioral analysis report sent to each ConfLab participant
- **Section D:** Details about out data-capture setup
- **Section E:** Implementation details for models used in our benchmark research tasks
- **Section F:** Additional experimental results and ablations
- **Section G:** Details for reproducibility following the ML Reproducibility Checklist [69]

A Hosting, Licensing, and Organization

The dataset is hosted by 4TU.ResearchData, available at https://doi.org/10.4121/c.6034313. The dataset itself is available under restricted access defined by an End-User License Agreement (EULA). The EULA itself is available under a CC0 license. The code (https://github.com/TUDelft-SPC-Lab/conflab) for the benchmark baseline tasks, and the schematics and data associated with the design of our custom wearable sensor called the Midge (https://github.com/TUDelft-SPC-Lab/spcl_midge_hardware) are available under the MIT License.

Figure 9 on the next page illustrates the organization of the ConfLab dataset on 4TU.ResearchData. The components are as follows:

-Annotations (restricted, https://doi.org/10.4121/20017664): annotations of pose, speaking status, and F-formations
-Datasheet for ConfLab (public, https://doi.org/10.4121/20017559): documentation of the dataset following Datasheets for Datasets [68] (see Appendix B)
-EULA (public, https://doi.org/10.4121/20016194): End User License Agreement to be signed for requesting access to the restricted components
-Processed-Data (restricted, https://doi.org/10.4121/20017805): processed video and wearable sensor used for annotations
-Raw-Data (restricted, https://doi.org/10.4121/20017748): raw video and wearable sensor data
-Data Samples (restricted, https://doi.org/10.4121/20017682): samples of the sensor, audio, and video data
Figure 9: File structure of the ConfLab dataset
**B Datasheet For ConfLab**

This document is based on *Datasheets for Datasets* by Gebru et al. [68]. Please see the most updated version [here](#).

## MOTIVATION

**For what purpose was the dataset created?** Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.

There are two broad motivations for creating this dataset: first, to enable the privacy-preserving, multimodal study of real-life social conversation dynamics; second, to bring the higher fidelity of wired in-the-lab recording setups to in-the-wild scenarios, enabling the study of fine time-scale social dynamics in-the-wild.

We propose the Conference Living Lab (ConfLab) with the following goals: (i) a data collection effort that follows a by the community for the community ethos: the more volunteers, the more data, (ii) volunteers who potentially use the data can experience first-hand potential privacy and ethical considerations related to sharing their own data, (iii) in light of recent data sourcing issues [13], we incorporated privacy and invasiveness considerations directly into the decision-making process regarding sensor type, positioning, and sample-rates.

From a technical perspective, closest related datasets (see Table 1 in the main paper) suffer from several technical limitations precluding the analysis and modeling of fine-grained social behavior: (i) lack of articulated pose annotations; (ii) a limited number of people in the scene, preventing complex interactions such as group splitting/merging behaviors, and (iii) an inadequate data sampling-rate and synchronization-latency to study time-sensitive social phenomena [11, Sec. 3.3]. This often requires modeling simplifications such as the summarizing of features over rolling windows [18, 32, 33]. On the other hand, past high-fidelity datasets have largely involved role-played or scripted interactions in lab settings, with often a single-group in the scene.

This dataset wasn’t created with a specific task in mind, but intends to support a wide variety of multimodal modeling and analysis tasks across research domains (see the Uses section).

**Who created this dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?**

ConfLab was initiated by the Socially Perceptive Computing Lab, Delft University of Technology in cooperation and support from the general chairs of ACM Multimedia 2019 (Martha Larson, Benoit Huet, and Laurent Amsaleg), Nice, France. Since this dataset was by the community, for the community, members of the Multimedia community contributed as subjects in the dataset.

**What support was needed to make this dataset?** (e.g., who funded the creation of the dataset? If there is an associated grant, provide the name of the grantor and the grant name and number, or if it was supported by a company or government agency, give those details.)

ConfLab was partially funded by Netherlands Organization for Scientific Research (NWO) under project number 639.022.606 with associated Aspasia Grant, and also by the ACM Multimedia 2019 conference via student helpers, and crane hiring for camera mounting.

**Any other comments?**

None.

## COMPOSITION

**What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)?** Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.

The dataset contains multimodal recordings of people interacting during a networking event embedded in an international multimodal machine learning conference.

Overall, the interaction scene contained conversation groups (operationalized as f-formations), composed of individual subjects, each of which had individual data associated to their wearable
sensors. The complete interaction scene was additionally captured by overhead cameras. Figure 10 shows the structure of these instances and their relationships.

Figure 10: Structure of some of the instances in the dataset and their relationships. The interaction space was captured via overhead videos, in which F-formations (conversation groups) were annotated. An F-formation consists of a set of people interacting for a variable period of time, and identified via a subject ID. Each person in the F-formation can be associated to their pose (annotated in the videos), their wearable sensor (IMU) data, and their action (speaking status) labels.

