Abstract

There has been significant progress in machine learning algorithms for human pose estimation that may provide immense value in rehabilitation and movement sciences. However, there remain several challenges to routine use of these tools for clinical practice and translational research, including: 1) high technical barrier to entry, 2) rapidly evolving space of algorithms, 3) challenging algorithmic interdependencies, and 4) complex data management requirements between these components. To mitigate these barriers, we developed a human pose estimation pipeline that facilitates running state-of-the-art algorithms on data acquired in clinical context. Our system allows for running different implementations of several classes of algorithms and handles their interdependencies easily. These algorithm classes include subject identification and tracking, 2D keypoint detection, 3D joint location estimation, and estimating the pose of body models. The system uses a database to manage videos, intermediate analyses, and data for computations at each stage. It also provides tools for data visualization, including generating video overlays that also obscure faces to enhance privacy. Our goal in this work is not to train new algorithms, but to advance the use of cutting-edge human pose estimation algorithms for clinical and translation research. We show that this tool facilitates analyzing large numbers of videos of human movement ranging from gait laboratories analyses, to clinic and therapy visits, to people in the community. We also highlight limitations of these algorithms when applied to clinical populations in a rehabilitation setting. Code for PosePipe can be found at https://github.com/peabody124/PosePipeline/.

Introduction

Accurate tracking of human movement is a critical prerequisite for movement science and rehabilitation research. The gold standard is a movement analysis lab where optical markers are tracked with high spatial and temporal precision in order to precisely reconstruct biomechanical movements. While this method is highly accurate, it requires significant expertise, is time consuming and expensive, and can only be performed in a lab with specialized equipment. Wearable sensors equipped with inertial measurement units can help track movement outside of the laboratory, but often require significant time for setup and calibration and are typically less accurate, as reconstructing the underlying biomechanics from sensor data is a challenging data processing problem1–3.

Deep learning-based approaches to human pose estimation (HPE) from video have advanced rapidly in recent years4 and show promise in enabling easy-to-use and precise movement analysis outside of a specialized laboratory setting. These approaches could be a key enabling technology for movement science and rehabilitation research. For example, it could enable more frequent and precise measurements of patient’s movement during recovery and enable longitudinal quantification of their movement impairments. This could allow better understanding of how movement impairments relate to functional abilities (i.e., ability to performing activities of daily living) and enable more sensitive clinical trials to improve them. A recent consensus paper on upper extremity rehabilitation after stroke highlighted the need for more routine kinematic measurements for this express purpose, while also pointing out this is impeded by the lack of easy to use measurement tools5.
Despite recent advancements, there are still numerous barriers that prevent video-based human pose estimation from fulfilling this goal for rehabilitation and movement science\(^6\). Among these barriers are: 1) there is a high technical barrier to using many state-of-the-art algorithms; 2) these algorithms are rapidly evolving; 3) many of the algorithms have interdependencies; 4) they require a significant amount of data management; 5) the accuracy of many of these algorithms have not been validated on clinical populations\(^7,8\); and 6) many algorithms do not produce clinically pertinent outputs. Here, we will briefly review some of the classes of algorithms for HPE before demonstrating how our work on PosePipe reduces barriers 1-4 listed above. We also highlight some issues that occur when these algorithms are tested on clinical populations, which relates to barrier 5, but we defer quantitative analyses of this and work on barrier 6 to future work.

**Types of HPE Algorithms**

The field of human pose estimation from computer vision is large and growing rapidly, and we refer interested readers to recent in-depth reviews on the topic for additional details\(^3,9-11\). Here, we will provide a brief high-level overview of some common classes of algorithms and taxonomic categories used in our framework and how these interact.

HPE algorithms either process all people in a frame (bottom-up approaches), or analyze a single person (top-down approaches). One bottom-up approach utilized in numerous clinical studies (e.g.\(^12-15\)) is OpenPose\(^16\). OpenPose locates keypoints in the image (e.g. joint locations, finger keypoints and some facial keypoints) for all people in the scene, and groups them by individuals. However, if multiple people are visible in a scene, then additional work is required to select the subject of interest. In contrast, top-down approaches require the person of interest to already be localized in each frame. For analyzing movement, it is critical to consistently and accurately localize that particular person throughout the video. Thus, the first step is running a tracking algorithm, and if there are multiple people, selecting the subject for analysis with subsequent algorithms. An additional benefit of top-down approaches are that the keypoint accuracy tends to exceed bottom-up approaches.

Top-down algorithms include a range of approaches with outputs that are either two- or three-dimensional. Two-dimensional algorithms localize a number of keypoints, such as the location of major joints in the image. A strength of 2D keypoint detection is that the algorithms are fairly mature and robust. However, to the best of our knowledge, there are no large-scale systematic evaluations of this robustness in clinical contexts or on patient populations. Therefore, it remains to be seen how well they will generalize to these situations.

Three-dimensional approaches include those that predict 3D joint locations, of which there are two common approaches. The first approach is “lifting” 2D keypoints into 3D coordinates\(^17,18\). Lifting algorithms are trained on datasets of paired 2D and 3D data and use the implicit prior distribution over body configurations learned from training data to resolve the inherent ambiguities involved in going from 2D to 3D. The second approach estimates the parameters of a body model, such as the Skinned Multi-Person Linear Model (SMPL) model\(^19\), including body shape and pose. Frequently, a neural network is trained to directly predict these parameters from an image or video\(^20-22\). While these approaches provide a rich description of the joint angles and body shape, 3D accuracy often lags behind lifting approaches (e.g.\(^23\)). Optimization based approaches can refine model fitting, but are much slower than regression approaches\(^24,25\). The representation of pose is less sensitive to the perspective the video was recorded from in 3D approaches, which provides a unique advantage. However, none of these 3D approaches produce the joint angle representations recommended by the International Standard of Biomechanics\(^26,27\), although we have previously shown that the SMPL parameters for the arm can be converted to this format\(^28\).

