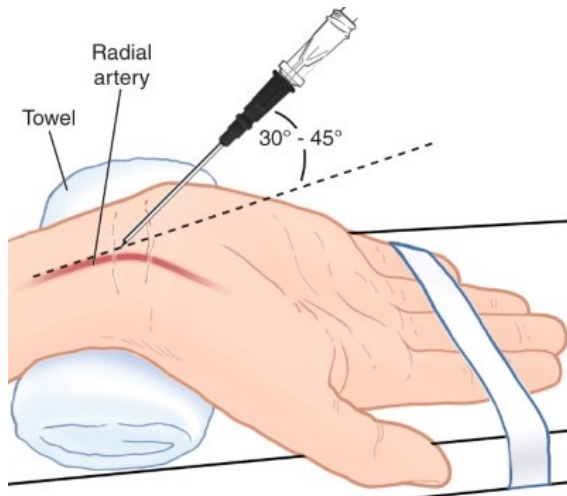# Algorithms for Continuous Absolute Blood Pressure Monitoring

Hanrui Wang*, Anand Chandrasekhar*, Joohyun Seo, Aaron Aguirre, Song Han, C. G. Sodini, H. S. Lee
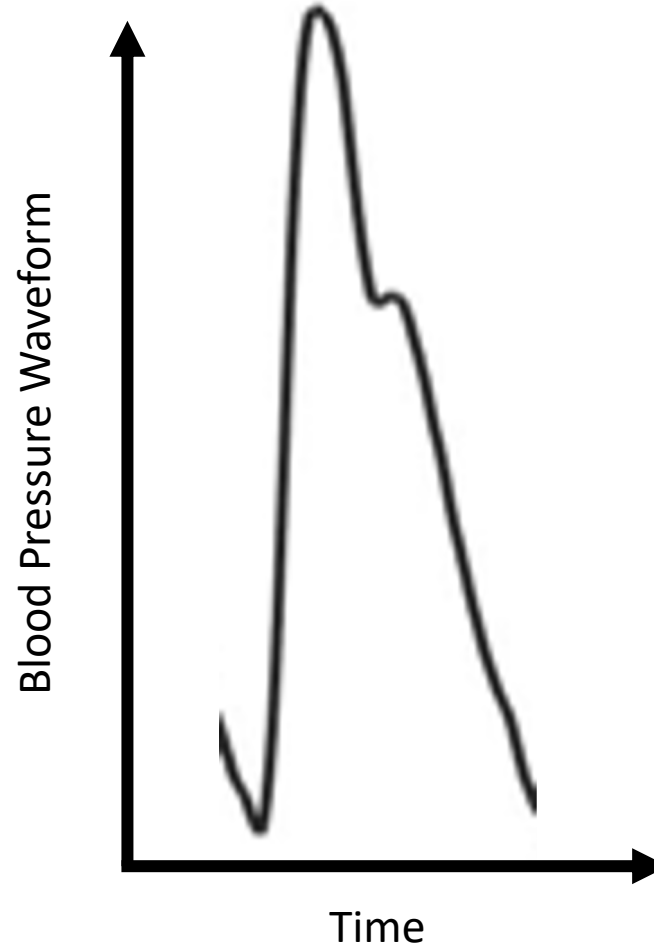
Microsystems and Technology Laboratory, MIT

How to measure BP ?

Intensive Care Unit

Radial artery Catheterization

Blood Pressure Waveform

Time

Outside Intensive Care Unit

Auscultation

Oscillometry

1. easyauscultation.com
2. 10.1126/scitranslmed.aap8674
3. Edwards Lifesciences
4. Emergency Medicine Procedures

