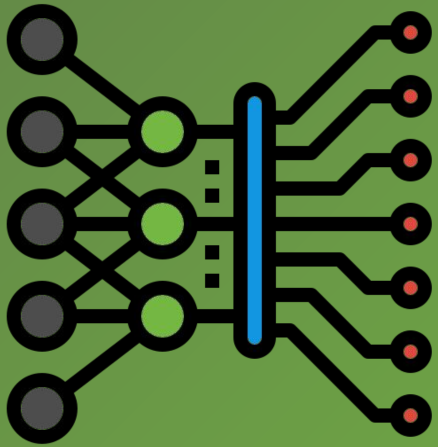
R & D Meeting
Project Report

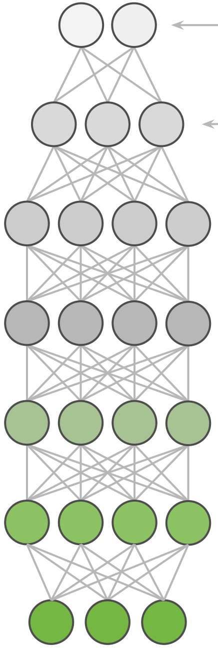


Detection of Out of Distribution Samples
in Human Motion Prediction Models

qualityminds

CONSTRUCTOR
LEARNING

Agenda



- Human Motion Prediction Applications
- QualityMinds Human Motion Prediction Project
- Objective: Data analysis and learning representation
- The Data we used
- Our Approach
- Key Results
- Outlook / Future Steps

qualityminds

CONSTRUCTOR LEARNING

About Us

Jonas Voßemer

Ph.D. Sociology

Alaa Elshorbagy

Ph.D. Mathematics

Vincent v. Zitzewitz

Industrial Engineer

CONSTRUCTOR LEARNING

Bootcamp: Data Science - Machine Learning, Deep Learning, Pandas, Numpy, Plotly, SQL, Keras, SciKit Learn, Git, Docker

qualityminds

CONSTRUCTOR LEARNING

HMP & QM Business Case

With Whom …

… we collaborated

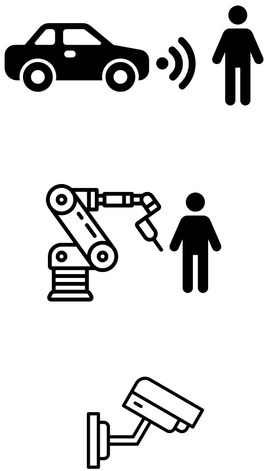
QualityMinds

- ➔ Agile **IT Consultancy**
- ➔ **Data Science** Branch
- ➔ **Project:** Human motion prediction for Autonomous Driving

qualityminds

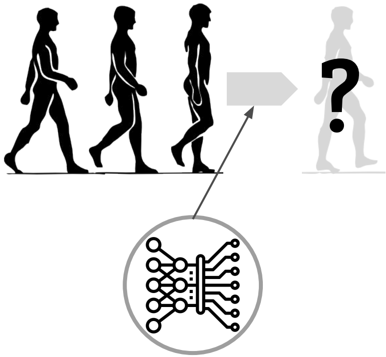
Why …

… Human Motion Prediction?



What …

… is Human Motion Prediction?

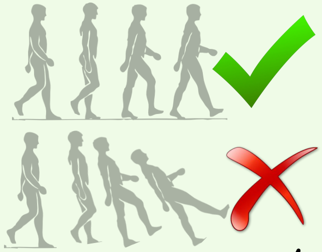


- ➔ **Example** scenarios: eating, walking, phoning

How …

… we improve Human Motion Prediction?

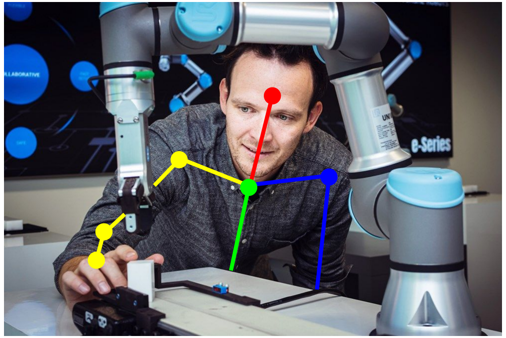
Our Task:

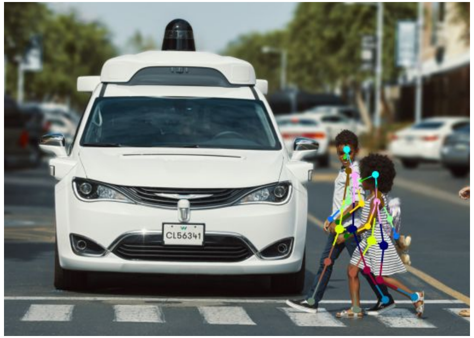


- ➔ Quantify **“Anomaly”**
- ➔ Unusual motions are **hard to predict**

qualityminds CONSTRUCTOR LEARNING

Human Motion Prediction Applications

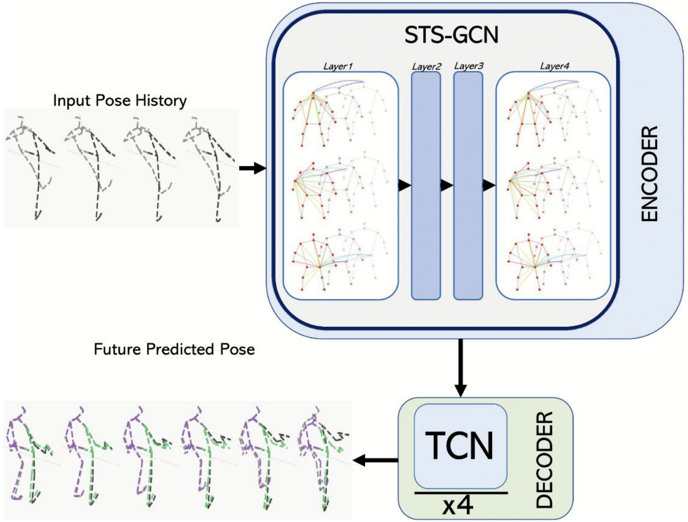




Sports Performance Analysis: Enhance athlete training programs | **Robotics & Manufacturing:** Optimize human-robot collaboration | **Autonomous Vehicles:** Improve pedestrian safety measures | **Healthcare Rehabilitation:** Guide physical therapy exercises | **Fitness Tracking:** Personalized exercise recommendations | **Security & Surveillance:** Anomaly detection in public spaces | **Ergonomics Design:** Workplace injury prevention planning | **Human-Computer Interaction:** Gesture-based interfaces advancement.| **Biomechanical Research:** Study human movement patterns

QM Human Motion Prediction Project

Motion prediction model



Data:
- Input: Sequence of 10 frames = 0.4 sec
- 10 frames x 32 joints x 3 coordinates

Model: STS-GCN
- **S**pace **T**ime **S**eparable -
Graph **C**onvolutional **N**etwork

Prediction:
- Output: Sequence of 25 frames = 1.0 sec

QM Human Motion Prediction Project

Five project branches

1. Data analysis (Learning representation): Find outliers in motion prediction dataset that decrease performance
2. Adversarial attacks (Robust learning): Important step for increasing model robustness
3. Model interpretability: Knowing, which layer contribute to which spatial / temporal aspect
4. Efficient learning (Self-supervised Learning): Useful when only few data available
5. Simulation: Simulation of crashes for crash prediction models

Data analysis and learning representation

What is our **main task / subproject** in this project branch?

- **Find outlying motion sequences**
  - **Quantify the degree of anomaly of a motion sequence as a vector,**
    e.g., idx=35, action=”walking” → decision scores: [0.83, 0.92, 0.67, 0.89]
- Characterize outlying vs. inlying motion sequences
  - Describe relevant sequence characteristics, e.g., velocity or acceleration of specific joints visually or statistically

qualityminds

CONSTRUCTOR LEARNING

Data analysis and learning representation

Why is this important in the context of the overall project?

