DEEP BREATH

Contactless respiratory rate monitoring

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Respiratory rate is a sensitive signal for clinical worsening, but current assessments have downsides

- Manually counting breaths per minute
- Rough estimation
- Equipment: capnographers, oximeters

Contactless respiratory rate monitoring has several advantages

HOME

- Assist telemedicine assessments
- Use equipment patients already have at home

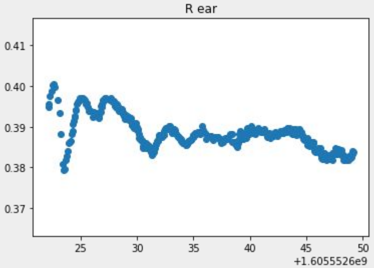
CLINICAL SETTING

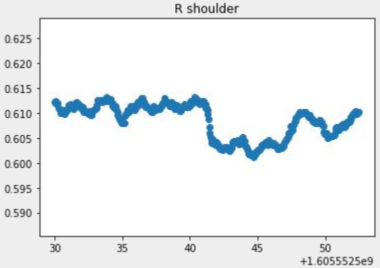
- Reduce infectious or other hazardous exposure
- Reduce medical waste
- More natural breathing pattern

Monitoring using pose detection models can preserve privacy

Patient's device

No personal identifying data





t_{001}, kp1…

t_{002}, kp1…

t_{003}, kp1…

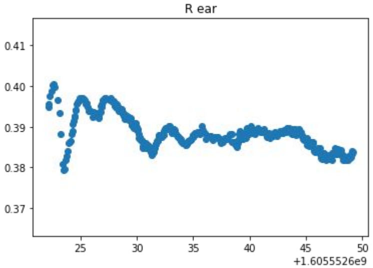
t_{004}, kp1…

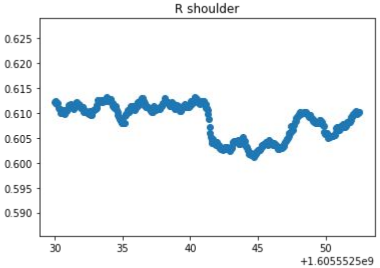
…

t_{450}, kp1…

Goal: detect respiratory rate from keypoint motion

Patient's device





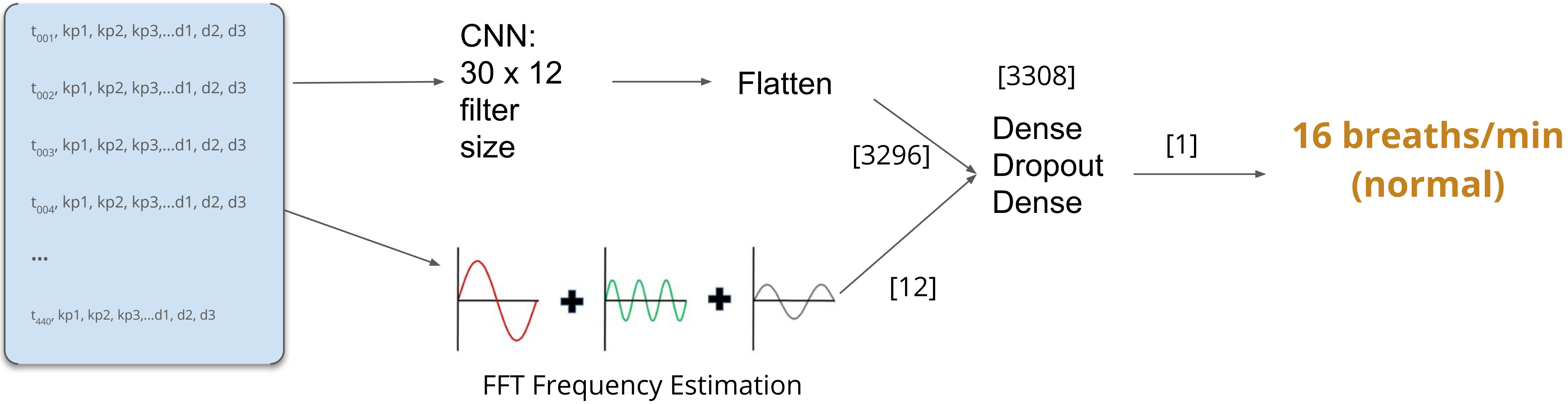
16 breaths/min (normal)