Ultrasound based device to measure BP waveform
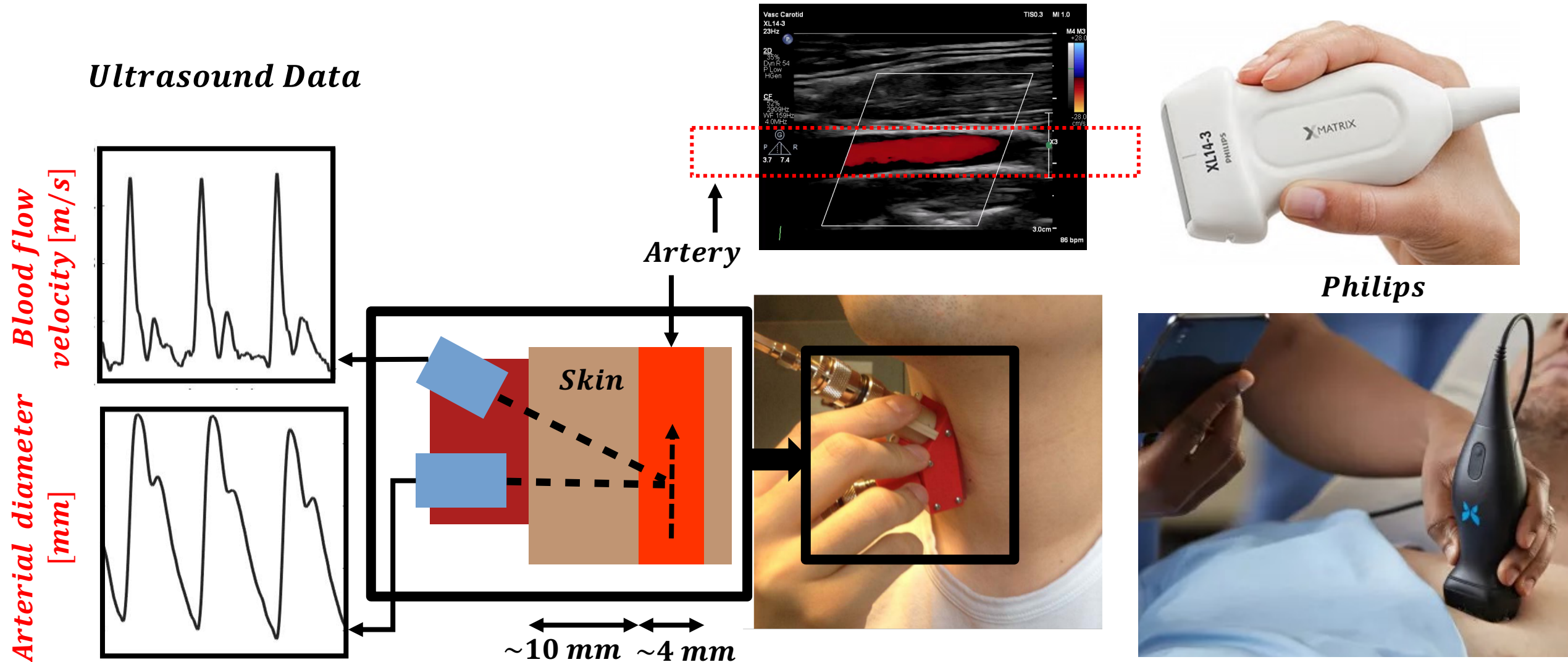
Ultrasound Data