**Overview of our approach**

Utilizing the evolving landscape of HPE tools, particularly when managing large numbers of videos, presents several barriers. The first is managing the dependencies between algorithms. For example, the bounding boxes from tracking algorithms are used in top-down 2D keypoint detection. The 2D keypoints sequences over time from a person are then used by lifting algorithms to generate 3D keypoint trajectories. There is no standardization over the formats of these datatypes, so typically additional processing or reformatting is required to use the output of one algorithm as input to another. A second challenge is managing data from different processing stages and running them through a pipeline when analyzing large sets of videos. Further, for each class of algorithm, there are numerous different versions that have been released with limited validation in clinical populations, making it hard a priori to determine the optimal combination of algorithms for a particular question. Thus, it is important to have flexible pipelines that allow analyzing videos using different algorithms, a task which is made additionally difficult due to the lack of consistency in data formats.
To facilitate HPE use in rehabilitation research and movement science, we have developed an open-source tool that addresses and minimizes these barriers. Video processing pipelines are created using DataJoint\textsuperscript{29}, which builds computational pipelines by managing all videos and outputs in a MySQL database, and manages dependencies between computations. We wrote wrappers for specific implementations of the algorithm classes previously described (bounding box tracking, 2d keypoints, lifting, and SMPL) that store data in DataJoint using a standardized format for each step. This standardization makes it easier to create a pipeline using any particular set of implementations. Using newly developed algorithms on data is also simplified in our method, as it only requires implementing a new wrapper that uses the consistent format, rather than creating a complete pipeline from scratch. This approach also allows mixing algorithms implemented in different frameworks (e.g. Jax, TensorFlow and PyTorch). DataJoint also provides a job management system that allows parallel computation across multiple GPUs or multiple computers with minimal overhead and no code changes. Finally, PosePipe makes it easy to visualize the outputs, which is essential when testing HPE algorithms on clinical populations. We have used this pipeline to analyze 10s of thousands of videos acquired in clinical settings, something only possible due to PosePipe.

Having HPE results in DataJoint provides additional benefits, as it is a very effective general data analysis tool with wide adoption in the neuroscience community\textsuperscript{30,31}. By associating videos with experiment-specific, DataJoint schemas, subsequent analysis becomes much easier (e.g., plotting longitudinal summary statistics from subjects can be done with only a few lines). A central database is also beneficial because multiple researchers on separate computers can easily collaborate and access the same data with a consistent organization and processing system. Code for PosePipe can be found at https://github.com/peabody124/PosePipeline/.

Contributions

In short, our contributions in this work are:

- We describe and release PosePipe, a DataJoint based pipeline for HPE that facilitates large scale analysis of videos acquired in a clinical context.
- We provide wrappers to several state-of-the-art algorithms for HPE including for bounding box tracking, 2D keypoint estimation, 3D lifting, and estimating SMPL meshes. Implementing wrappers for newly released algorithms is substantially easier than creating custom pipelines to test algorithms.
- We describe the pros and cons of different algorithm types and implementations and give examples of the types of errors that occur when using these algorithms on clinical populations.

Methods

PosePipe is written in Python and uses DataJoint\textsuperscript{29} for data and computation management. We briefly highlight several pertinent details of DataJoint that are important for understanding PosePipe, but refer to the documentation for details. Under the DataJoint model, Python classes that inherit from DataJoint base classes have a corresponding table in a database. DataJoint classes can be of several types including: Manual, Lookup, and Computed. As names suggest, Manual corresponds to rows manually entered into the database (e.g. by uploading videos), Lookup corresponds to a lookup table and is commonly used to indicate specific computation types, and Computed are tables computed based on existing parent data in the database. When required inputs are available, dependent rows in the database are automatically computed (or populated) with the populate method on a Computed table, which can also be performed for many entries in parallel using the job management system built into DataJoint.

The relationship between the classes (i.e., tables) must correspond to a directed acyclic diagram (DAG) and is described in the Python class definitions and is enforced in the database through foreign key constraints. This ensures data integrity; for example, a row can only exist if the required rows in parent tables also exist. Individual rows are identified in the database by primary keys, which are a set of fields that must be unique. Child tables inherit the primary keys of their parents (with the foreign key constraint) and can extend the primary key with additional fields, which allows multiple descendent rows (e.g., when using different specific algorithms or analyzing multiple subjects of interest in a video).

The core classes (tables) for PosePipe and dependencies are diagramed in Fig. 1, which illustrates the structure previously described, such as 2D keypoints depending on bounding box calculations and 3D lifting keypoints depending on 2D keypoints. We also illustrate examples of these outputs.

PosePipe Stages

Video importing Rows in the Video table Fig. 1 correspond to individual videos imported into PosePipe. PosePipe provides optional scripts to recompress videos with a consistent codec to ensure that downstream
analyses can read them. The primary keys for videos are two strings: one for the filename and one for a project name. The latter prevents potential name collisions for identically named videos from two projects, and also makes it easy to restrict analysis to videos from a particular project.

Because storing large files such as videos in a database can result in poor performance, we use the DataJoint attach type to store the videos externally on the filesystem. When retrieving a video from the database, it is copied to the current working directory and the checksum is validated against the original video checksum to ensure data integrity. This design enables additional, more granular, access control to the raw videos by controlling which users have filesystem permissions to access the external video storage. This is a necessary and important feature when working with clinical data where wider access might be granted to the extracted movement trajectories stored in the database compared to the raw videos that contain identifiable information, such as faces. In a situation where multiple computers need to access the raw videos, it does introduce an additional step of ensuring the same directory is shared and available on all of the computers.

Subject of Interest Identification  Frequently, multiple people are visible in videos (i.e., patient, physical therapist, and background individuals), but it is only necessary to perform HPE on one or some of them. The most common solution to this challenge are algorithms which first identify all individuals in a frame by computing a bounding box that surrounds the individual, followed by grouping the bounding boxes over time into tracklets. These tracklets often cannot be used immediately. For example, if there are multiple tracklets (for different people), it is first necessary to identify which corresponds to the person of interest. In some cases, the tracklets may also have two types of problems: splitting or swapping.