- **Motivating assumption** for our task
  - **Outlying motion sequence → high error in motion prediction models**
  - Improve motion prediction model
- Examples of an **outlying motion sequence**
  - Combining different actions: “eating” while “walking”
  - Sudden movements

Data: Different Datasets

Pose Prediction Datasets:

- **AMASS:** Motion capturing & in the wild recordings. Annotated with skeleton information
- **Human3.6M:** 3.6 million poses, motion capturing, 11 actors, 17 scenarios (walking, phoning, eating,...), 3D laser scans of the actors
- **3DPW:** Generated from real-world videos. Includes varying clothing, background, activities
- **CMU:** Motion capturing, 2D and 3D joint trajectories
- **ExPI:** Understand human emotions in human-robot interaction scenarios of human pushing the robot

Human3.6M: Labeling (although not always reliable), good as a generalizing approach, high variability

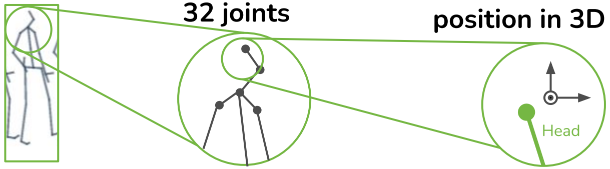
Our Approach

Dataset → 3.6 million human poses

Data Structure

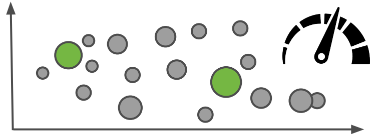
180k sequences → 35 frames ~ 1.4 second → 32 joints, position in 3D

Input | Output (Prediction)



Methodology

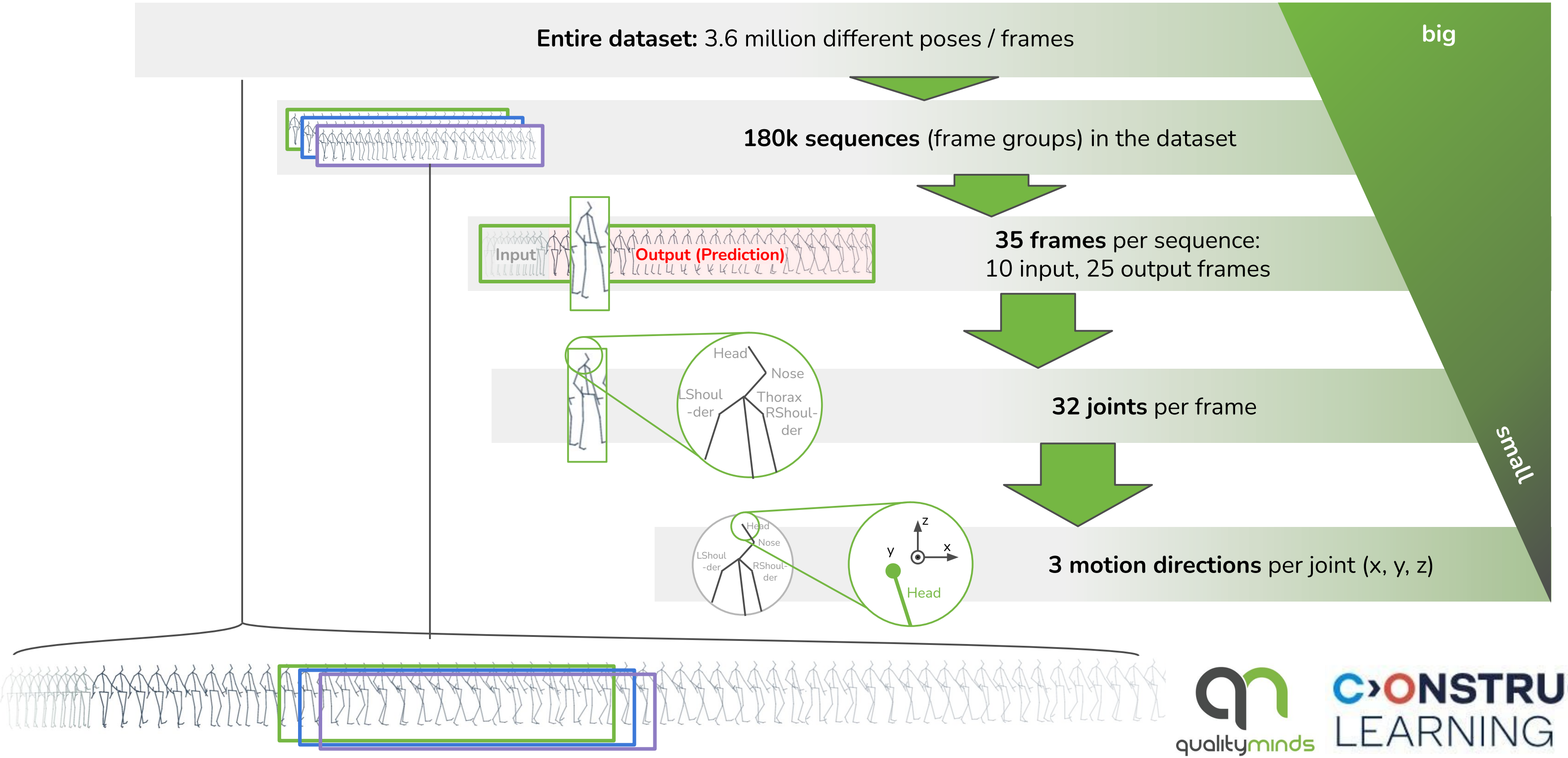
Huge dataset → Dimensionality Reduction → Simple dataset → Scaling → Scaled dataset → Outliers Detection Models → Quantification of “anomaly”



Validation

Prediction Error — ? — Decision Score

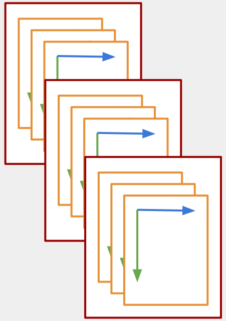
Data: H3.6M Dataset Structure



Data: Processing and Transformations

Raw Data

4D Array:
180k sequences
x 35 frames
x 32 joints
x 3 motion directions



Data Processing

2D Array / Dataframe:
180k sequences
x (35 x 32 x 3)

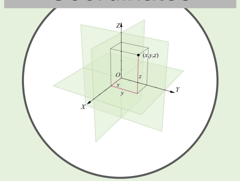
3360 columns

180k rows

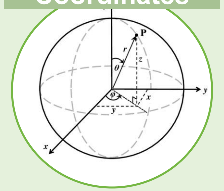
	idx	0	1	2	3	4	5	6
0	0	0.0	0.0	0.0	-132.948593	0.0	0.0	-71.220520
1	1	0.0	0.0	0.0	-132.948593	0.0	0.0	-70.484131
2	2	0.0	0.0	0.0	-132.948593	0.0	0.0	-69.480377
3	3	0.0	0.0	0.0	-132.948593	0.0	0.0	-71.031143
4	4	0.0	0.0	0.0	-132.948593	0.0	0.0	-71.140823

Data Transformation 1

Cartesian Coordinates

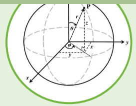


Spherical Coordinates



Data Transformation 2

Spher. Coordinates

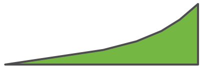


dt

Velocity in Spherical Coords

dt

Acceleration in Spherical Coords.



Methodology - Overview of our pipeline

How do we find outlying motion sequences?