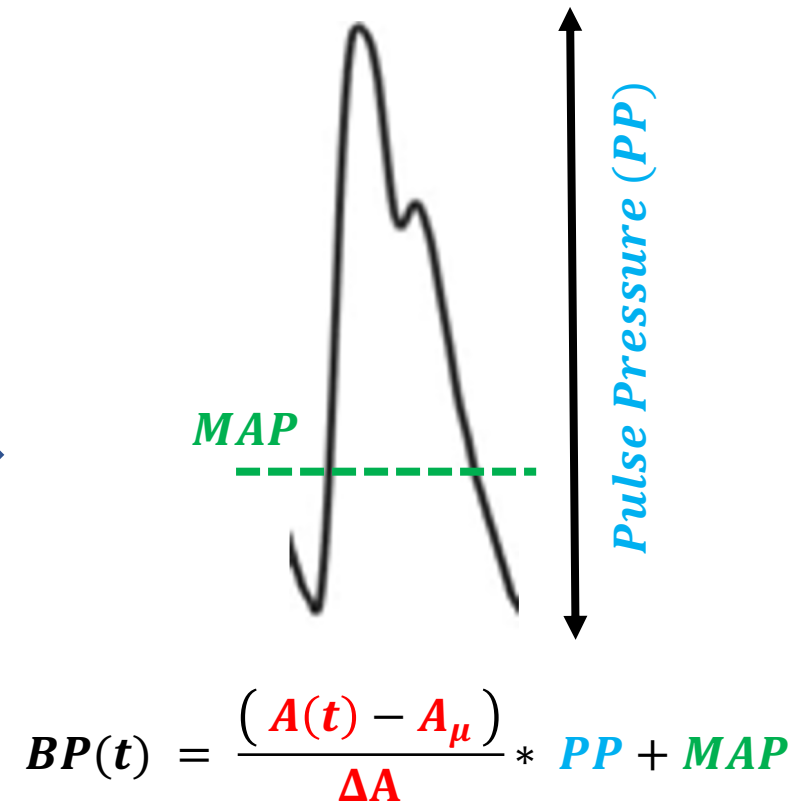Blood flow velocity [m/s]

Arterial diameter [mm]

Artery

Skin

~10 mm ~4 mm

Philips

Butterfly IQ

A Non-invasive Central Arterial Pressure Waveform Estimation System using Ultrasonography for Real-time Monitoring , MIT Thesis 2018

Ultrasound based device to measure BP waveform

Ultrasound Data

Blood flow velocity [m/s]

Arterial diameter [mm]

A_μ

ΔA

Pulse Pressure = f(Slope)

$\sqrt{\text{Arterial area}}$ [mm]

Slope

Blood flow velocity [m/s]

BP Waveform

MAP

Pulse Pressure (PP)