In the case of splitting, the subject of interest is represented by multiple tracklets at different points of times, sometimes with a gap. This can occur because the subject was briefly occluded and the algorithm failed to reidentify them when they reappeared. In other cases, it can occur spontaneously due to a failure of the algorithm to detect people. These separate tracklets can be manually linked to allow consistent tracking throughout the video, provided any gaps are not too long. Swapping indicates that a single tracklet contains two different people at different time points. In this case the tracklet cannot be used without contaminating subsequent analyses. If the video contains additional uncontaminated tracklets at different time points, these can be used without issue, but the subject of interest will only be tracked for a subset of the video. The video can also be reanalyzed with a different algorithm, which normally show different idiosyncrasies.

In Figure 1, TrackingBboxMethodLookup, TrackingBboxMethod, TrackingBbox, PersonBboxValid, and PersonBbox are pipeline classes (and tables) used to track and annotate the subject of interest.
TrackingBboxMethodLookup is a simple lookup table that enumerates the implemented algorithms. TrackingBboxMethod are manually entered rows that specify which algorithms to compute on which videos. TrackingBbox is a computed class that calls the wrapper for the selected algorithm indicated by the TrackingBboxMethod entries with the specific video. We use this design pattern throughout PosePipe and it is shown in Lst 1. Wrappers must produce the bounding boxes tracklets in a standardized format, which often takes minimal manipulation from output of the released implementations. It is a list with entries for each frame and each entry is itself a list of dictionaries. Each element in the dictionary contains the tracklet ID, the bounding box coordinates and dimensions, and the confidence the algorithm assigned to identifying the person in that frame.

PosePipe provides wrappers for several algorithms. This includes MMTrack\textsuperscript{32}, which provides a consistent API to several trackers and is under active development. It also includes the released implementations of DeepSort\textsuperscript{33}, FairMOT\textsuperscript{34}, TraDeS\textsuperscript{35}, TransTrack\textsuperscript{36}. We implemented several tracking algorithms into our pipeline because the optimal tracking algorithm for rehabilitation subjects is an open question. Some algorithms seem to generalize poorly to rehabilitation subjects and poor tracking precludes any subsequent analysis.

**Listing 1** TrackingBbox Listing. This shows a standard DataJoint design pattern used throughout PosePipe to allow selecting specific algorithm implementations.

```python
class TrackingBbox(dj.Computed):
    definition = """"
    -> TrackingBboxMethod
    ---
    tracks : longblob
    num_tracks : int
    ""

    def make(self, key):
        video = Video.get_robust_reader(key, return_cap=False)

        if (TrackingBboxMethodLookup & key).fetch1('tracking_method_name') in 'MMTrack_traktor':
            from pose_pipeline.wrappers.mmtrack import mmtrack_bounding_boxes
            tracks = mmtrack_bounding_boxes(video, 'traktor')
            key['tracks'] = tracks
        elif (TrackingBboxMethodLookup & key).fetch1('tracking_method_name') == 'MMTrack_deepsort':
            from pose_pipeline.wrappers.mmtrack import mmtrack_bounding_boxes
            tracks = mmtrack_bounding_boxes(video, 'deepsort')
            key['tracks'] = tracks
        elif (TrackingBboxMethodLookup & key).fetch1('tracking_method_name') == 'MMTrack_bytetrack':
            from pose_pipeline.wrappers.mmtrack import mmtrack_bounding_boxes
            tracks = mmtrack_bounding_boxes(video, 'bytetrack')
            key['tracks'] = tracks
        else:
            os.remove(video)
            raise Exception(f"Unsupported tracking method: {key['tracking_method']}")

        track_ids = np.unique([t['track_id'] for track in tracks for t in track])
        key['num_tracks'] = len(track_ids)

        self.insert1(key)

        # remove the downloaded video to avoid clutter
        if os.path.exists(video):
            os.remove(video)
```

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After computing the tracklets, the next step is manual annotation of the subject of interest. If there is only a single tracklet for the whole video, it can be automatically selected. However, when there are multiple tracklets, experimenter input is needed to properly identify the one containing the subject of interest. We implemented a simple GUI Fig. 2 that runs in a Jupyter Notebook and shows the video with the tracklets overlaid (discussed more below). This allows the user to select one of multiple tracklets that reflect the subject of interest. This information is stored as rows in PersonBboxValid with a subject ID. In most cases, we use a subject ID of 0 to indicate the primary subject of interest or a subject ID of -1 if the video was invalid for subsequent analysis (i.e., identity swaps or missed detection). However, this field could also reflect unique subject IDs if using PosePipe alone to study multiple individuals without additional experiment-specific DataJoint schemas, as discussed more below. By having multiple PersonBboxValid entries per video with different subject IDs, it is possible to track multiple subjects in a video, such as for analyzing interaction between patients and therapists. Based on this information, the PersonBbox rows is populated and contains the validated tracklets for individuals used for subsequent top-down algorithms.

Figure 2: Screenshot from GUI for annotation. Bounding boxes of tracklets are shown with their identities, allowing the experimenter to efficiently annotate the tracklets corresponding to the subject of interest.

2D Keypoint Detection Computing 2D keypoints using top-down algorithms depends on the PersonBbox computed in the prior section and follows a similar design pattern Fig. 1. The supported list of 2D keypoint algorithms are enumerated in the TopDownMethodLookup table and the user selects specific algorithms to run by manually inserting the corresponding rows into the TopDownMethod table. Populating TopDownMethod runs a similar function as Lst 1, where the selected algorithm determines which wrapper is called. In each case, the wrappers use the video and bounding box for each frame to extract a cropped portion of each image with the subject of interest centered that will be passed to top down algorithms. The output from the wrappers are a 3D array of dimension frames × num joints × 3, where the last dimension has the keypoint x and y coordinates and confidence estimates for each keypoint. For any frame where there is no bounding box detected for the subject of interest, the returned elements are NaN. For 2D keypoint detection, we used the MMPose Toolbox, which provides a wide range of state-of-the-art neural network architectures pretrained on multiple datasets.