Pose detection on Jetson with pre-trained ResNet18

- Simultaneous person detection and keypoint estimation
- Pre-trained on data from MSCOCO
- Our model: 8 upper body keypoints (eyes, ears, shoulders, nose, neck) and 3 distances (ear-shoulder x2, nose-neck)

https://github.com/NVIDIA-AI-IOT/trt_pose

Respiratory rate estimation using fast Fourier transform ensembled with CNN-based model



Training respiratory rate detection model

- >200 video clips annotated with respiratory rate
- Model trained on Jetson devices (NX, AGX) for 100 epochs

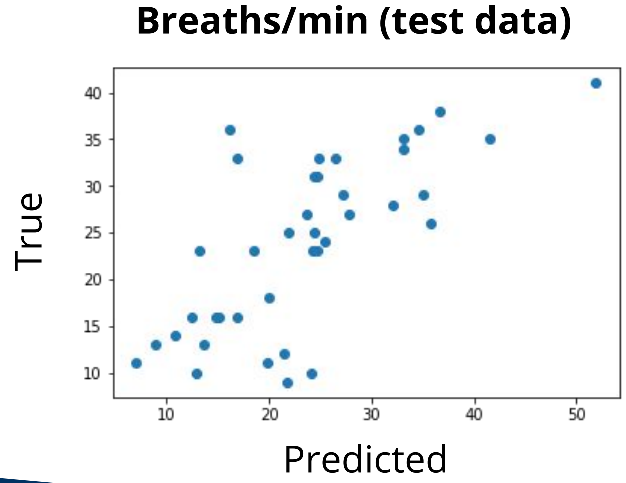
Model	Training MAE	Validation MAE
Frequency Estimation + Heuristics	n/a	10.89
Frequency Estimation + LR	8.44	7.91
FFT + Feedforward Network	6.31	9.50
CNN	3.42	7.37
Ensemble: FFT FNN + CNN	2.79	5.49

Ensemble: FFT FNN + CNN

Berkeley SCHOOL OF INFORMATION

Results

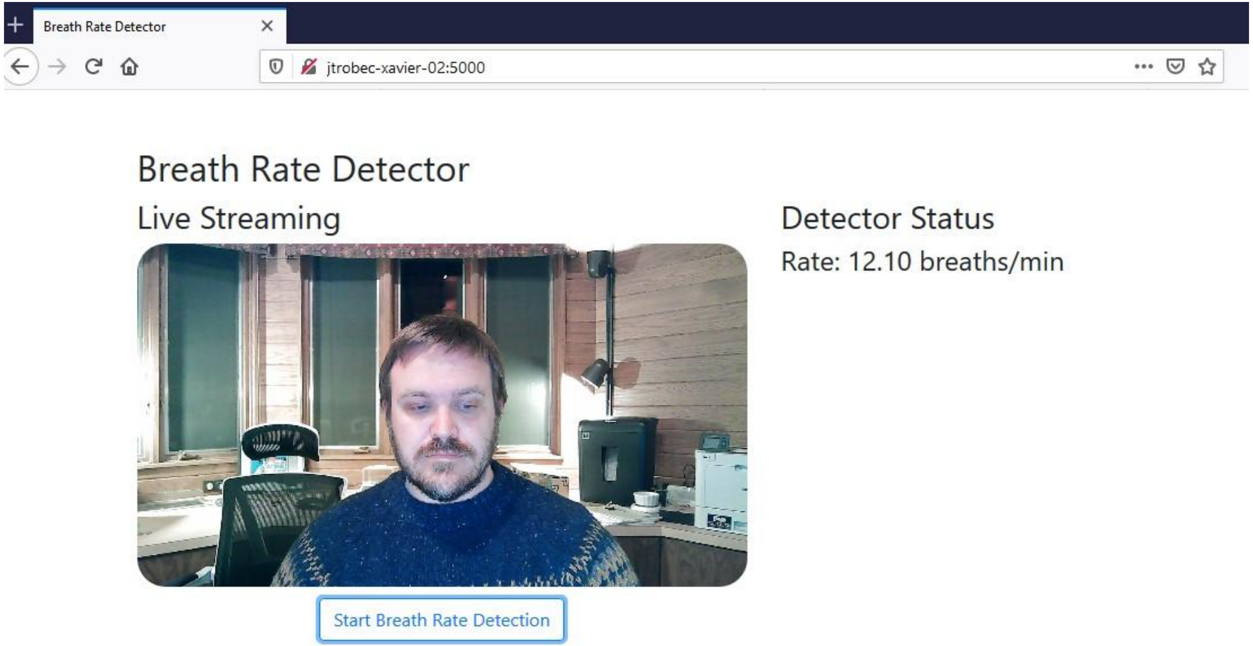
- Validation MAE for 15-second clips ~5.49