$$BP(t) = \frac{\left(A(t) - A_\mu\right)}{\Delta A} * PP + MAP$$
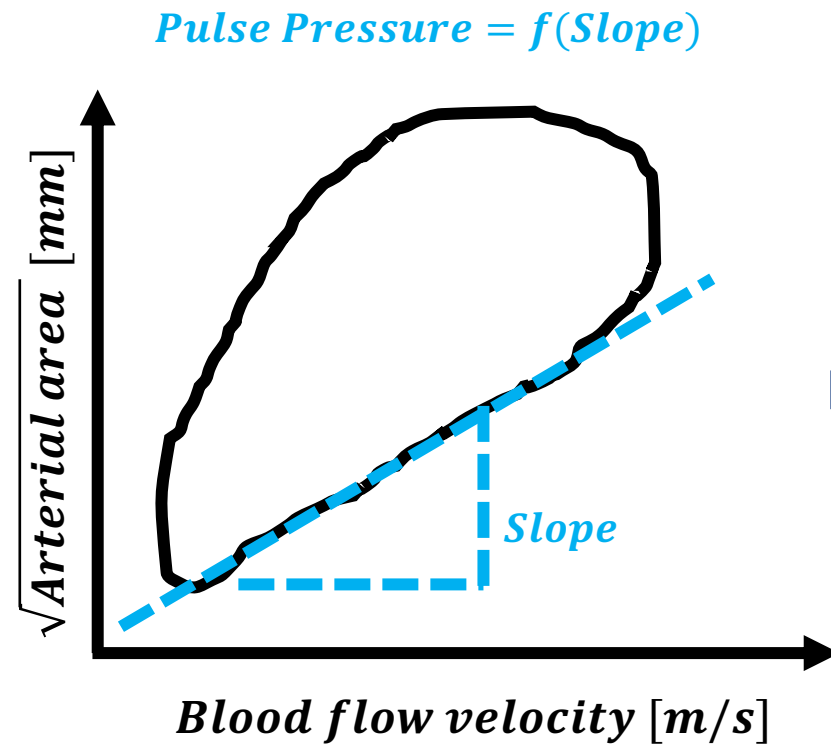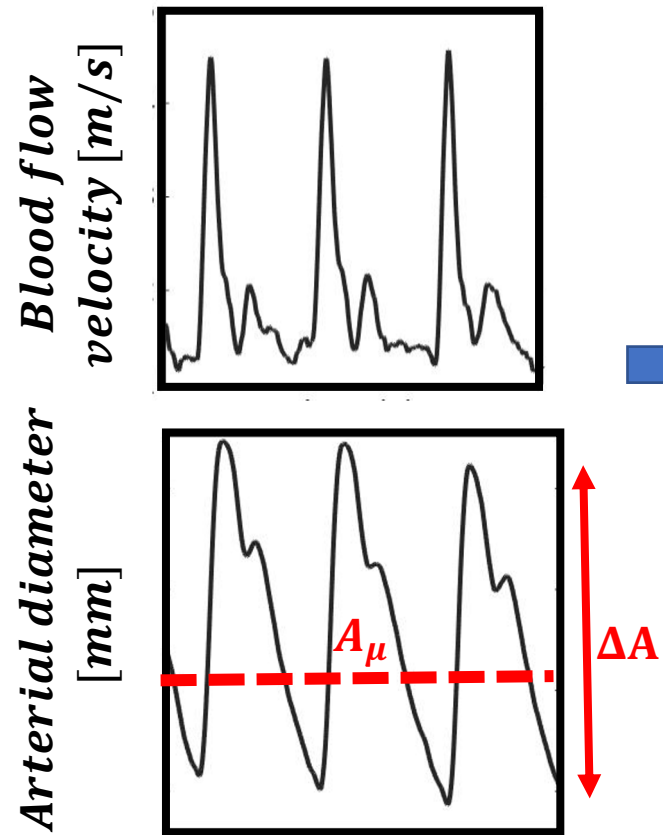
Overview

- Predict the blood pressure (BP) waveform from the photoplethysmogram (PPG) waveform
  - Both in time domain
- Setting 1: only regress the shape of the BP from the shape of PPG
  - No information on the scale of the waveform (no information on MAP and pulse pressure)
- Setting 2: Regress the absolute values of BP from absolute PPG
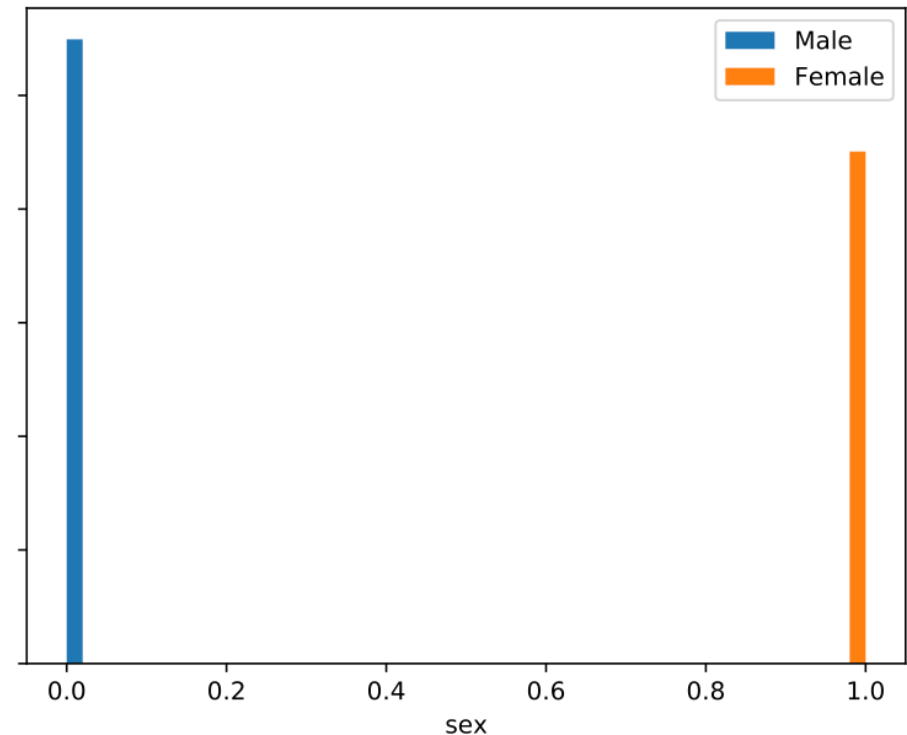 - Contains information of MAP and pulse pressure