3D Keypoint Lifting The sequence of 2D keypoints can be ‘lifted’ to 3D with a number of algorithms that have been trained on datasets of paired 2D-3D data in order to resolve the ambiguity of the 2D observations and to constrain the results to plausible 3-dimensional body configurations. Again, the same design pattern is used with LiftingMethodLookup containing the list of supported lifting methods and manually inserted rows in LiftingMethod indicating which files and methods the user would like to fill in when populating LiftingPerson. Wrapper functions take the 2D keypoint array output from the previous step and transform this into a 3D keypoint sequence with dimension frames × num joints × 3, where the last dimensions are the x, y and z coordinates (lifting methods typically do not produce a confidence estimate for each joint). We implemented a wrapper for GAST-Net, which lifts a sliding windows of 27 frames into 3D joint locations.
**SMPL Fitting** The SMPL body model is parameterized with 10 parameters to describe the body shape and the rotation at 23 joints, each of which has 3 degrees of freedom. There are an additional 6 degrees of freedom to capture the overall body rotation and position. It is worth noting that this is over-parameterized compared to the typical human body. For example, a real knee and elbow do not have 3 degrees of freedom. The SMPL-X model is an extension of SMPL with more degrees of freedom in the hands and face to more expressively capture human movement.

PosePipe implements this class of algorithms with the same design pattern used above: the **SMPLMethodLookup** table lists the specific algorithms supported to estimate the parameters, **SMPLMethod** is manually inserted into the database to indicate that the user wants to analyze a particular video with a particular algorithm, and **SMPLPerson** is populated using the bounding box information and video to estimate the parameters using the selected algorithms. Wrappers for various algorithms that estimate SMPL or SMPL-X parameters are implemented, which use a similar approach to the 2D keypoints by passing the cropped frames from the video to the selected algorithms. The returned values from the wrappers include the model type, body shape as a function of time, body pose as a function of time, the 3D keypoint positions and 2D keypoints after reprojecting the 3D keypoints into the image via the camera model, and the camera model used during video acquisition. Different algorithms use inconsistent rotation representation (e.g., rotation vectors passed through the Rodriguez equation, quaternion rotations, rotation matrices, and 6D representations), which are standardized by the wrappers to a rotation vector. Additionally, the mathematical representation of the camera model varies between algorithms from a weak perspective model (e.g., HMR) to a full camera model (e.g.,), which is relevant because this can change the accuracy of the ultimate inference and when producing the visualizations described below.

We implemented wrappers for several recent state-of-the-art SMPL or SMPL-X parameter inference algorithms. VIBE processes video sequences rather than individual frames to estimate SMPL trajectories. PARE uses an attentional mechanism to improve alignment between body segments in the image and the body model reconstruction, although processes frames independently. Expose and a recent successor PIXIE produces individual frames to estimate parameters of an SMPL-X model, which enables tracking finer scale changes like finger movements and facial expression. PIXIE uses a similar attentional mechanism with an SMPL-X model to improve the accuracy of hand tracking over Expose. ProHMR produces a probability distribution over body poses for each frame which can be fine-tuned based on the alignment to 2D keypoint estimates, producing accurate fits at the expense of computation time. Finally, HuMoR takes an alternative approach by optimizing the body model parameter trajectory over time to accurately match the detected 2D keypoints. We implemented this many algorithms because the field is advancing incredibly rapidly and different approach have different strengths and might be appropriate depending on the question.

**Visualization**

Visualizing the output of different stages in the pipeline is critical to identify failure modes and ensure these algorithms generalize reliably to clinical populations. Because PosePipe is also designed for data collected in clinical settings, a default behavior to preserve privacy — such as obscuring faces — is an important feature. OpenPose is a popular and efficient bottom-up HPE algorithm that detects keypoints, including facial ones, for all people in a frame. Populating the OpenPose table computes these keypoints for all videos and allows populating the BlurredVideo table, which places a circle over all faces detected by OpenPose. Like the Video table, the video files from all visualizations are stored in external storage. The BlurredVideo is then used to create overlays from other algorithms such as computing TrackingBboxVideo, which show all of the tracklets and are used for manual annotation. The TopDownPersonVideo to show the bounding box for the person of interest along with the detected 2D keypoints, or SMPLPersonVideo to show the estimated body mesh shape overlaid on the video. The visualizations are implemented with a consistent API that only needs to be provided a callback that takes in the individual frame and frame index and then overlays the desired information. This tool is also useful when producing visualizations with additional analyses to estimate clinically relevant parameters, for example gait event timing. It is also worth noting in the PosePipe data schema that the HPE algorithms results do not depend on the visualizations, so they can be not computed or deleted if space is a concern.

**Organization of algorithms and weights**

There are several additional challenges to using multiple released algorithms. Firstly, the code is often architectured primarily for evaluating performance on one or several datasets, and not for being called from other software like a typical library. This includes the challenge that multiple implementations may use identical directory names, which can prevent Python from correctly identifying them if all are added to the same path. Many algorithms also have a large number of parameters that must be configured and passed into the script from the command line, which further hinders calling them from external tools. Secondly, deep
learning algorithms are only partially specified by their code and also require the weights determined after training algorithms. These are often not distributed directly with the source code and must be downloaded separately. In general, both the code and weights cannot be universally distributed as a monolithic bundle as they may have license requirements that must be respected. For example, one must register and agree to the license to download the weights for the SMPL/SMPL-X body models.

PosePipe reduces these challenges through two approaches. First, the user configures PosePipe with a list of paths where each of the algorithms has been downloaded locally. PosePipe then transiently adds the specific algorithm to the path when running it and removes it when complete. This prevents any namespace collision that would occur if all algorithms were added to the path at once. To handle the weights, the user must download them to a subdirectory in the PosePipe installation (named 3rdparty). The wrappers specify the path within the subdirectory and pass them to the initialized models, which avoids having to follow algorithm-specific installation instructions for weights. Finally, the wrappers also provide the list of configuration options compatible with those weights and avoid the need for passing command line parameters to external scripts.