Note however that the precise notion of what constitutes an instance in the dataset is very much task-specific. In our baseline tasks we considered the following instances:

**Person and Keypoints Detection** Frames, containing pose annotations (17 body keypoints per person per frame @60 Hz) from 5 overhead videos (1920 × 1080, 60 fps) for 16 minutes of interaction.

**Speaking Status Detection** Windows (3 seconds) of wearable sensor data and speaking status annotations (60 Hz) extracted from each subject’s data.

**F-formations** Operationalized conversation groups, annotated at 1 Hz from the 16 minutes of annotated data, and the pose data associated to the people in the F-formation.

**How many instances are there in total (of each type, if appropriate)?**

The notion of instance is very much dependent on how a user intends to use the data. Regarding the instances in Figure 10, our full dataset consist of 45 minutes of:

**Video recordings** from 9 overhead cameras placed over the interaction area. Five of these videos, enough to cover the complete interaction area, were used in annotation.

**Individual wearable sensor data** For the 48 subjects in the interaction area, a chest-worn conference-type badge recorded: audio (1250 Hz), and Inertial Measurement Unit (IMU) readings (accelerometer @ 56 Hz, gyroscope @56 Hz, magnetometer @56 Hz and Bluetooth RSSI-based proximity @5 Hz)

**Conference experience label** For each of the 48 subjects, an associated self-report label indicating whether it was their first time in the conference.

A segment of 16 minutes of interaction (out of 45 minutes of interaction) was additionally annotated with:
2D body poses For each of the 48 subjects, full body pose tracks annotated at 60Hz (17 keypoints per person). These were annotated using 5 of the 10 overhead cameras due to the significant overlap in views (cameras 2, 4, 6, 8, and 10). Annotations were done separately for each camera by annotating all of the people visible in each video, for each of the 5 cameras, and tagged with a participant ID.

Speaking status annotations For each of the 48 subjects, these include a) a binary signal (60 Hz) indicating whether the person is perceived to be speaking or not; b) continuous confidence value (60 Hz) indicating the degree of confidence of the annotator in their speaking status assessment. These annotations were done without access to audio due to issues with the synchronization of the audio recordings at the time of annotation. The confidence assessment is therefore largely based on the visibility of the target person and their speaking-associated gestures (e.g. occlusion, orientation w.r.t. camera, visibility of the face)? Note: both annotations were done via continuous annotation and contain annotator delay.

F-formation annotations These annotations label the conversing groups in the scene following previous work. Each individual belongs to one F-formation at a time or is a singleton in the interaction scene. The membership is binary. The annotations were done by one of the authors at 1 Hz by watching the video.

In our baseline tasks, which made use of the complete annotated section of the dataset, the instance numbers were the following:

Person and Keypoints Detection 119k frames (60fps) containing 1967k person instances (poses) in total, from 48 subjects recorded in 5 cameras (16 minutes of annotated segment).

Speaking Status Detection 42884 3-second windows, extracted from the 48 participants’ wearable data and speaking status annotations.

F-formations 119 conversation groups. Details are in Section 5.

Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).

The participants in our data collection are a sample of the conference attendees. Participants were recruited via the conference website, social media posting, and approaching them in person during the conference. Because participation in such a data collection can only be voluntary, the sample was not pre-designed and may not be representative of the larger set.

Additionally, 16 minutes of sensor data has been annotated for keypoints, speaking status and F-formations out of the total of 45 minutes recorded. The remaining part (across all modalities) is provided with no labels. For privacy reasons, the elevated cameras (distinct from the previously mentioned 8 overhead cameras) and also individual frontal headshots that were used for manually associating the video data to the wearable sensor data is not being shared.

Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.

Camera 5 failed early during the recording, but the space underneath it was captured by the adjacent cameras due to the high overlap in the camera field-of-views. Nevertheless we share what was recorded before the failure from camera 5, bringing the total number of cameras to 9.

Are relationships between individual instances made explicit (e.g., users’ movie ratings, social network links)? If so, please describe how these relationships are made explicit.

The F-formations, subjects, and their associated data relate as shown in Figure 10. These associations are made explicit in the dataset via anonymous subject IDs, associated to pose tracks, speaking status annotations, and wearable sensor data. These same IDs were used to annotate the F-formations.

Pre-existing personal relationships between the subjects were not requested for privacy reasons.

Are there recommended data splits (e.g., training, development/validation, testing)? Since the dataset can be used to study a variety of tasks, the answer to this question is task dependent.
Please refer to our reproducibility details (Appendix G of our associated paper) for information about the splits that we used in our baselines.

Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.

**Individual audio** Because audio was recorded by a front-facing wearable device worn on the chest, it contains a significant amount of cocktail party noise and cross-contamination from other people in the scene. In our experience this means that automatic speaking status detection is challenging with existing algorithms but manual annotation is possible.