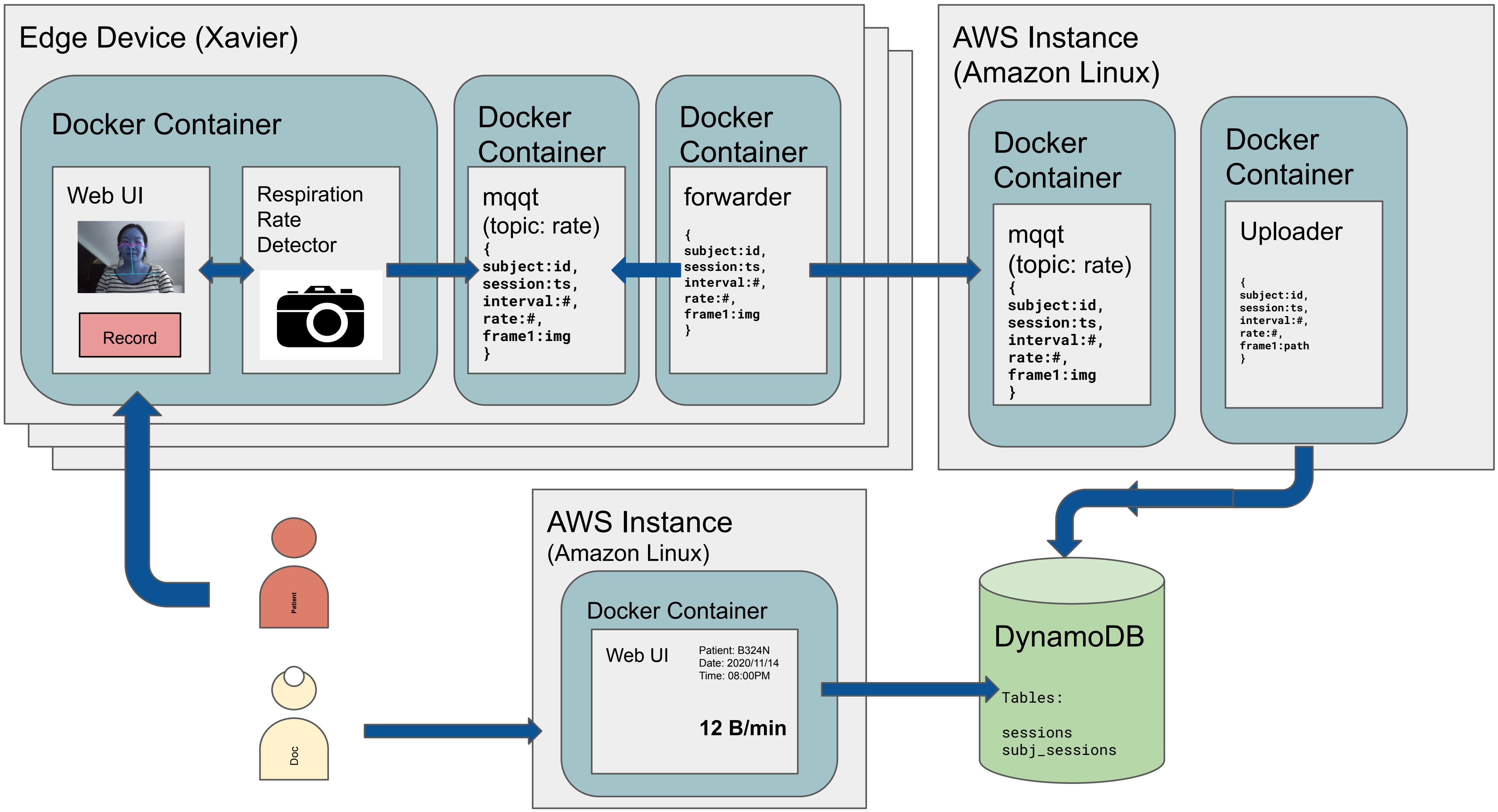


- Example: 15-second clip of breathing at 15 BPM

Clip1	13.74
Clip2	15.48
Clip3	15.93
Clip4	19.38
Average	16.14

Demo

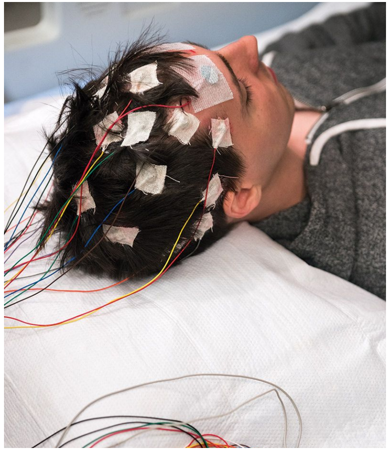

Breath Rate Detector
jtrobec-xavier-02:5000
Breath Rate Detector
Live Streaming
Detector Status
Rate: 12.10 breaths/min
Start Breath Rate Detection



Edge Device (Xavier)
Docker Container
Web UI
Record
Respiration Rate Detector
Docker Container
mqqt (topic: rate)
{ subject:id, session:ts, interval:#, rate:#, frame1:img }
Docker Container
forwarder
{ subject:id, session:ts, interval:#, rate:#, frame1:img }
AWS Instance (Amazon Linux)
Docker Container
mqqt (topic: rate)
{ subject:id, session:ts, interval:#, rate:#, frame1:img }
Docker Container
Uploader
{ subject:id, session:ts, interval:#, rate:#, frame1:path }
Patient
Doc
AWS Instance (Amazon Linux)
Docker Container
Web UI
Patient: B324N
Date: 2020/11/14
Time: 08:00PM
12 B/min
DynamoDB
Tables:
sessions
subj_sessions

Implications

- Contactless monitoring can be cheap, accurate, and privacy-preserving
- Other applications: baby monitors, home sleep studies, seizure detection