Running the pipeline
The components described make up stages in a particular pipeline for analyzing videos for HPE. An example of a common pipeline might look like: 1) import videos, 2) run bounding box detection, 3) annotate subject of interest, 4) run 2D keypoints detection, 5) run 3D keypoint detection, 6) produce visualization. A specific pipeline can be implemented using PosePipe with a short script, as shown in Lst. We refer readers to the DataJoint documentation for details about the syntax. In this example, videos are imported directly from a source directory. In most of our use of PosePipe, videos to be analyzed have additional information pertaining to the experimental question and we use additional DataJoint schemas to organize the videos as part of the video import step. This script can easily be modified to run in parallel on multiple GPUs by simply adding reserve=True to the parameter of each populate method.

Results
In our work, we found PosePipe is an effective tool for analyzing tens of thousands of videos acquired in clinical settings. It greatly reduces the barriers to testing emerging state-of-the-art algorithms for use in HPE, as this can be done by only writing the wrapper to the novel algorithms rather than creating de novo pipelines between all the requisite components. By storing the final outputs in DataJoint with an associated experiment-specific schema, PosePipe makes subsequent analysis for clinical variables of interest significantly easier. Because this manuscript is primarily to introduce and describe PosePipe, we will show some sample outputs, including errors, and note some qualitative trends. However, we do not attempt a quantitative analysis comparing specific algorithms.

Subject tracking In most videos, especially videos with an unobstructed view of the whole person throughout, we found that bounding box estimation produced a single tracklet that uniquely mapped to the subject of interest. However, several types of error were also noted Fig. 3. The most problematic type of error was when the tracklet swaps from tracking the person of interest to another person. This is particularly common when a subject and therapist are working closely together, and one briefly occludes the other. In these cases, unless it is a brief tracklet that can simply be discarded, we typically mark the tracking output as invalid and process the video with a different algorithm. As different algorithms have different idiosyncrasies this usually produces a usable output. For videos where the subject is briefly occluded, multiple tracklets are sometimes produced, but the annotation GUI allows stitching these together. In rare cases, people would fail to be detected despite being clearly visible. This seems to occur most commonly with assistive devices, especially children with assistive devices, and was more pronounced when using FairMOT. Related to this, when people are sitting in wheelchairs, they are less likely to be detected or the bounding box may only include the upper torso (example shown in Fig. 4). From these error observations, our typical initial tracking algorithm is DeepSort as it quite reliably detects people and tracks them smoothly.

Top Down 2D Keypoint Detection For top down 2D keypoint detection, we use two pretrained algorithms from the MMPose Toolbox. One algorithm detects the main body joints and several facial keypoints, which uses an HRNet architecture and a distribution-aware coordinate representation trained on the COCO keypoints (ankles, knees, hips, shoulders, elbows, wrists, eyes, ears and nose). The other uses the same architecture but is trained on the COCO-WholeBody dataset, which includes 68 facial keypoints and 42 on the hands to produce much more fine-grained tracking. We noted that people interacting closely also can introduce errors at this step. These algorithms are fairly reliable, provided the bounding box was detected accurately and the joint is not visually obscured. However, errors do occur when limbs appear
Listing 2 Example pipeline that produces an example from each of the algorithm classes.

```python
# insert videos into database
video_path = '/path/to/files'
videos_files = os.listdir(video_path)
for v in videos_files:
    insert_local_video(v, os.path.join(video_path, v), video_project='PROJECT_NAME')

# run tracking algorithms
keys = (Video - TrackingBboxMethod).fetch('KEY')  # find videos without bounding boxes computed
tracking_method = (TrackingBboxMethodLookup & 'tracking_method_name'='MMTrack').fetch1('tracking_method')
TrackBboxMethod.insert([k.update({'tracking_method': tracking_method}) for k in keys])
TrackingBbox.populate()  # compute all of the tracking boxes

# prepare blurred video for overlays
OpenPose.populate()
BlurredVideo.populate()

# annotate videos
TrackingBboxVideo.populate()

### run annotation GUI here, or automatically compute if only one person is in videos ###

PersonBox.populate()  # and compute the final bounding box for subjects of interest

# compute 2D keypoints on videos
keys = (PersonBox - TopDownMethod).fetch('KEY')  # find videos without top down method selected
top_down_method = (TopDownMethodLookup & 'top_down_method_name'='MMPose').fetch1('top_down_method')
TopDownMethod.insert([k.update({'top_down_method': top_down_method}) for k in keys])
TopDownPerson.populate()  # analyze videos using selected algorithm

# find videos waiting to be processed with lifting algorithm and run them
keys = (PersonBox - LiftingPersonMethod).fetch('KEY')  # find videos waiting to be processed with lifting algorithm and run them
lifting_method = (LiftingMethodLookup & 'lifting_method_name'='GastNet').fetch1('lifting_method')
LiftingPersonMethod.insert([k.update({'lifting_method': lifting_method}) for k in keys])
LiftingPerson.populate()  # analyze videos using selected algorithm

# find videos waiting to be processed with SMPL algorithm
keys = (PersonBox - SMPLPersonMethod).fetch('KEY')  # find videos waiting to be processed with SMPL algorithm
smpl_method = (TopDownMethodLookup & 'top_down_method_name'='VIBE').fetch1('top_down_method')
SMPLPersonMethod.insert([k.update({'smpl_method': smpl_method}) for k in keys])
SMPLPerson.populate()  # analyze videos using selected algorithm

# produce visualizations
TopDownPersonVideo.populate()
LiftingPersonVideo.populate()
SMPLPeronVideopopulate()
```

different than able bodied adults, such as thin limbs wearing braces or some prosthetic users. In these cases, a custom model can be trained with DeepLabCut\(^{48,49}\), which allows manually annotating the location of prosthetic joints. A custom algorithm can be created and entered in TopDownPersonLookup and can then be used to combine the keypoints from MMPose of the intact joints with the prosthetic joint locations from DeepLabCut. Examples of these algorithms and examples of errors are shown in Fig. 4.