**Videos and 2D body poses** It is important to consider that the same person may appear in multiple videos at the same time if the person was in view of multiple cameras. Because 2D poses were annotated per video, the same is true of pose annotations. Each skeleton was tagged with a person ID, which should serve to identify such cases when necessary.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)?
The dataset is self-contained.

**Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals’ non-public communications)?** If so, please provide a description.
The data contains personal data under GDPR in the form of video and audio recordings of subjects. The dataset is shared under an End User License Agreement for research purposes, to ensure that the data is not made public, and to protect the privacy of data subjects.

**Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety?**
No.

**Does the dataset relate to people?**
Yes, the dataset contains recordings of human subjects.

**Does the dataset identify any subpopulations (e.g., by age, gender)?** If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.

Data subjects answered the following questions before the start of the data collection event, after filling in their consent form:

- Is this your first time attending ACM MM?
- Select the area(s) that describes best your research interest(s) in recent years. Descriptions of each theme are listed here: https://acmmm.org/call-for-papers/

Figure 11 shows the distribution of the responses / populations.

Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset?
We do not share any directly identifiable information as part of the dataset. However, individuals
May be identified in the video recordings if the observer knows the participants in the recordings personally. Otherwise, individuals in the dataset may potentially be identified in combination with publicly available pictures or videos (from conference attendees or conference official photographer) from other media from the conference the dataset was recorded at. In any case, re-identifying the subjects is strictly against the End User License Agreement under which we share the dataset.

Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.

We did not request any such information from data participants. Here, the ACM Multimedia ’19 General Chair Martha Larson also helped advocate on behalf of the attendees during the survey-design stage. As a result of these discussions, information such as participant gender, ethnicity, or country of origin was not asked.

Any other comments?
None.

**COLLECTION**

**How was the data associated with each instance acquired?** Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or language)? If data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

The collected data is directly observable, containing video recordings, low-frequency audio recordings and wearable sensing signals (inertial motion unit (IMU) and Bluetooth proximity sensors) of individuals in the interaction scenes. Accompanying data includes self-reported binary categorization of experience level which is available upon request from the authors. The self-reported interests categories are not shared because of privacy concerns.

Video recordings capture the whole interaction floor where the association from multi-modal data to individual is done manually by annotators by referring to frontal (not-shared) and overhead views. The rest of the data was acquired from the wearable sensing badges, which is person-specific (i.e., no participant shared the device). Video and audio data were verified in playback. Wearable sensing data was verified through plots after parsing.

**Over what timeframe was the data collected?** Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created. Finally, list when the dataset was first published.

All data was collected on October 24, 2019, except the self-reported experience level and research interest topics which are either obtained on the same day or not more than one week before the data collection day. This timeframe matches the creation time frame of the data association for wearable sensing data. Video data was associated with individual during annotation stage (2020-2021), but all information used for association was obtained on the data collection day.

**What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)?** How were these mechanisms or procedures validated?

To record videos, we used 14 GoPro Hero 8 cameras.

The wearable sensor hardware has been documented and open-sourced at [https://github.com/TUDelft-SPC-Lab/spcl_midge_hardware](https://github.com/TUDelft-SPC-Lab/spcl_midge_hardware). The validation of the sensors was completed through an external contractor engineer. The data collection software was documented and published in [45], which includes validation of the system. These hardwares and mechanisms have been open-sourced along with their respective publication.

The synchronization setup for data collection (intramodal and intermodal) was documented and published in [11], which includes validation of the system.
To lend the reader further insight into the process of setting up the recording of such datasets in-the-wild, we share images of our process in Figure 12.

What was the resource cost of collecting the data? (e.g. what were the required computational resources, and the associated financial costs, and energy consumption - estimate the carbon footprint.)

The resources required to collect the data include equipment, logistics, and travel costs. Equipment include video cameras, wearable sensors, and fixation infrastructure to the data collection venue. In our case, we used 14 GoPro Hero 8 ($350 per camera), and 60 wearable sensors ($25 per sensor). The full data synchronization setup costs approximately $2000. The logistics costs include two personnel contracted by the conference organizers to facilitate fixating data recording scaffold on the ceiling for approximately 2 hours. Travel costs include flights and accommodation for six team members.

No additional energy consumption was incurred for collecting the data. However, the ancillary activities (e.g., flights, accommodation) resulted in energy consumption. Flights from the Netherlands to France round-trip for six passengers results in 1020 kg carbon emissions. Accommodation for six members resulted in 22 kWh energy consumption. For benchmarking, various deep learning models were trained, which results in approximately $500 computational cost.

If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?

ConfLab contains both annotated and unannotated segments of multi-modal data. The segment where the articulated pose and speaking status were annotated is selected to maximize crowd density in the scenes. The annotated segment is 16 minutes; the whole set is roughly 1 hour of recordings.

Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?

The Conflab dataset was captured during a special social event called Meet the Chairs! at an international conference on signal processing and machine learning. Newcomers and old-timers
to the conference freely donated their social behaviour data as part of a *by the community, for the community* data collection effort. Aside from the chance to meet the chairs and create a community dataset, the attendees also received a personalised report of their social behaviour from the wearable sensors (see Appendix C) Conference student volunteers were involved in assisting the set-up of the event. Conference organizers (mentioned in the *Motivation* section) assisted in connecting us with conference venue contacts to mount our technical set-ups in the room. Volunteers and conference organizers were not paid by us. Conference venue contacts were paid by the conference organizers.

Data annotations were completed by crowdsourced workers. The crowdsourced workers were paid $0.20 for qualification assignment (note that typically requesters do not pay for qualification tasks). Depending on the submitted results, workers earn qualification to access of the actual tasks. The annotation tasks were categorized into low-effort ($150), medium-effort ($300), and high-effort ($450), corresponding to the amount of estimated time each would take. The duration of the tasks was determined by the crowd density and through timing of the pilot studies. The average hourly payment to workers is around $8.

**Were any ethical review processes conducted (e.g., by an institutional review board)?**  
If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.

The data collection was approved by the Human Research Ethics Committee (HREC) of our university (Delft University of Technology), which reviews all research involving human subjects. The data collection protocol is also compliant to the conference location’s national authorities (France). The review process included addressing privacy concerns to ensure compliance with GDPR and university guidelines, review of our informed consent form, data management plan, and end user license agreement for the dataset and a safety check of our custom wearable devices.

**Does the dataset relate to people?**  
If not, you may skip the remainder of the questions in this section.

Yes.

**Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?**

We collected the data from individuals directly.

**Were the individuals in question notified about the data collection?**  
If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.

The individuals were notified about the data collection and their participation is voluntary. The data collection was staged at an event called *Meet the Chairs* at ACM MM 2019. The ConfLab web page ([https://conflab.ewi.tudelft.nl/](https://conflab.ewi.tudelft.nl/)) served to communicate the aim of the event, what was being recorded, and how participants could sign up. This allowed us to embed the

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**Figure 13:** Screenshots of the ConfLab web-page used for participant recruitment and registration.
informed consent into this framework so we could keep track of sign ups. See Figure 13 for screenshots. This event website was also shared by the conference organizers and chairs (https://2019.acmmm.org/conlab-meet-the-chairs/index.html).

Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to the mechanism (if appropriate)

All the individuals who participated in the data collection gave their consent by signing a consent form. A copy of the form is attached below in Figure 14.

If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate)

Yes, the consenting individuals were informed about the possibility of revoking access to their data within a period of 3 months after the data collection experiment, and not after that. The description is included in the consent form.

Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted? If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation.

No.

Any other comments?
None.

PREPROCESSING / CLEANING / LABELING

Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remainder of the questions in this section.

Figure 14: Consent form signed by each participant in the data collection.
We did not pre-process the signals obtained from the wearable devices or cameras. The only exception is the audio data. Due to a hardware malfunction (this is resolved for the Midges by using different SD cards), the audio needed to be post-processed in order to synchronize it with the other modalities. The synchronization against other modalities was manually checked.

Labeling of the dataset was done as explained in the Composition section.

**Was the “raw” data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)?** If so, please provide a link or other access point to the “raw” data.

The dataset is separated into raw data and the post processed data. For the audio, the original raw data is not suitable for most use cases due to the mentioned synchronization issue. So we share the synchronized version in the raw part of the repository.

**Is the software used to preprocess/clean/label the instances available?** If so, please provide a link or other access point.

The processing / fixing of the audio files did not require special software.

The annotation of keypoints and speaking status was done by making use of the Covfee framework: [https://josedvq.github.io/covfee/](https://josedvq.github.io/covfee/)

**Any other comments?**

None.

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**USES**

**Has the dataset been used for any tasks already?** If so, please provide a description.

In the main paper, we have benchmarked three baseline tasks: person and keypoints detection, speaking status detection, and F-formation detection. The first task is a fundamental building block for automatically analyzing human social behaviors. The other two demonstrate how learned body keypoints can be used in the behavior analysis pipeline for inferring more socially related phenomena. We chose these benchmarking tasks since they have been studied on other in-the-wild behavior datasets.

**Is there a repository that links to any or all papers or systems that use the dataset?** If so, please provide a link or other access point.

None at the time of writing of the paper.

**What (other) tasks could the dataset be used for?**

Given the richness and the unscripted open-ended nature of the social interactions, ConfLab can be used for many other tasks.