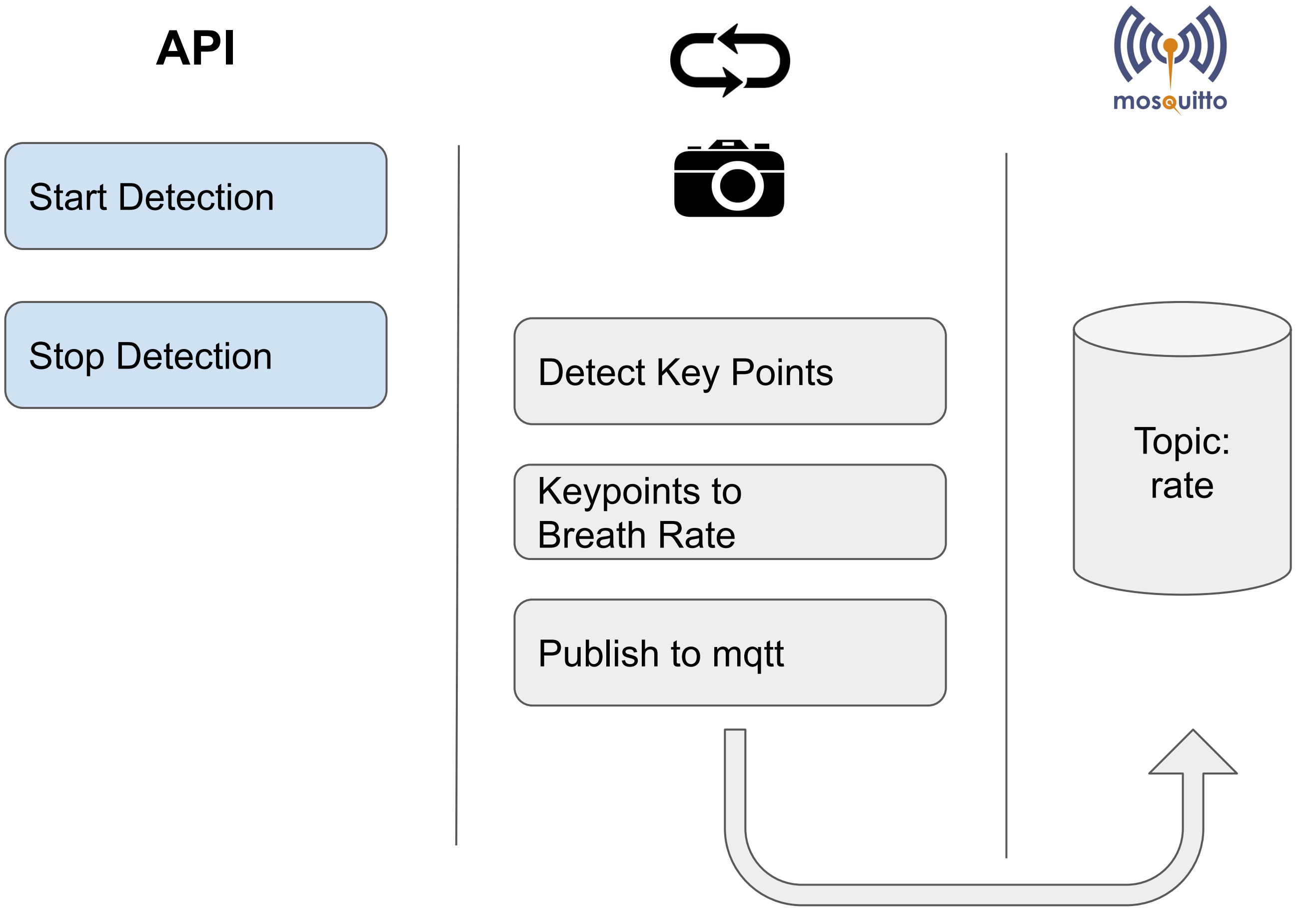
Next steps

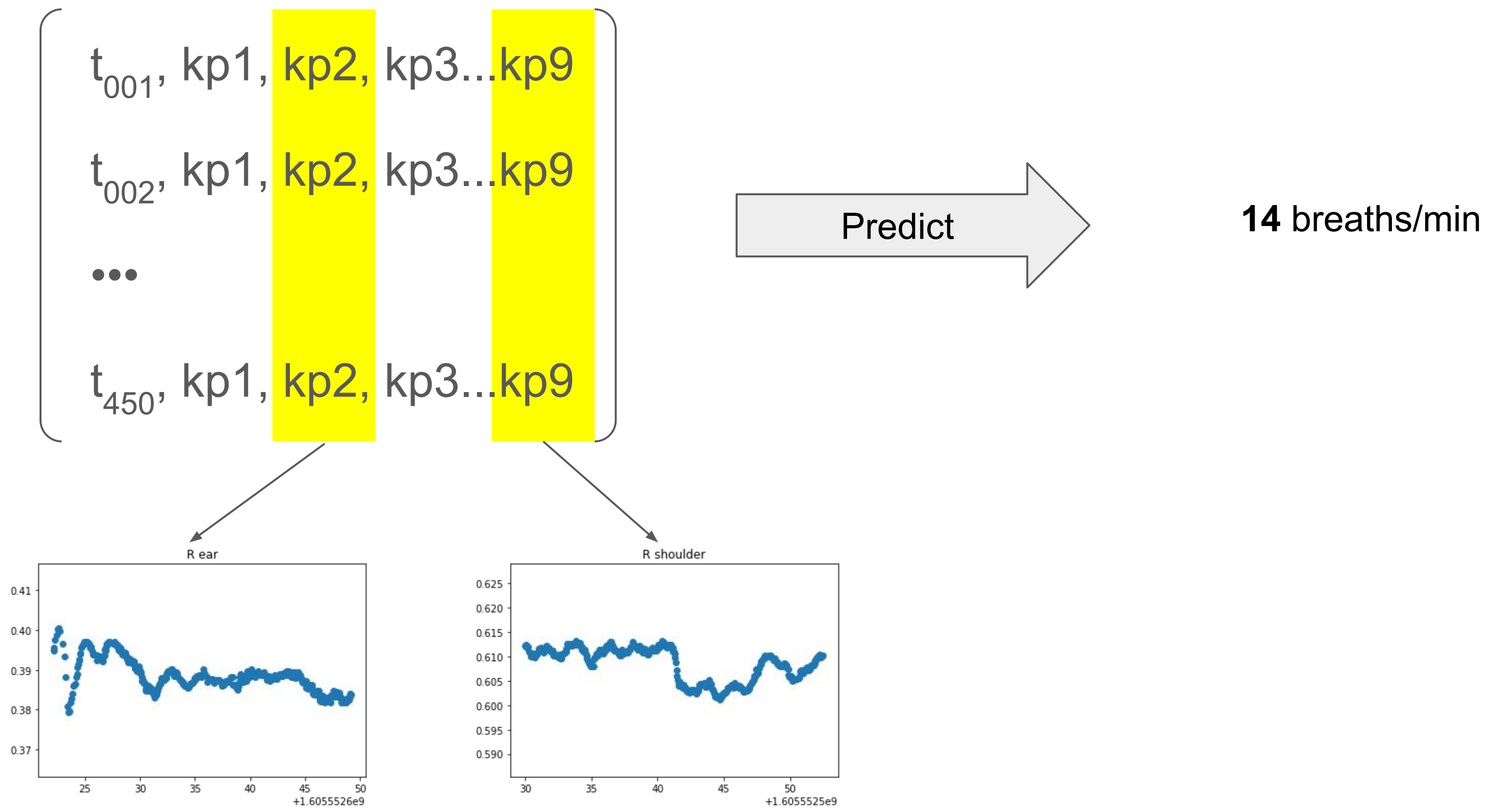
- Expand training examples
  - Different poses (side view, full body, lying down)
  - Include other types of motion (e.g., talking)
- Monitor multiple people in frame (e.g., disaster field hospitals)
- Optical flow for motion estimation may improve accuracy over keypoints alone