**3D Keypoint Lifting.** GAST-Net\(^{23}\) produces realistic appearing 3D keypoint trajectories, provided the bounding box and 2D keypoints were visible and detected accurately. These trajectories are also quite smooth, likely due to the combination of information over multiple frames. However, because of the scale ambiguity from pure 2D keypoints, the joint locations are only relative and do not scale to the individual. Example
PosePipe: Open-Source Human Pose Estimation Pipeline for Clinical Research

Figure 3: Samples frames analyzed with different tracking algorithms. A-C) Show an identity swap occurring after a brief obstruction. D and E) are processed with FairMOT and shows how in some frames where the subject of interest is not detected and false positives from the walker wheels. F and G) analyze the same video without showing those errors.

Fig. 5 shows an example stick figure reconstruction of a subject walking, clearly showing the concordance between the frames and body positions.

**SMPL Fitting** Estimating SMPL parameters produced mixed results. In many cases, the results were promising, but sometimes contained notable examples of brittleness (i.e., sensitivity to irrelevant features) Fig. 6. For example, with VIBE\(^2\) we noted instances where the presence of assistive device caused significant errors. PARE\(^3\) makes estimation of body models more robust to occlusion through an attentional mechanism, and seemed to reduce this sensitivity. Expose\(^4\) and PIXIE\(^5\) uses the SMPL-X model and estimates parameters for the shape of the hand. PIXIE is more recent and produces more consistent results, although both outputs contain high frequency jitter in the details and particularly struggled when the video contained motion blur artifacts or additional hands nearby. Another approach that improves the alignment of the mesh output with limbs in the image is ProHMR\(^6\). It infers a probability distribution over poses for each frame which can be combined with the robustly estimated 2D keypoints to compute optimized SMPL parameters that are consistent with both the image and keypoints. This has the benefits of capturing nuance that is not contained in the 2D keypoint location of major body joints (e.g., wrist supination and pronation), while reducing gratuitous errors. However, the additional optimization step takes several seconds per frame, making analyzing many videos with this algorithm very time consuming. It also analyzes individual frames independently, so can contain jitter. HuMoR\(^7\) is another algorithm that uses an optimization approach to 2D keypoints and specifically optimizes a trajectory over time. The outputs from HuMoR are very smooth.
and well aligned to the body, although in rare cases it fails to converge to a good solution. It also can take multiple hours to optimize the pose trajectory for a video.

**Experiment-specific schema**  The pipeline can be easily used with experiment specific DataJoint schemas that help perform and organize subsequent analyses Fig. 7. In this example case shown, the **Subject** table contains rows with information for each subject, and the **Activity** table contains rows for each activity they performed and is linked to entries in the **Video** table. SMPL trajectories are computed using the pipeline we have described and stored in **SMPLPerson**. The **FtnStatistics** and **RamStatistics** classes compute summary statistics of specific activities (in this case performing finger to nose movements or rapid alternating movements). The link to the **Activity** table ensures the specific analysis are only performed on appropriate activities and makes it easy to retrieve the right data. For example to retrieve the frequency of movement at different time points for an individual, it is as simple as:

```python
    timepoints, frequency = (FtnStatistics & 'subject_id=5') \
    .fetch('timepoints', 'frequency')
```

**Discussion**

We developed PosePipe as a simplified, easy to use method for HPE analysis on large volumes of videos acquired in clinical situations. We find this system makes it much easier to test and compare different algorithms on videos within a consistent framework. This comes from using DataJoint as the framework for PosePipe, which stores the results of each stage of the HPE pipeline in a database while managing all of
PosePipe: Open-Source Human Pose Estimation Pipeline for Clinical Research

Figure 5: A-C) Several frames of someone walking with bounding box and 2D keypoints that correspond to the beginning, middle and end of the trajectory shown below. D) The 3D skeleton trajectory lifted using GAST-Net showing the gait cycle. Note that the skeleton appears accurate, despite being viewed orthogonally to the camera perspective. Red corresponds to the left side and blue the right.

The accuracy of the outputs from PosePipe depends upon the accuracy of specific implementations and their performance when combined. Our goal with this work is very intentionally not to produce or train a state-of-the-art algorithm, but to build a tool that advances the use of new HPE algorithms for clinical and translation research, with a particular focus on rehabilitation. A systematic evaluation of the accuracy of specific components applied to clinical populations, while extremely important, is outside the scope of this work. However, our qualitative results offer several tips and warnings for using various HPE algorithms for clinical and translation research. Our broadest and most strongly recommended tip is the importance of rendering and reviewing the visualizations of different algorithms, rather than blithely trusting the outputs. While HPE tools are advancing rapidly, they are still not completely reliable; this is particularly true when they are applied to clinical populations that may be systematically different from the data the algorithms were trained on.

Subject tracking For tracking algorithms, identity swaps of the tracklets are most common when two individuals are in close proximity (e.g., patient and therapist) and can render the output unusable in some cases. Frequently, reprocessing a video with identity swaps with a different algorithm produces a better result. Fragmented tracklets are a lesser problem, but these increase the time needed to manually annotate the subject of interest in videos and are an obstacle to high throughput, fully automated approaches. Detection gaps commonly occur when an individual is transiently not detected, either due to occlusion or because of an algorithm error. These failures to detect seem to occur more frequently when people use an assistive device and this was particularly notable with FairMOT\textsuperscript{34}. Further, the use of a wheelchair sometimes results in bounding boxes that miss the subject’s legs. Whether one algorithm is consistently the most reliable for rehabilitation patients remains an open question. Our current impression is that each algorithm has different idiosyncrasies. However, we are optimistic that the continual advances in tracking for HPE will continue to
Figure 6: Examples estimating SMPL/SMPL_X meshes. A,B) Two frames processed with VIBE showing confusion about the direction of the subject. C) In comparison, PARE did not have this error and more accurately aligned with the limbs. D) PIXIE can capture detail hand gestures, such as a thumbs up. E,F) Both VIBE and PIXIE do not always capture the leg placement properly, although the later still captures fine hand movements. G) ProHMR can improve the alignment of the mesh joints with the image. H) HuMoR shows particularly good tracking of the joints with smooth trajectories.