**Forecasting, causal relationship discovery** Recently, tasks pertaining to the forecasting low-level social cues in conversations have been receiving increased attention from the community [70, 71]. The real-life nature of ConfLab along with the increased data and annotation fidelity can prove a valuable resource for such tasks. Similarly, ConfLab can also be used for efforts towards discovering causal relationships between social behaviors [72].

**Data Association.** A crucial assumption made in many former multimodal datasets [9, 17, 21] is that the association of video data to the wearable modality can be manually performed. Few works [40, 41] have tried to address this issue but using movement cues alone to associate the modalities is challenging as conversing individuals are mostly stationary. This remains a significant and open question for future large scale deployable multimodal systems. One solution may be to annotate more social actions as a form of top-down supervision. However, detecting pose and actions robustly from overhead cameras remains to be solved.

**Conversation floor and F-formation estimation** Prior analysis on the MatchNMingle dataset has demonstrated that F-formations can contain multiple simultaneous conversations when the F-formations contain a least 4 people [49]. If this is the case for the ConfLab dataset, this may drastically change how F-formations should be labelled (e.g. returning to being a more subjective task [8]) as more time-precise labelling could enable a more nuanced take on F-formation and conversation floor membership over time.
Multi-class social action estimation More annotations resources were focused on speaker status, F-formation, and keypoint estimation. However, there are a wealth of other social actions in the data that could be interesting to combine into a more complex multi-class social action estimation task. Example social actions include drinking, mobile phone use, hand and head gesture types [9, 73].

Estimation and analysis of socially-related phenomena Beyond the modeling of human behavior which is of interest to the Computer Vision and Machine Learning communities, our benchmarked tasks form the basis for further explorations into downstream prediction of socially-related constructs which is of interest to the Social Science and Social Psychology communities. Such constructs include conversation quality [66, 74], dominance [51], rapport [47], and influence [67].

Investigation of novel crossmodal fusion strategies The baseline tasks in our paper rely only on a late fusion strategy. However, ConfLab’s sub-second expected cross modal latency of $\sim 13 \text{ms}$ along with higher sampling rate of features (60 fps video, 56 Hz IMU) opens the gateway for the in-the-wild study of nuanced time-sensitive social behaviors like mimicry and synchrony (for predicting e.g. attraction [75]) which need tolerances as low as 40 ms [11, Sec.3.2]. Prior works coped with lower tolerances by computing summary statistics over input windows [18, 32, 33]. ConfLab enables for the first time, the exploration of Multimodal machine learning approaches for social behaviour analysis in these highly dynamic in-the-wild settings [63]. Through the provided annotations ConfLab also enables research in the topic of usage of mobile phones in small-group social interactions in-the-wild.

Person attribute estimation Estimating individuals that are newcomers/old timers from the dataset may be possible based on their networking strategies.

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?

Although ConfLab’s long-term vision is towards developing technology to assist individuals in navigating social interactions, such technology could also affect a community in unintended ways: e.g. causing lack of agency, worsened social satisfaction, or benefiting only those members of the community who make use of the system at the expense of the rest. All of these must be considered when developing such systems. Moreover, despite our best efforts and lack of direct personally identifiable data, ConfLab and its trained models may be exploited to develop technologies to deanonymize or track subjects in privacy-invasive ways (i.e. harmful surveillance). Finally, since the data was collected during a scientific conference, there is an implicit selection bias which users of the data need to take into account.

Are there tasks for which the dataset should not be used? If so, please provide a description.

Beyond the cautionary discussion in the previous question, tasks involving the re-identifying the subjects is strictly against the End User License Agreement under which we share the dataset.

Any other comments?
None.

DISTRIBUTION

Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created? If so, please provide a description.
The dataset is available for third parties outside of Delft University of Technology to use for academic research purposes subject signing and approval of our End User License Agreement. The dataset will be hosted by 4TU.ResearchData (see the Maintenance section for description of the 4TU entity).

How will the dataset be distributed (e.g., tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?
The dataset will be distributed via the 4TU.ResearchData user interface where the data can be downloaded. The dataset has a DOI: https://doi.org/10.4121/c.6034313
When will the dataset be distributed?
The dataset has been available since June 9, 2022.

Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.
The dataset will be distributed under a restricted copyleft license, specified within our End User License Agreement, accessible through the 4TU.ResearchData dataset website. No fees are associated with the license.

Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.
No.

Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.
The terms of our EULA and the European General Data Protection Regulations (GDPR) apply.

Any other comments?
None.

MAINTENANCE

Who is supporting/hosting/maintaining the dataset?
The dataset is hosted by 4TU.ResearchData (https://www.4tu.nl/en/about_4tu/), and supported and maintained by The Socially Perceptive Computing Lab at TUDelft.

How can the owner/curator/manager of the dataset be contacted (e.g., email address)?
Via email: H.Hung@tudelft.nl.

Is there an erratum? If so, please provide a link or other access point.
No.

Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?
Updates will be done as needed as opposed to periodically. Instances could be deleted, added, or corrected. The updates will be posted on the 4TU.ResearchData dataset website.