Questions?

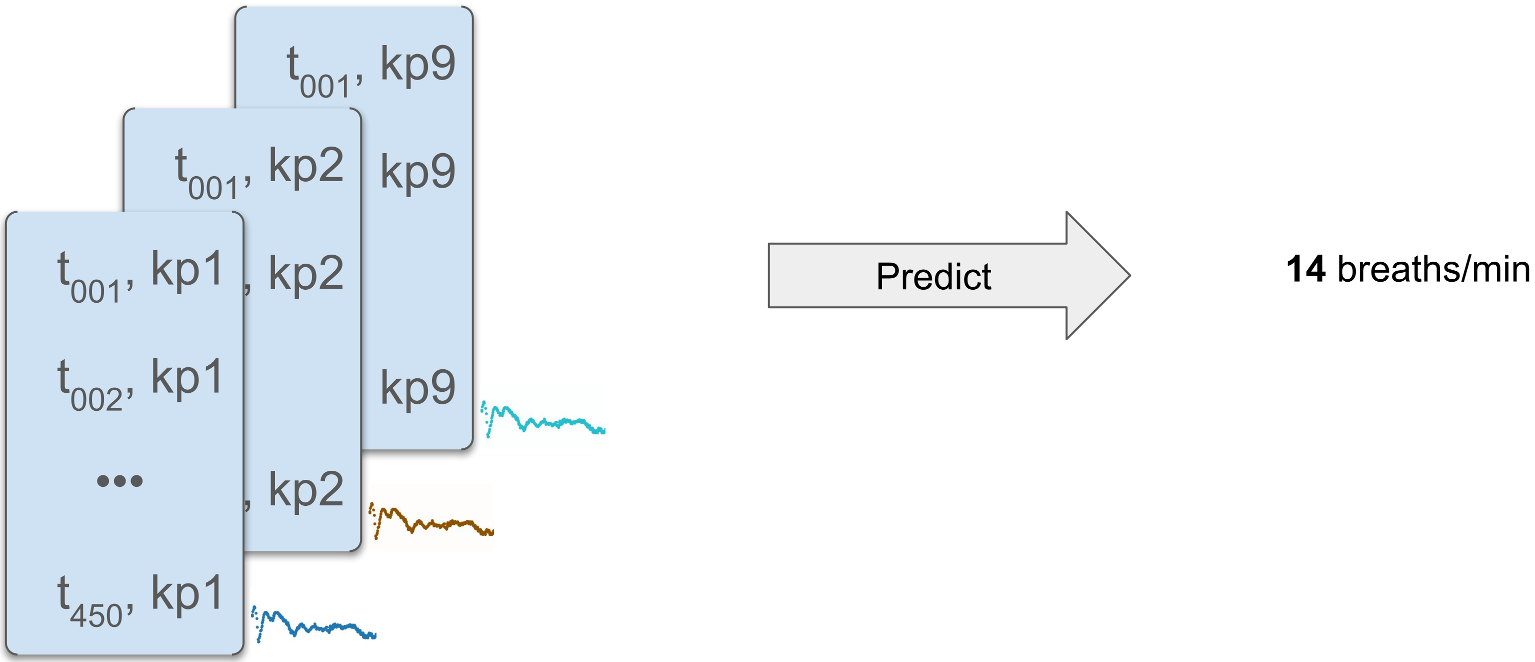
EXTRA SLIDES

Respiration Rate Detector

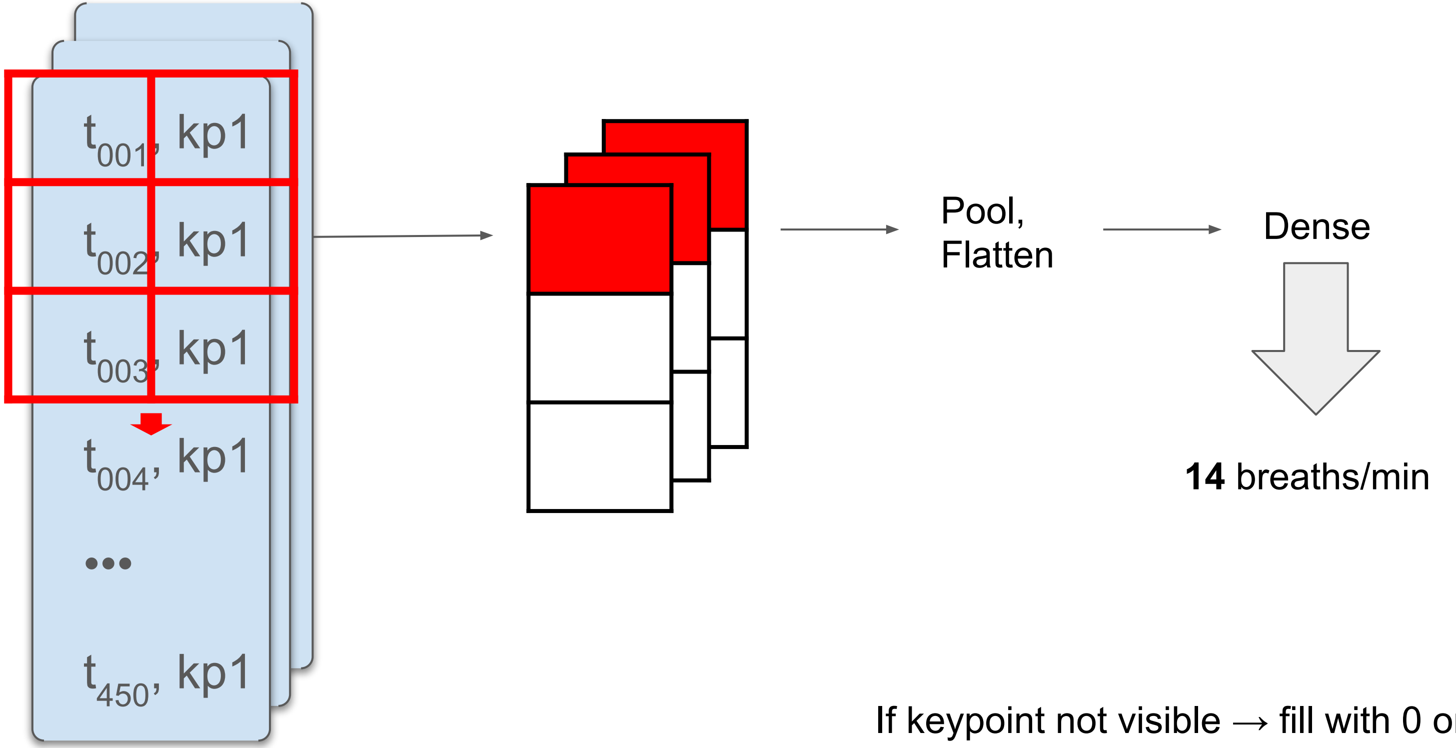




t001, kp1, kp2, kp3...kp9
t002, kp1, kp2, kp3...kp9
•••
t450, kp1, kp2, kp3...kp9
Predict
14 breaths/min
R ear
R shoulder
+1.6055526e9
+1.6055525e9


t_{001}, kp9
kp9
kp9
t_{001}, kp2
, kp2
, kp2
t_{001}, kp1
t_{002}, kp1
•••
t_{450}, kp1
Predict
14 breaths/min

Conv2D, 9 channels (keypoints)
-> Flatten
-> Dense
-> Output layer w/ linear activation



If keypoint not visible → fill with 0 or other constant?