Data representation

Cartesian coordinates
- joint pos. (35 x 32 x 3)

Spherical coordinates
- joint pos.
- velocity
- acceleration

Select # of frames

Full:
All 35 frames

Input only:
First 10 frames

Output only:
Last 25 frames

Reduce # of dimensions (optional)

PCA
- 50 principal components
- contain about 96% of variation in original space

(35x32x3 = 3360 dim.)

Scale data (optional)

Standard scaler (z-score)
- Mean = 0, SD=1

Outlier detection method(s)

4 different unsupervised methods

- CBLOF
- HDBSCAN
- IFOREST
- LOF

Decision score(s)

Quantification of “anomaly”:

Higher values → more outlying

Lower values → less outlying

Methodology - Outlier Detection

Main interest of QM: **Vector of normalized decision scores**

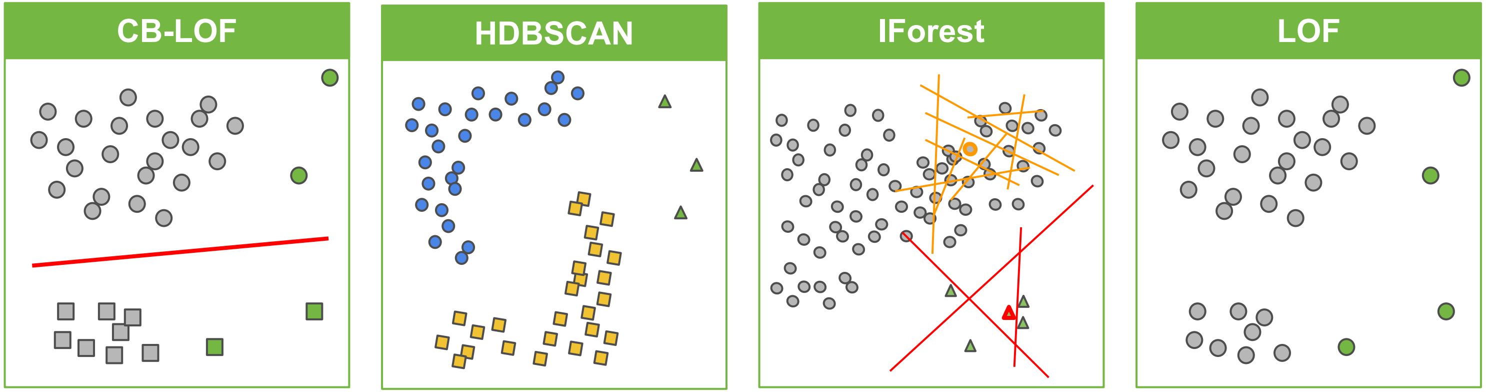
idx	action	CB-LOF	HDBSCAN	IFOREST	LOF
10	walking	0,85	0,76	0,59	0,80
84	eating	0,23	0,35	0,28	0,50
...	...	...	...	...	...

But why multiple outlier detection methods? → Each defines anomaly differently

→ **More diverse representation!**

Methodology - Outlier Detection

Method	Which sequences are considered anomalous, i.e. have a higher decision score?
CB-LOF	Separating into small/large clusters (k-means) → Sequences with a high distance to the nearest large cluster
HDBSCAN	Sequences not belonging to any density-based cluster or being at the edge of a density-based cluster
IFOREST	Sequences that are easily isolated in a random tree, i.e. a low number of splits required (averaged over a forest)
LOF	Sequences with significantly lower local density compared to their k nearest neighbors



Methodology - Overview of our pipeline

How do we find outlying motion sequences?

Data representation	Select # of frames	Reduce # of dimensions (optional)	Scale data (optional)	Outlier detection method(s)
Cartesian coordinates - joint pos. (35 x 32 x 3) **Spherical coordinates** - joint pos. - velocity - acceleration	**Full:** All 35 frames **Input only:** First 10 frames **Output only:** Last 25 frames	**PCA** - 50 principal components - contain about 96% of variation in original space (35x32x3 = 3360 dim.)	**Standard scaler (z-score)** - Mean = 0, SD=1	**4 different unsupervised methods** - CBLOF - HDBSCAN - IFOREST - LOF

Decision score(s)

Validation of outliers

Prediction errors from motion models

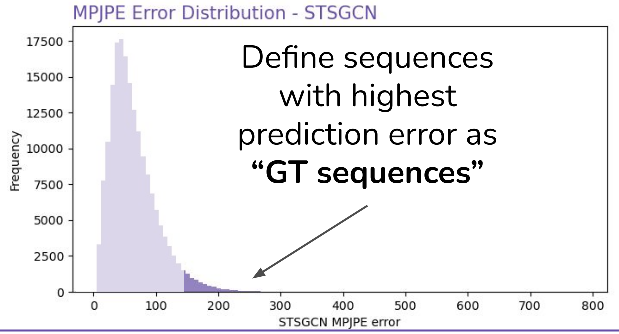
Methodology - Validation

Problem: Unsupervised approach lacks ground truth - Does it work?

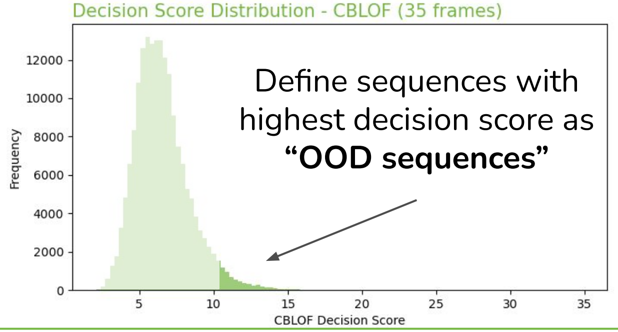
- **Explorative:** Compare outlying / inlying sequences on relevant characteristics
  - Visualize sequences, e.g. motion GIFs, velocity/acceleration of joints
  - Characterize them statistically, e.g., average velocity/acceleration of joints
- **Artificial Metrics:** Compare outlying / inlying sequences using prediction errors
  - Merge **prediction errors** from **two motion models** (STS-GCN, motionmixer) to Data

Methodology - Validation

Prediction error distribution
from motion models →
Ground truth abnormal sequences



Decision score distribution
outlier detection methods →
Sequences found using OOD methods



The higher the decision score, the more abnormal is a sequence

Methodology - Validation

- **Terminology:** TP = True Positive; FP = False Positive ; FN = False Negative
- **Artificial “precision” and “recall”**
  - Precision = TP / TP+FP
    - Rate of OOD detected sequences with high prediction error
  - Recall = TP / TP+FN
    - Rate of high error sequences captured by ground truth
- **Flexibility in definitions due to:**
  - Variable thresholds for highest X%
  - Use single outlier detection method or combinations of these
  - Use single motion model or combination of two motion models