If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced.
No limits were communicated to our data participants.

Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to users.
Only the latest version of the dataset will be maintained. If applicable, we will also host older versions of the data, accessible through the 4TU.ResearchData website.

If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.
We are open to contributions to the dataset. In accordance with our End User License Agreement, contributions should be made available, indicating if there are any restrictions on their contribution. We encourage the potential contributors to contact us to discuss how they wish to be attributed (e.g., citation of a paper or repository related to code/annotations). After finalizing the attribution discussion, we can add the attribution as an update following the same process explained above.
C Sample Participant Report

ACMMM 19 - ConfLab Report
Socially Perceptive Computing Lab - Delft University of Technology

ConfLab: Meet the Chairs!
While you were at ACM MM in Nice earlier this year, you had participated in our event called ConfLab: Meet the Chairs! We want to thank everyone for helping us out during the event, and we hope that you had a great experience.

We thought you might be curious about some basic statistics that we have extracted from the collected data. You can find below some general information about all the event participants and some personal information particular to you. Please keep in mind that 1) these are preliminary analyses that we have performed and these results could be revised in our estimation, and 2) to protect your privacy, these results are only available to you.

General information about Conflab participants
When you signed up, we had asked 1) if this was your first time at ACM MM and 2) your research interests (multi-select multiple choice). We had a total of 18 participants. You can see below the statistics over all 18 people.

And that’s it from the Socially Perceptive Computing Lab for now!

(1) Holmström, R. et al. "Reliability of on-body acceleration data. Excluding accelerometer errors (KNEV) and mean amplitude deviation (MAD) approaches." PloS one 11.10 (2016): e0164045.

Thank you for your interest and we hope to see you again in the future!
D Data Capture Setup Details

The Midge  We improved upon the Rhythm Badge in three ways towards enabling more fine-grained and flexible data capture: (i) enabling full audio recording with a frequency up to 48 KHz, with an on-board switch to allow physical selection between high and low frequency capture directly at acquisition; (ii) adding a 9-axis Inertial Measurement Unit (IMU) with an on-board Digital Motion Processor (DMP) to record orientation; and (iii) an on-board SD card to directly store raw data, avoiding issues related to packet loss during wireless data transfer required by the Rhythm Badge. IMUs combine three tri-axial sensors: an accelerometer, a gyroscope, and a magnetometer. These measure acceleration, orientation, and angular rates respectively. These sensor measurements are combined on-chip by a Digital Motion Processor. Rough proximity estimation is performed by measuring the Received Signal Strength Indicator (RSSI) for Bluetooth packets broadcast every second (1 Hz) by every Midge. During the event, IMUs were set to record at 50 Hz. We recorded audio at 1250 Hz to mitigate extraction of verbal content while still ensuring robustness to cocktail-party noise.

Wireless Synchronization at Acquisition  The central idea for our synchronization approach involves using a common Network Time Protocol (NTP) signal as reference for the camera and wearables sub-networks. The set-up achieved a cross-modal latency of 13 ms at worst, which is well below the 40 ms latency tolerance suitable for behavior research in our setting [11, Sec. 3.3]. Additionally, our synchronization approach allowed for dynamic addition of sensors to the network while still obtaining synchronized data streams. This is crucial in extreme in-the-wild events where some participants might arrive late.

Sensor Calibration  For computing the camera extrinsics, we marked a grid of 1 m × 1 m squares in tape across the interaction area floor. We ensured line alignment and right angles using a laser level tool (STANLEY Cross90). For computing the camera intrinsics, we used the OpenCV asymmetric circles grid pattern [76]. The calibration was performed using the Idiap multi camera calibration suite [77]. All wearable sensors include one TDK InvenSense ICM-20948 IMU [78] unit that provides run time calibration. To establish a correspondence with the camera frame of reference, the sensors were lined up against a common reference-line visible in the cameras to acquire an alignment so that the camera data can offer drift and bias correction for the wearable sensors.

E Implementation Details

E.1 Person and Keypoint Detection Models

Data Cleaning  The keypoint annotations contained some incorrectly labeled keypoints, a product of annotation errors like mis-assignment of participant IDs. We removed these using a threshold on the proximity to other keypoints of the same person. As the bounding box of a person is inferred from the keypoint annotations, missing keypoints might result in wrong bounding box. If there are more than 50% keypoints missing for a person, we remove the person bounding box and keypoints from the ground-truth. For the rest, missing keypoints were ignored during back-propagation at training. Moreover, if there are more than 10% missing keypoints in an image, we also discard that image from the experiment. This resulted in a training set with 112k frames (1809k person instances) and a test set with 7k frames (158k person instances).