Figure 7: Examples of an experiment specific schema. The complete PosePipe diagram from Fig 1 is abstracted into the blue box and additional nodes indicate the data organization for a particular experiment.
lessen this problem (e.g.\textsuperscript{50,51}), with the caveat that underrepresentation of people with disabilities in the publicly available training datasets may bound the performance when they are applied for those who might benefit the most from this technology.

**Top down 2D keypoints** For 2D keypoint detection, we used the MMPose toolbox\textsuperscript{37}, which offers many benefits including a standardized API to use multiple different cutting-edge architectures trained on a range of datasets and the fact it is actively maintained, with new algorithms routinely added. In our results, we have primarily utilized their implementation of a HRNet trained on the COCO body keypoints (ankles, knees, hips, shoulders, elbows, wrists, eyes, ears and nose)\textsuperscript{46} and find this generally works quite well for most cases tested. It primarily fails when tested on people with limbs that do not resemble an intact limb of an able-bodied person, such as amputees using a prosthetic device and particularly for people with more proximal or bilateral amputations. In this case, the visual difference between a prosthetic and intact limb makes it unlikely that any contemporary algorithm trained on able-bodied data alone will succeed in this task, because the neural networks trained to solve this task are designed to recognize relatively low level visual properties rather than reason about the functional homology of a prosthetic and intact limb. As such, we found it was occasionally necessary to use a tool like DeepLabCut\textsuperscript{48,49}, which allows training a custom detection algorithm after manually annotating prosthetic joints in some videos. We have previously found this is also required when videos do not include the upper torso of people\textsuperscript{52}. In general, we see 2D keypoint trajectories an impoverished representation for the true 3D biomechanical movement a subject performs in the world. This is unfortunate as they are some of the most robust HPE algorithms available. In many works, these estimates are referred to as a 2D pose, but avoid this nomenclature as the true pose cannot be recovered directly from these estimates.

**Lifted 3D joint locations** When the 2D keypoints were accurately detected and the person was fully visible, the lifted 3D keypoint trajectories appeared accurate. It is worth noting that lifting algorithms are not calibrated to match the height of an individual, which is particularly relevant when analyzing the movements of children who will be scaled towards an adult. As mentioned, 3D joint locations cannot be recovered analytically from 2D keypoints. This is because any 3D location along an epipolar line from the camera would project to the same point in the image plane, creating a fundamental ambiguity. Lifting methods address this ambiguity by not just trying to find 3D points consistent with these epipolar lines, but also those consistent with plausible human configurations. Essentially, they learn a priori over poses from the training data. This raises the concern that they may exhibit biases when tested on people who move differently than the able-bodied population these algorithms were trained on, such as people with range of motion restrictions or people with dystonic cerebral palsy or other movement disorders.

**SMPL Methods** Algorithms that estimate parameters of body-models such as SMPL\textsuperscript{19} or SMPL-X\textsuperscript{25} are particularly promising as they provide an inference that is closer to the biomechanical understanding than 3D joint locations by finding the joint angles or pose that recreates the body configuration in the image. However, the SMPL/SMPL-X models were developed with a focus on realistic computer graphics and producing an accurate external body shape rather than with a detailed biomechanical focus, so there is not a 1:1 mapping from these parameters to the International Standard of Biomechanics recommended descriptions\textsuperscript{26,27}, although we have previously shown these can be computed from the SMPL parameters for the arm\textsuperscript{28}.

A limitation of these algorithms is they sometimes have significant errors, particularly in the presence of occlusions. Because of this, we find visualizing the outputs prior to using them is a critical step. More recent methods that include attentional mechanisms, like PARE\textsuperscript{39}, are more robust to occlusions. With the exception of VIBE\textsuperscript{22} and HuMoR\textsuperscript{43}, the methods we tested analyze frames independently which also results in increased jitter. Most also do not typically produce confidence estimates to know when they are accurate and can be trusted. An exception is ProHMR\textsuperscript{42} produces a probability distribution over poses that can be refined using detected keypoints. This produces very promising results for HPE analysis as it reduces these inconsistencies by optimizing the parameters to align the mesh to the keypoints, but the time to run this is quite limiting and it tends to have a fair amount of jitter between frames. Expose\textsuperscript{40} and PIXIE\textsuperscript{41} are useful for questions involving hand function with the later being more accurate in our experience, but these also tend to have some jitter that limits analyzing detailed hand trajectories. If expressive hand movement isn’t required, HuMoR\textsuperscript{43} produces excellent results that are very smooth, although the time required to optimize the trajectories can be prohibitive.

**Need for systematic evaluation** With the increasing use of deep learning systems in medicine, there is a concern that they function as a black box and the need for Explainable Artificial Intelligence (XAI) has been emphasized\textsuperscript{53,54}. XAI has multiple components and perspectives\textsuperscript{55}, with one notion being that intermediate
steps produce outputs that can be meaningfully interpreted and reviewed, as well as understanding the influence of those intermediate steps on the final output. The trajectory of a subject’s movement – regardless of the specific representation – is typically an input used to compute clinically pertinent metrics (e.g., gait cadence and deviation index\textsuperscript{53}, gait temporal parameters\textsuperscript{52}, or Parkinson’s Disease motor symptom severity\textsuperscript{56}). They also have the benefit of being very interpretable and can be easily checked with visualizations. Thus, to improve the explainability of these systems, it is critical to know how accurate the pose estimate inputs are and how that accuracy influences overall algorithm reliability.