Results - Out of distribution (OOD) sequences

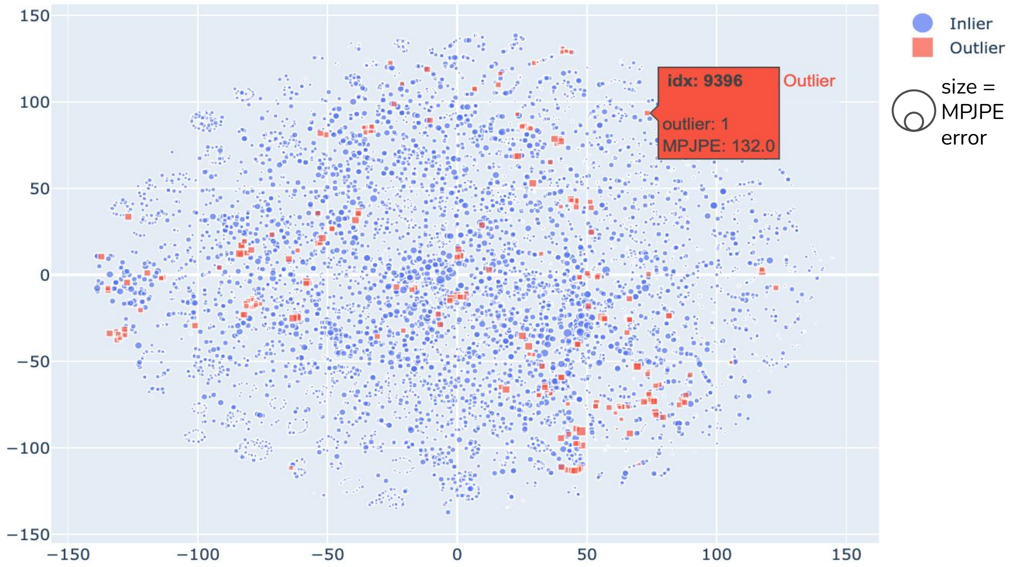
OOD Methods

- CBLOF
- IForest
- HDBScan
- LOF

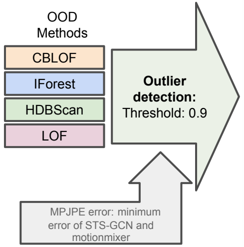
OOD sequence detection:
Threshold: 0.9

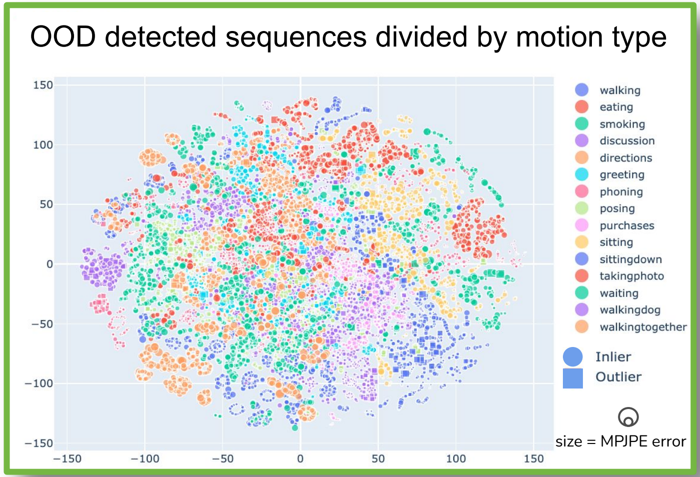
MPJPE error: minimum error of STS-GCN and motionmixer

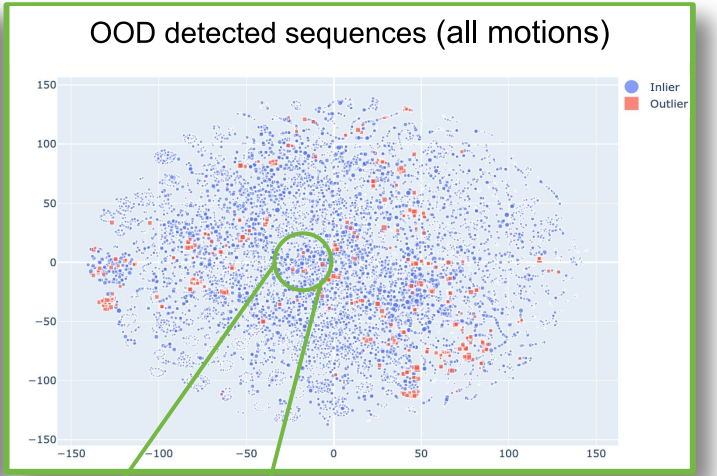
OOD detected sequences projected in 2D plane (using t-SNE)



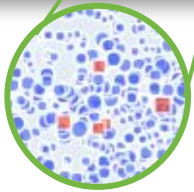
Results - Out of Distribution Sample Detection





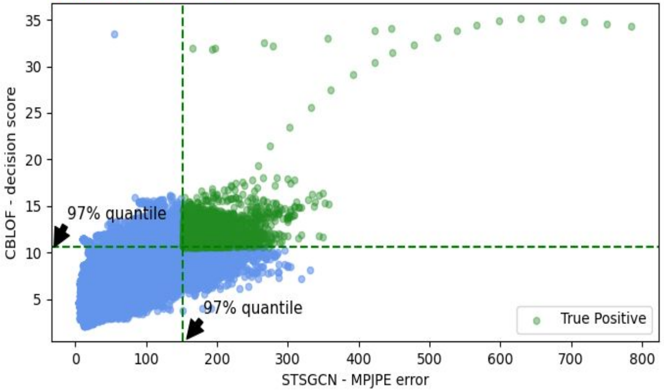


Detail view



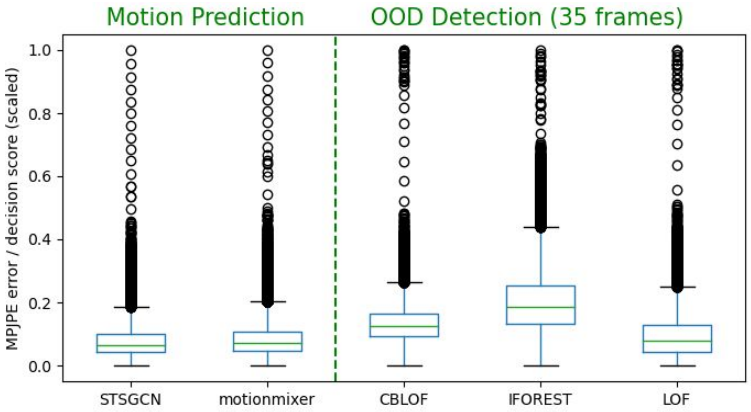
Results - Analysis Toolkit

Comparison of ground truth samples based on motion model and decision scores



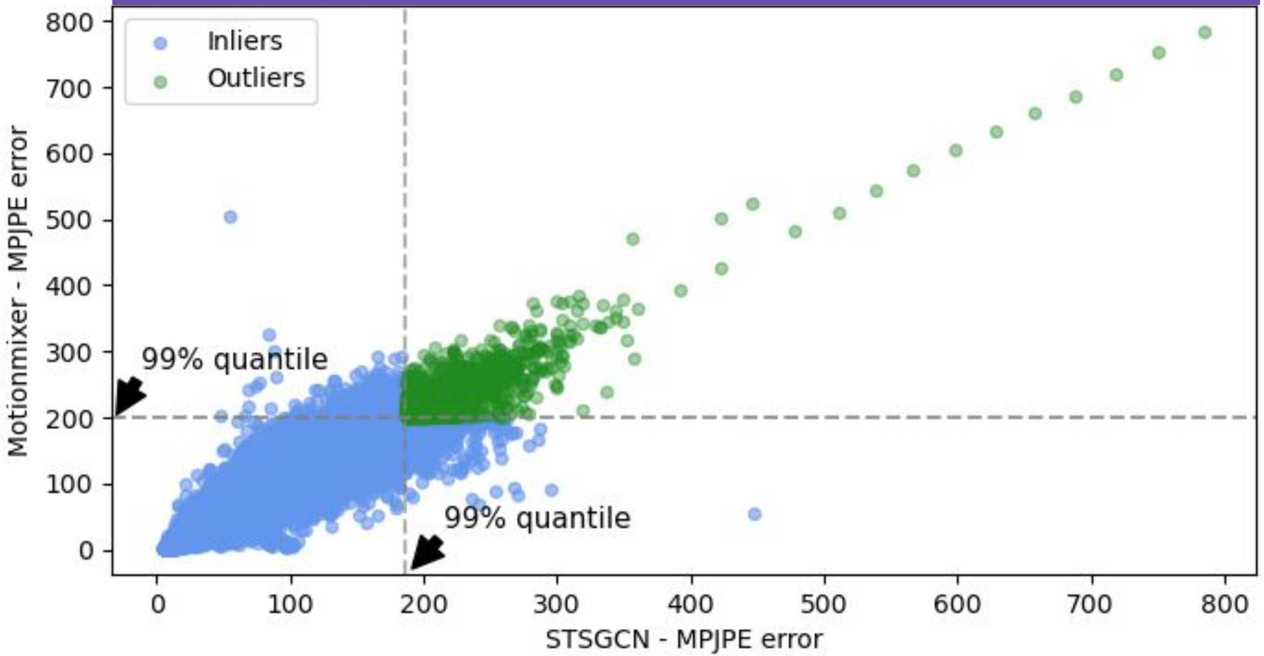
Top 3 % of MPJPE Errors in STSGCN model and decision scores of CBLOF (anomaly detection model)