Training  We resized the images to $960 \times 540$, and augmented the data by randomizing brightness and horizontal flips. The learning rate was set to 0.02 and batch size to 4. We trained the models for 50 k iterations, using the COCO-pretrained weights for initialization. All hyper-parameters were chosen based on the performance on a separate hold-out camera chosen as validation set.

E.2 F-formation Detection

Data Cleaning  Because keypoint annotations of the subjects are based on camera view and that the F-formation clustering methods cannot group subjects that do not exist under one camera view (e.g., when there are more identities than in associated ground truths), we processed the ground truth
also based on camera number. This filtering pre-processing was decided based on the best camera view of the F-formations.

**Feature Extraction** The required features of GCFF and GTCG include location and orientation of the subjects. We used the X and Y position of subjects’ head (as it is the most visible from the top-down view) for location, and extracted orientations for head, shoulders and hips. The orientations are calculated based on corresponding vectors determined by head and nose keypoints, left and right shoulder keypoints, and left and right hip keypoints, respectively.

**Training** We used pre-trained parameters for field of view (FoV) and frustum aperture (GTCG) and minimum description length (GCFF), provided in these models trained on the Cocktail Party. FOV and aperture are related to human eye gaze and head anatomical constraints reported by [79], and hence not dataset specific. The minimum description length is an initialized prior dictated by the same form of the Akaike Information Criterion, and becomes part of the optimization formulation. We tuned parameters such as frustum length (GTCG) and stride (GCFF) to account for average interpersonal distance in Conflab based on Camera 6, as they vary across different datasets.

### F Additional Results

**F.1 Person and Keypoints Detection**

**Predictions from pretrained SOTA models** Figure 16 shows predictions from SOTA human keypoint estimation models, namely, RSN [12], MSPN[80], HigherHRNet [81], and HourglassAENet [82], for the testing images of the Conflab dataset. Note that RSN and MSPN are top-down networks, i.e., they require person bounding boxes to predict the keypoints in each bounding box. We use COCO pretrained faster-RCNN network for bounding box estimation. HigherHRNet and HourglassAENet are bottom-up models, i.e., they directly predict keypoints from the full image. We use publicly available COCO pretrained checkpoints for prediction. The results show that the state-of-the-arts 2D body keypoint detection models fail to capture the body keypoints in the Conflab dataset. We infer that training on the dataset (e.g., COCO) that contains mostly side-view images does not work well in top-view images, for which Conflab dataset is important to the community.

**Qualitative Results from ResNet-50 Finetuning** Figure 17 illustrates more qualitative results from our finetuning experiments. We find that finetuning on our non-invasive top-down camera perspective significantly improves the keypoint estimation performance.

**Ablations** Tables 5 and 6 include the results of our experiments investigating the effect of varying the training data size on keypoint detection performance (see main paper Section 6.1). In Table 7, we show keypoint detection scores for experiments with different number of keypoints. We first focus on the five upper body keypoints: {head, nose, neck, rightShoulder, leftShoulder}. We then additionally considered the torso region keypoints for a total of nine: {rightElbow, rightWrist, leftElbow, leftWrist}. Finally, we add the hip keypoints {rightHip, leftHip} to the set. The experiments in the main paper are performed with all 17 keypoints. The results show that performance drops slightly when adding the arms keypoints (5 → 9, AP\textsubscript{50} and AP\textsubscript{OKS}), and that the relative gain when adding the hip keypoints (9 → 11) is lower than when adding the lower body keypoints (11 → 17, especially AP\textsubscript{OKS}). We believe this is largely due to the lower body being more static relative to the arms that move a lot to execute gestures during conversations.

**F.2 Speaking Status Detection**

**Experiments with different sensor modalities** Table 8 displays the results from experiments using specific modalities from our IMUs for the task of speaking status detection. We used the best performing classifier (Minirocket [62]) among the ones tested in Table 3. The experiment setup is the same as detailed in Section 6.2, and the model is not changed between runs, except for the fact that different modalities may have a different number of input channels.
Figure 16: Results from Pretrained keypoint detection models. From top to bottom - predictions from RSN [12], MSPN[80], HigherHRNet [81], and HourglassAE[Net 82]. Results show that SOTA 2D body keypoint detection models fail to capture the body keypoints in the ConfLab dataset.

Figure 17: Results from (top) COCO pretrained Mask-RCNN model, (bottom) our ConfLab finetuned Mask-RCNN model.