Given the potential benefit of these algorithms for rehabilitation research and outcome measures, there is a substantial need for large-scale validation studies of these algorithms when applied to clinical populations. Quantitatively evaluating the accuracy of HPE algorithms on any clinical populations is challenging because there are few datasets that reflect real world use cases with ground truth annotation. These are challenging to collect because ground truth using optical motion tracking requires bringing subjects into a motion analysis laboratory. Advances in wearable sensors or pose estimation with multiple cameras could reduce this barrier while producing sufficiently accurate annotation.

Additionally, these validation studies are important for understanding how algorithmic fairness\textsuperscript{57–59} interacts with people with disabilities\textsuperscript{60}. For example, our observations that the use of assistive devices, such as a walker, seems to reduce the probability that a person (particularly a child) is detected or that in some cases prosthetic limbs are poorly tracked. One contribution to this type of bias may be the underrepresentation of people with disabilities in the datasets used to train the algorithms. It is also important to note that dataset bias is only one source of algorithmic bias. Because applying these algorithms to clinical populations may be the situation where they can provide the most societal benefit, it is critical to understand and address sources of any systematic errors.

**Facilitating analysis of HPE outputs**

PosePipe makes analysis of the HPE outputs for the primary research questions much easier. DataJoint provides an efficient mechanism to allow multiple users to easily access the outputs from multiple computers (if enabled) and benefits from all the development making MySQL highly performant. DataJoint provides a pythonic API to retrieve the specific data desired that maps to MySQL queries. For example, retrieving a SMPL pose trajectory for a specific video over a remote connection takes a negligible amount of time. This also avoids recurring challenges associated with using a file system for data organization. DataJoint allows granular user access controls, including assigning users read-only access to certain tables, which can prevent them from accidentally deleting raw data. Controlling access to the external data stores also determines who can or cannot view the raw videos and/or visualizations, which may help to restrict access to identifiable information.

In many cases, videos are collected with additional metadata and experimental information that is critical for subsequent analysis of the HPE results from those videos. In these cases, we recommend designing an experiment-specific DataJoint schema that organizes the videos accordingly and is used to insert them into PosePipe (as opposed to Lst 2 which imports them directly from a directory organized only by filename). Experiment-specific schemas provide a tremendous benefit. For example, there may be a table containing demographic or clinical information about subjects and another table that computes a clinically relevant feature from the 3D keypoints, such as walking speed. In this case, a one-line query can return the walking speed of a subject associated with their demographic data and the data of measurements in a Pandas dataframe\textsuperscript{61}. We defer further specific examples to subsequent manuscripts using outputs from PosePipe.

**Limitations**

In addition to limitations on accuracy from the individual components just discussed, PosePipe itself has several limitations. Setup requires several steps. These include setting up a DataJoint database, which is fairly straightforward using the provided Docker container. It also includes downloading the code and model weights for each of the algorithms the user wishes to apply to videos. Detailed installation instructions for all steps are provided in the PosePipe repository.

The facial blurring is an important default privacy-preserving feature, but is only as reliable as the face detection algorithm used (currently OpenPose). This makes additional manual review an important step before releasing any videos requiring anonymization.

The DataJoint model also introduces some friction when interacting with experiment-specific schemas. For example, videos may be conceptually organized as children of other tables, such as a table of experimental sessions which itself is a descendent from a table of clinical subjects with demographic information. However, when working with multiple experiments it is not possible for some Video rows to have a parent from one
experimental table and in other cases a different parent table. One future option is to adopt DataJoint Elements[62], which allows creating reusable pipelines that can be attached to different experimental tables.

**Future Directions**

Consistent with our goal to facilitate HPE in research, an important future step is to simplify the installation process. We envision doing so by developing a Docker container with all the required files for a minimal pipeline, including the DataJoint database and a minimal set of algorithms that could be distributed consistent with their licenses. This will likely heavily leverage implementations provided by MMPose[37] and MMTrack[32], which provide installable libraries and numerous competitive pretrained algorithms that can be accessed with a straightforward API.

Further, we hope to support new classes of algorithms that are becoming available. We are particularly excited about approaches that integrate physics-based biomechanical modeling to constrain estimates to more physically plausible ones while also inferring joint torques and ground reaction forces[66], although these will also require substantial amounts of validation. We also plan to include action recognition algorithms in future revisions[67].

Additionally, we will use PosePipe to perform systematic evaluations on the performance of specific algorithms on videos of rehabilitation subjects, as described above. The lack of appropriate datasets with ground truth annotation makes this task difficult, but does not preclude having human raters evaluate the quality of outputs, which would still allow quantitative comparison of different algorithms. We are currently developing tools to enable collection of simultaneous video and wearable sensor data and video data with multiple cameras, which can provide additional signals for both evaluation and training of algorithms on data acquired in the clinic[28,68].

Most importantly, we will use our PosePipe tool to further our ultimate goal: to develop clinically useful tools and outcome measures that can be used in wide ranging clinical contexts. High-quality HPE analysis, even if it produces near-perfect biomechanical understanding, will need additional analysis to produce clinically useful measures. As an example, when performing gait analysis, the first step is detecting the timing of gait events, such as foot contact and toe off, and then, after aligning the gait cycle, additional statistics can be computed and compared to normative datasets[69,70]. Thus, advancing the clinical utility of HPE will also require developing similar high-level clinical measures and validating the properties of these measures on clinical populations.

**Conclusion**

We introduce PosePipe, an open-source tool based on DataJoint that makes it easy to implement pipelines to analyze videos of human movement acquired in clinical situations using cutting-edge algorithms for human pose estimation. It supports several released implementations from different classes of algorithms including bounding box tracklet computation to track an individual in videos, top-down 2D keypoint estimation, lifting 2D keypoints to 3D joint locations, and estimating the parameters of SMPL/SMPL-X body models. We anticipate that this tool will facilitate the use of these algorithms in clinical and translational research for movement science and rehabilitation and help enable much needed systematic evaluation of their performance when tested on clinical populations.

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**Author Contribution**  RJC developed PosePipe, analyzed the videos used as examples in this work, and wrote the manuscript.

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