Comparison of motion prediction models vs OOD detection methods



Results - Analysis Toolkit

Ground Truth: STSGCN vs motionmixer



Results - Analysis Toolkit Recall & Precision

	motion_model_th:0.97	OOD_model_th:0.9	mode	recall	precision	recall_&	precision_&	recall_or	precision_or
0	STSGCN	CBLOF	full	0,71	0,21	0,50	0,30	0,80	0,15
1	STSGCN	IFOREST	full	0,61	0,18				
2	STSGCN	HDBSCAN	full	0,42	0,13				
3	STSGCN	LOF	full	0,65	0,19				
4	STSGCN	CBLOF	Ti_10	0,32	0,10	0,21	0,14	0,44	0,08
5	STSGCN	IFOREST	Ti_10	0,31	0,09				
6	STSGCN	HDBSCAN	Ti_10	0,26	0,08				
7	STSGCN	LOF	Ti_10	0,34	0,10				
8	STSGCN	CBLOF	To_25	0,74	0,22	0,52	0,31	0,84	0,16
9	STSGCN	IFOREST	To_25	0,65	0,19				
10	STSGCN	HDBSCAN	To_25	0,60	0,18				
11	STSGCN	LOF	To_25	0,68	0,21				
12	motionmixer	CBLOF	full	0,71	0,21	0,51	0,31	0,80	0,15
13	motionmixer	IFOREST	full	0,62	0,19				
14	motionmixer	HDBSCAN	full	0,43	0,13				
15	motionmixer	LOF	full	0,66	0,20				
16	motionmixer	CBLOF	Ti_10	0,34	0,10	0,22	0,15	0,47	0,09
17	motionmixer	IFOREST	Ti_10	0,33	0,10				
18	motionmixer	HDBSCAN	Ti_10	0,27	0,08				
19	motionmixer	LOF	Ti_10	0,36	0,11				
20	motionmixer	CBLOF	To_25	0,74	0,22	0,52	0,32	0,84	0,16
21	motionmixer	IFOREST	To_25	0,64	0,19				
22	motionmixer	HDBSCAN	To_25	0,61	0,18				
23	motionmixer	LOF	To_25	0,69	0,21				

Results - Analysis Toolkit Recall & Precision

```
general_analysis(metrics_df,model_threshold = 0.90, error_threshold= 0.97)
```

	modes_mt=0.9_et=0.97	recall_&	precision_&	recall_or	precision_or
0	full	0,44	0,34	0,83	0,08
1	Ti_10	0,20	0,13	0,50	0,05
2	To_25	0,54	0,29	0,89	0,10

```
general_analysis(metrics_df,model_threshold = 0.95, error_threshold= 0.90)
```

	modes_mt=0.95_et=0.9	recall_&	precision_&	recall_or	precision_or
0	full	0,16	0,74	0,48	0,37
1	Ti_10	0,10	0,44	0,28	0,23
2	To_25	0,20	0,70	0,50	0,48

Results: Outlier Detection App

Outlier Detection App

Select Your Analysis

Set Decision Score Threshold

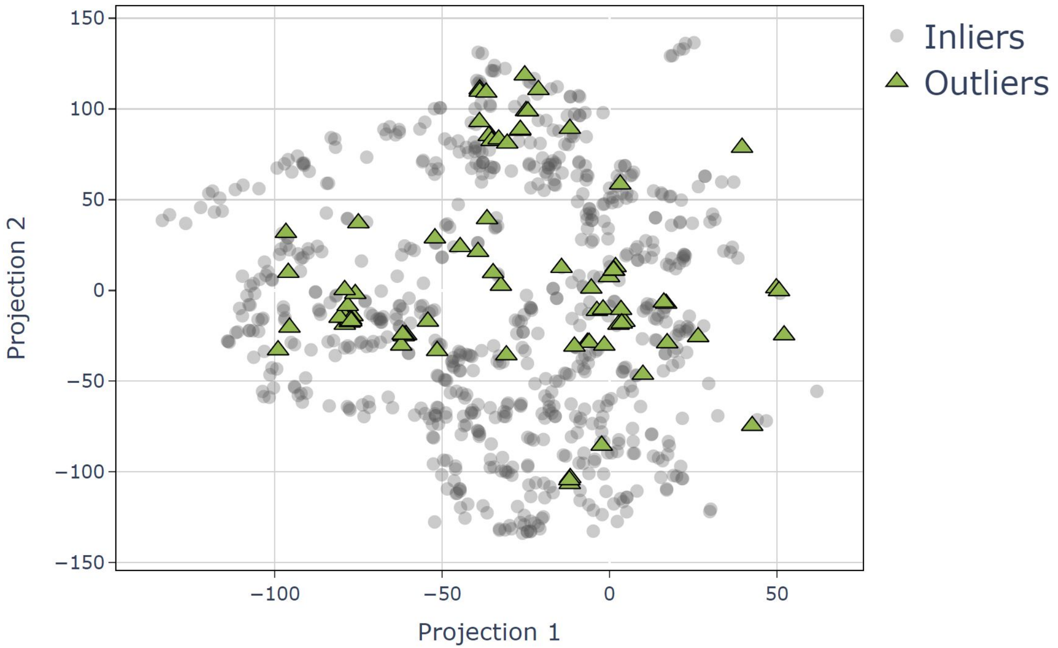
0.70 0.75 0.80 0.85 0.90 0.95

Select Outlier Detection Model:

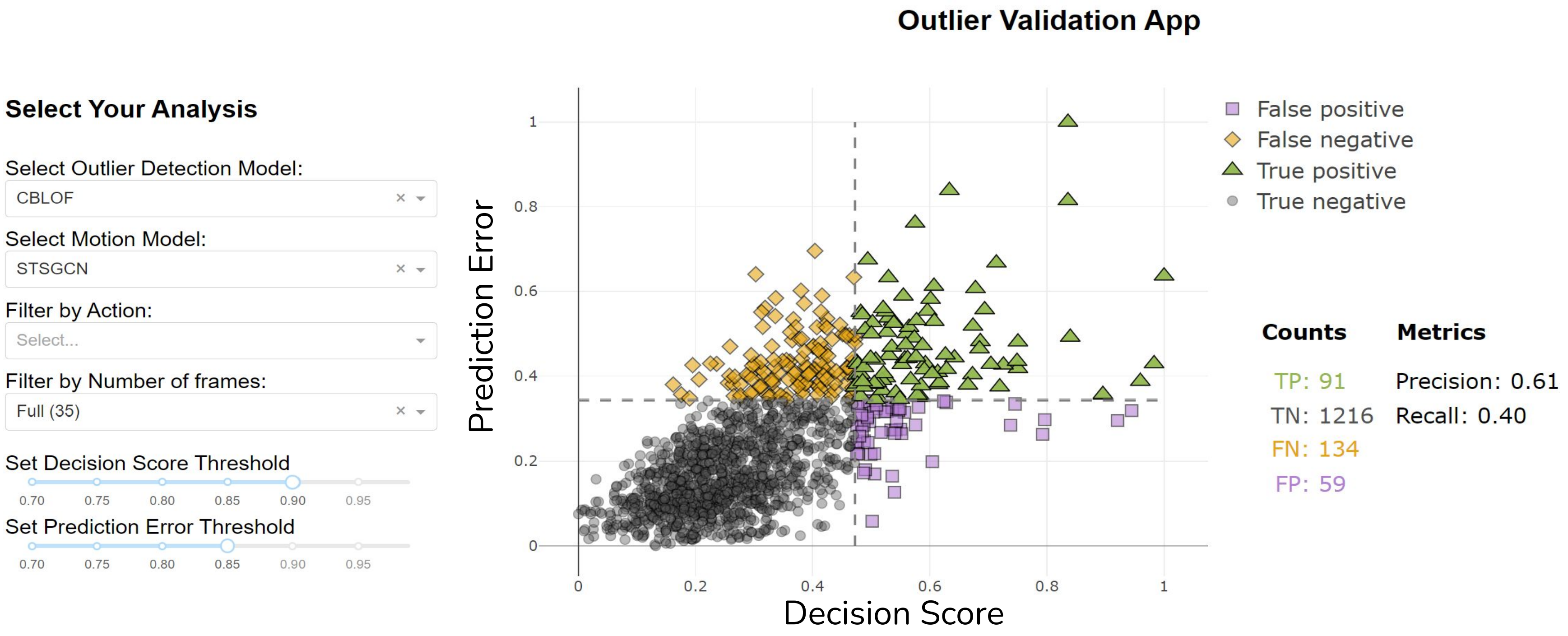
CBLOF

Color by:

Decision Score Threshold



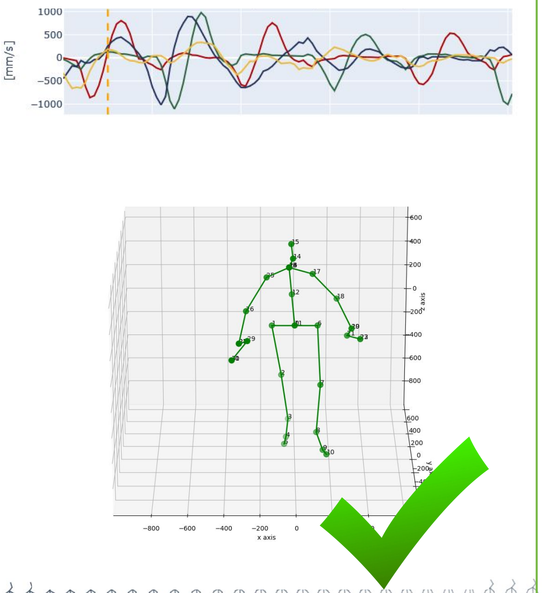
Results: Outlier Validation App



Results - Kinematic Comparison Toolkit

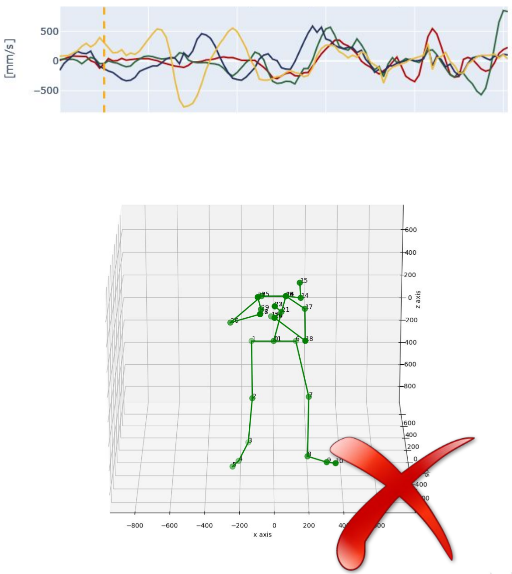
Inlier "walking"

Velocity

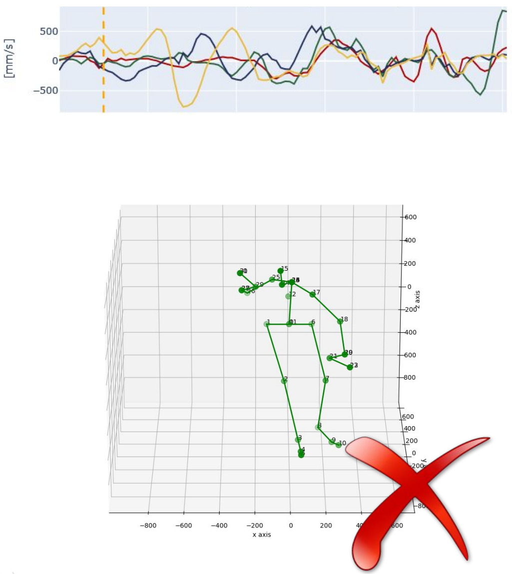


Outliers "walking"

Velocity



Velocity

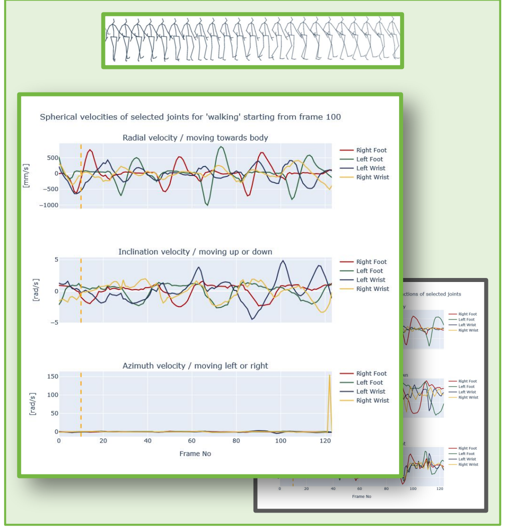


Results - Kinematic Comparison Toolkit

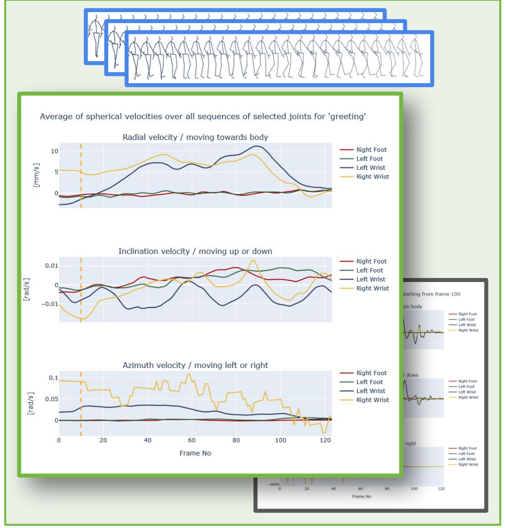
Velocity in Spherical Coordinates

Acceleration in Spherical Coordinates

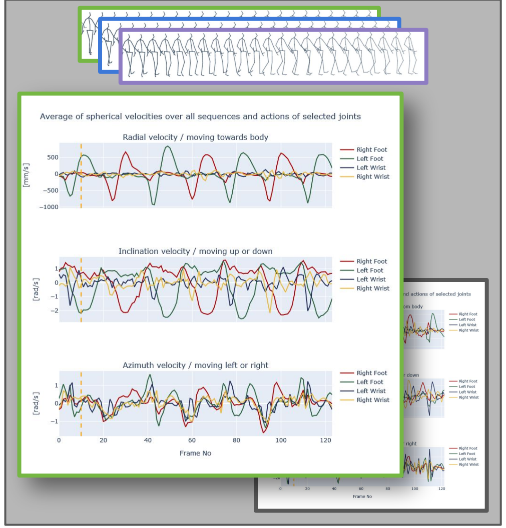
Sequence Analysis (e.g. walking sequence 100)