Table 5: Effect of varying % frames from each camera at training on keypoint estimation.

| % of training samples | AP<sub>OKS</sub> |
|-----------------------|----------------|
| 1.6%                  | 29.0           |
| 3.2%                  | 35.9           |
| 8%                    | 39.0           |
| 16%                   | 44.5           |
| 100%                  | 45.3           |

Table 6: Effect of adding all frames from individual cameras to the training set on keypoint estimation.

| Train Camera          | # (training samples) | AP<sub>OKS</sub> |
|-----------------------|----------------------|----------------|
| cam 2                 | 34k                  | 8.6            |
| cam 2 + cam 4         | 69k                  | 31.1           |
| cam 2 + cam 4 + cam 8 | 112k                 | 45.3           |
Table 7: Keypoint estimation ablation with keypoints from different body sections: head and shoulders (5), + torso (9), + hips (11), + knees and feet (full 17).

| #Keypoints | AP$^{OKS}_{50}$ | AP$^{OKS}_{75}$ | AP$^{OKS}_{90}$ |
|------------|----------------|----------------|----------------|
| 5          | 26.6           | 7.1            | 1.4            |
| 9          | 26.5           | 6.9            | 2.0            |
| 11         | 35.8           | 9.5            | 2.2            |
| 17         | 45.3           | 13.5           | 3.3            |

Table 8: ROC AUC and accuracy for different sensor modalities from out 9-dof IMU in speaking status detection using the Minirocket classifier [62]. The number of channels in the corresponding modality is indicated in parentheses.

| Input Modality | AUC  | Accuracy |
|----------------|------|----------|
| Acceleration (3) | 0.813 | 0.768    |
| Gyroscope (3)    | 0.765 | 0.716    |
| Magnetometer (3) | 0.610 | 0.656    |
| Rotation vector (4) | 0.726 | 0.696    |
| All (13)         | 0.774 | 0.739    |

G Reproducibility Checklist

G.1 Person and Keypoints Detection

- Source code link: https://github.com/TUDelft-SPC-Lab/conflab
- Data used for training: 112k frames (1809k person instances).
- Pre-processing: See Section 4, Appendix E.1.
- How samples were allocated for train/val/test: cameras 2, 4, and 8 are selected for training. For hyperparameter tuning, camera 8 are held out for validation.
- Hyperparameter consideration: We considered learning rates (0.001/0.005/0.05/0.01), number of epochs (10/20/50/100), detection backbone (R50-FPN/R50-C4). Also see Appendix E.1
- Number of evaluation runs: 5
- How experiments were ran: See Section 6.1.
- Evaluation metrics: Average precision at different thresholds.
- Results: See Section 6.1 and Appendix F.1.
- Computing infrastructure used: All baseline experiments were ran on Nvidia V100 GPU (16GB) with IBM POWER9 Processor.

G.2 Speaking Status Detection

- Source code link: https://github.com/TUDelft-SPC-Lab/conflab
- Data used for training: 42884 windows (3 seconds), extracted from 48 participants’ wearable data and speaking status annotations
- Pre-processing: Data was windowed into 3-second segments (see Section 6.2). The source code includes this pre-processing step.
- How samples were allocated for train/val/test: 10-fold cross-validation at the subject level (48 subjects) to test generalization to unseen data subjects. The splits can be reproduced exactly using the source code.
- Hyperparameter considerations: For acceleration-based methods, we used default network hyper-parameters and architectures from their tsai implementation [83]. For the MS-G3D baseline [59], we used default hyperparameters from the authors’ implementation. For both, we determined the early stoppage point using a small subset (10%) of the training set.
- Number of evaluation runs: 1 run of 10-fold cross-validation
- How experiments were ran: For each fold, the early stoppage point was first determined using 10% of the training data as validation set and AUC as performance metric. The model at this stoppage point was then applied to the test set for evaluation.
- Evaluation metrics: Area under the ROC curve (AUC)
- Results: See Section 6.2
• Computing infrastructure used: Experiments were ran on a personal computer with GPU acceleration (NVidia RTX3080).

G.3 F-formation Detection

• Source code link: https://github.com/TUDelft-SPC-Lab/conflab

• Data used for training: Camera 6

• Pre-processing: See Section E.2 for data cleaning and feature extraction.

• How samples were allocated for train/val/test: samples from Camera 6 were used to select the best model parameters. The rest are for test (evaluation). However, we note that Table 4 shows averaged performance on all cameras to provide a holistic view of the F-formation detection performance on ConfLab.

• (Hyper)parameter considerations: Both baseline methods are not deep-learning based and model parameters are interpretable. For GTCG, the parameters are frustum length (275), frustum aperture (160), frustum samples (2000), and sigma for affinity matrix (0.6). For GCFF, the parameters are minimum description length (30000) and stride (70).

• Number of evaluation runs: 1

• How experiments were ran: A total of eight experiments were run for choosing the best parameters, and three for evaluation (for camera 2, 4, and 8). The parameters were chosen based on grid-search. For optimizing frustum length in GTCG, we searched over [170, 195, 220, 245, 275] with 275 being averaged interpersonal distance based on Camera 6. For optimizing stride $D$ in GCFF, we searched over [30, 50, 70].

• Evaluation metrics: F1

• Results: See Section 6.3

• Computing infrastructure used: The experiments were run on Linux-based cluster instances on CPU with Matlab 2018a.