Motion Analysis (e.g. greeting)



All data analysis

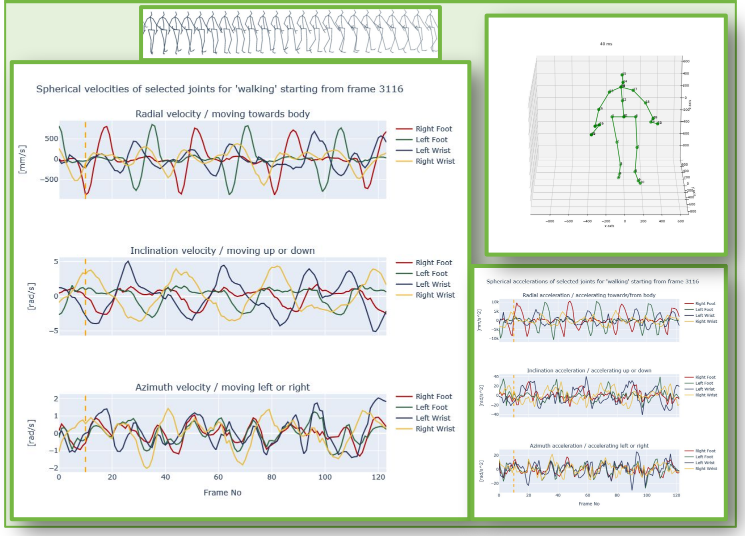


Results - Kinematic Comparison Toolkit

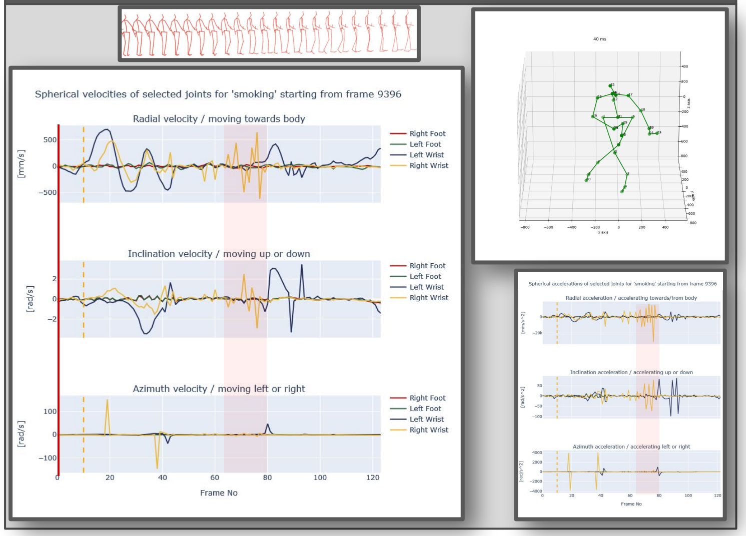
Velocity in Spherical Coordinates

Acceleration in Spherical Coordinates

Inlier Analysis (e.g. walking sequence 3116)



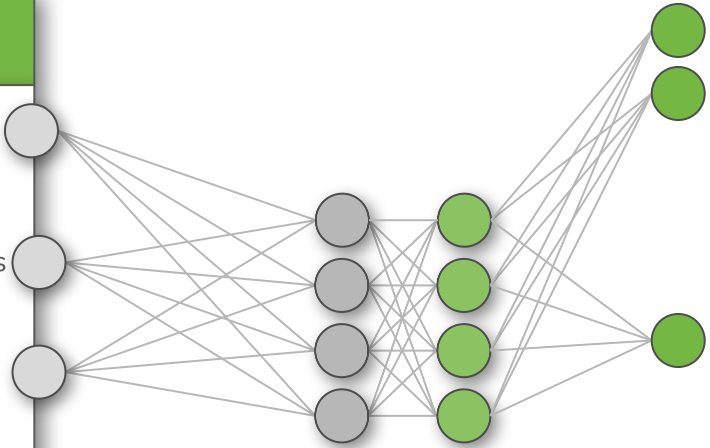
OOD sequence (e.g. smoking frame 9396)



Outlook

Summary

- ➔ **Business Case:** Autonomous Driving
- ➔ **Approach:** Outlier detection models
- ➔ **Results:** Apps for outlier analysis



Expand: Generalize to other public datasets

Improve: Use the vector representations to enhance the performance of state of the art motion predictions models

- Regularize the loss function (test the OOD methods validity)
- Do a parallel / meta network to modify the weights of the original motion prediction models

Utilize: Use the representation in the other four stages of the project

- Perform adversarial attacks based on the found outliers
- Enhance model Interpretability
- Support the self learning of the model
- Adapt the simulation branch

Any Questions?

One Step Ahead - Stay in touch

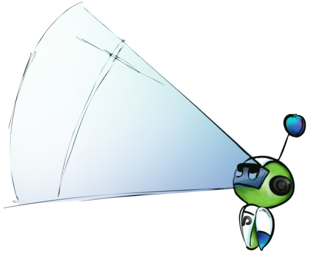
Don't be shy, just talk to us ;)

Jonas Voßemer

Alaa Elshorbagy

Vincent v. Zitzewitz

Our LinkedIn + App Demo here

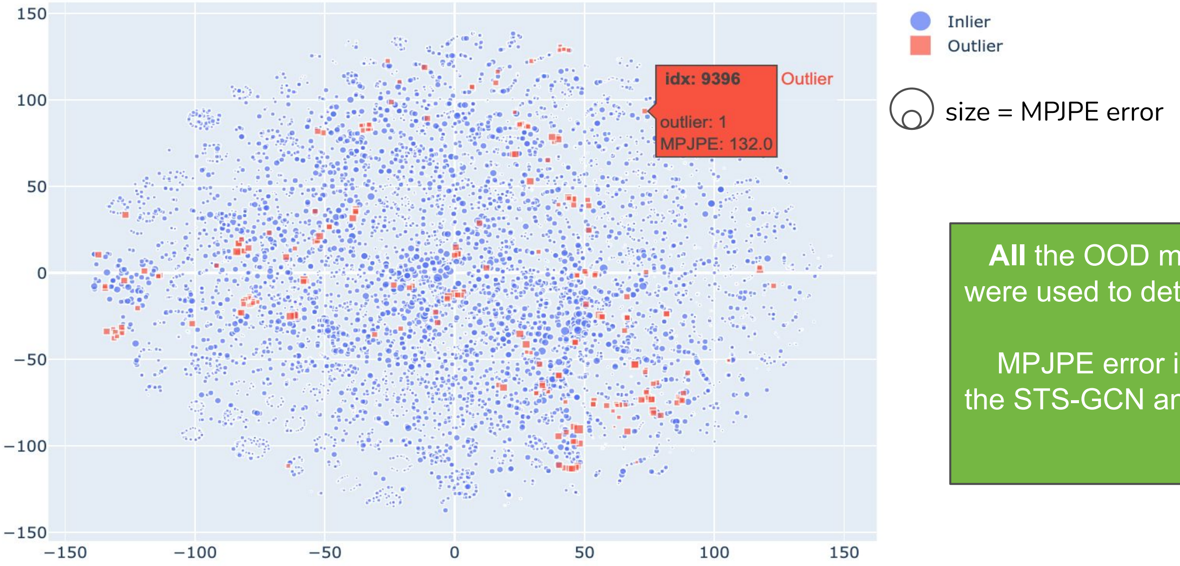


qualityminds CONSTRUCTOR LEARNING

Backup

Results - OOD (methods combined)

T-SNE plot

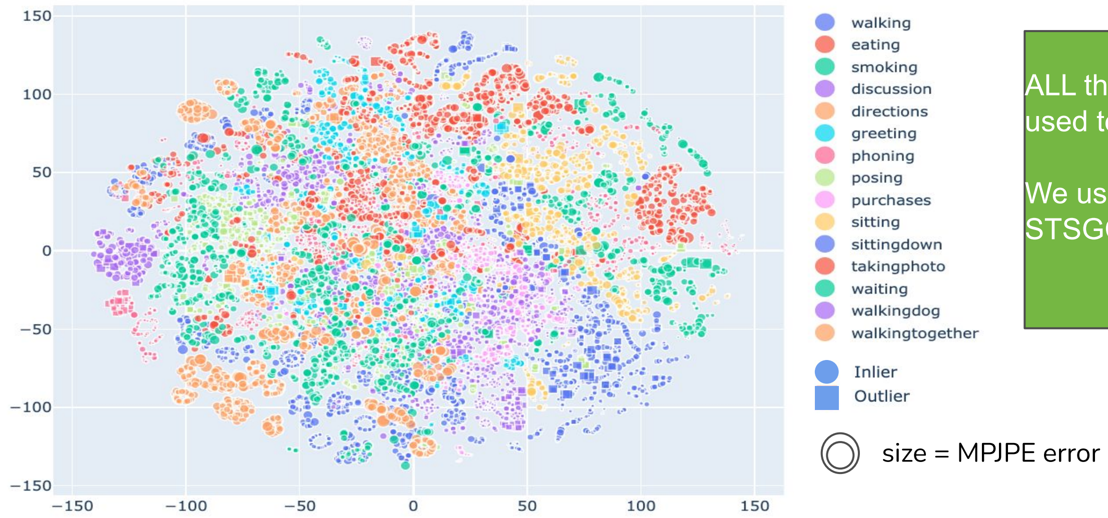


All the OOD methods (threshold 0.90) were used to detect outliers.

MPJPE error is the minimum error of the STS-GCN and motionmixer.

Results - Out of Distribution Sample Detection

T-SNE plot



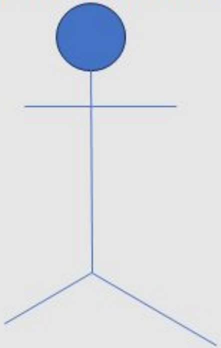
ALL the OOD methods (threshold 0.90) is used to detect outliers.

We use the minimum MPJPE error of the STSGCN and motionmixer. .

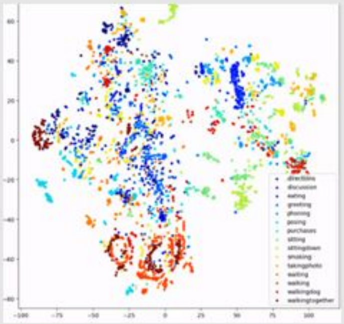
Frame set 100 (frame 100 + frame length, e.g. +75 frames)

Frame set 2 (frame 205 + frame length, e.g. +75 frames)

Viz of the pose
(take from demo file)

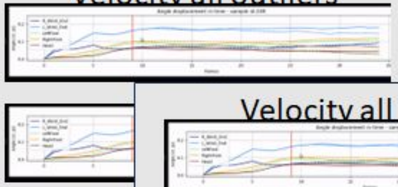


Scatter plot:

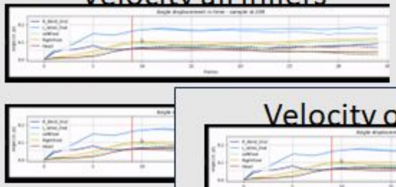


Metric numbers:
*

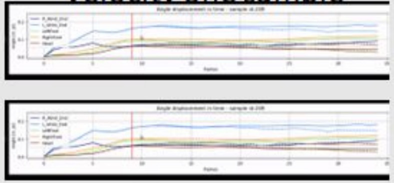
Velocity all outliers



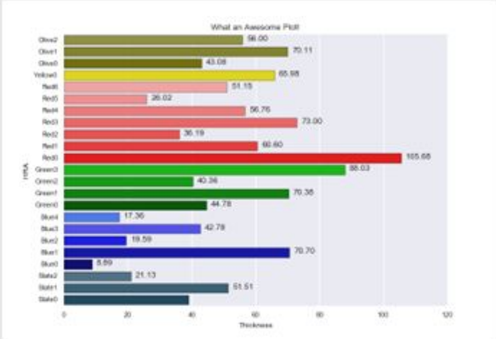
Velocity all inliers



Velocity one sample



Decision Score: Probability of the point being an outlier / Error of point



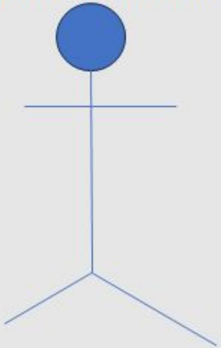
Frame set 100 (frame 100 + frame length, e.g. +75 frames)

Frame set 2 (frame 205 + frame length, e.g. +75 frames)

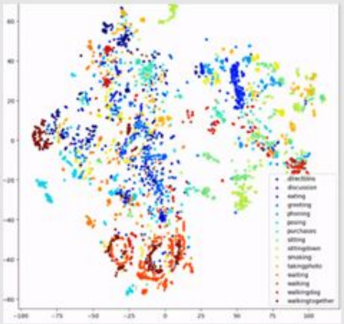
Metric numbers:

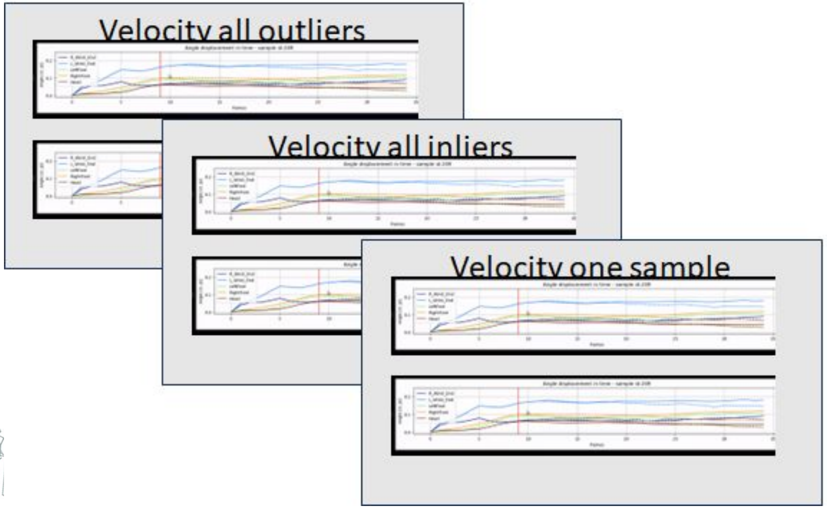
*

Viz of the pose (take from demo file)

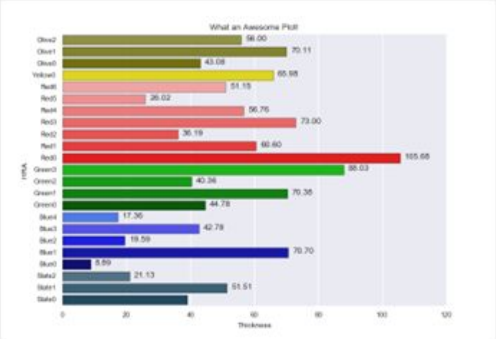


Scatter plot:





Decision Score: Probability of the point being an outlier / Error of point



Title Slide	Background on bootcamp and us	Motion models	Background on QM human motion prediction project (HMPP) and its branches	Zoom in: Our branch: 1. Data Analysis
Data			Methodology big picture	Methodology: Unsupervised - mode
Methodology: Check true outliers - Validation	KR: t-SNE graph	Isolated models vs AND vs OR operators	Boxplot of single models, Outputs: Outlier score that can be used flexible	KR: velocity / acc did not lead to much
			Outline / Future steps	Q & A