Dataset: VitalDB database*

- 3045 patients data

- Each contains around 10000 beats

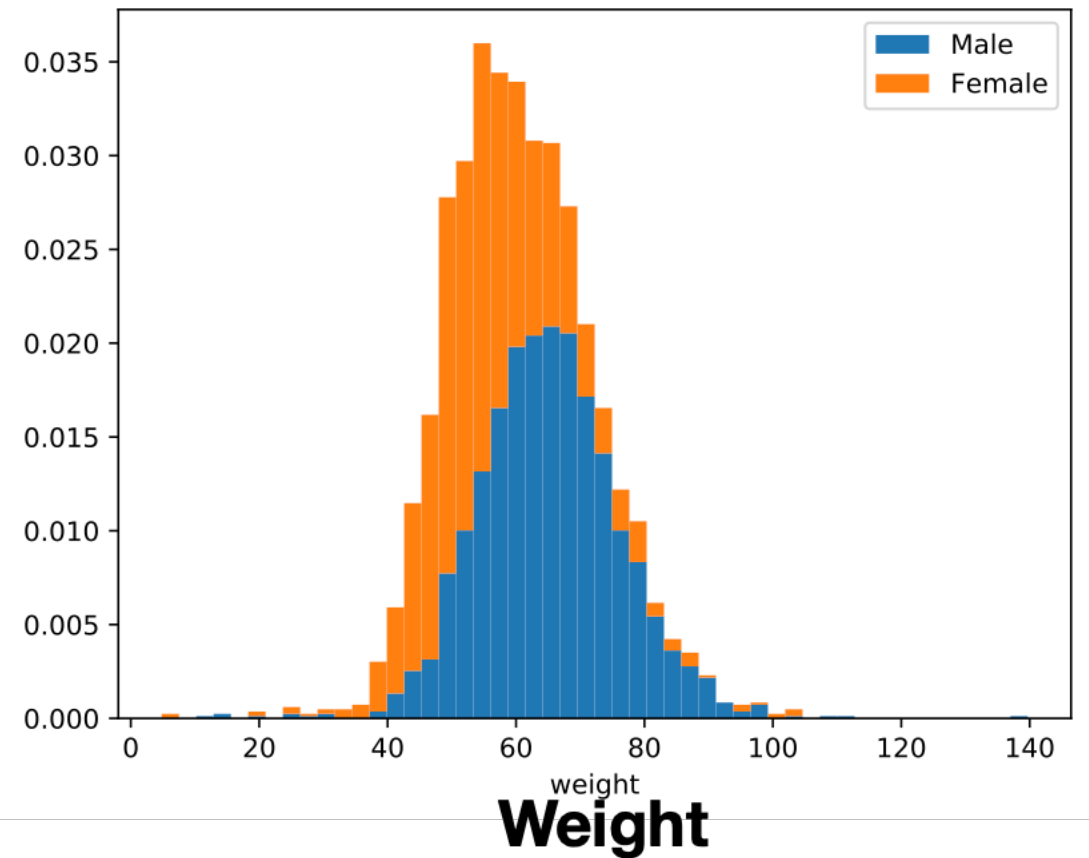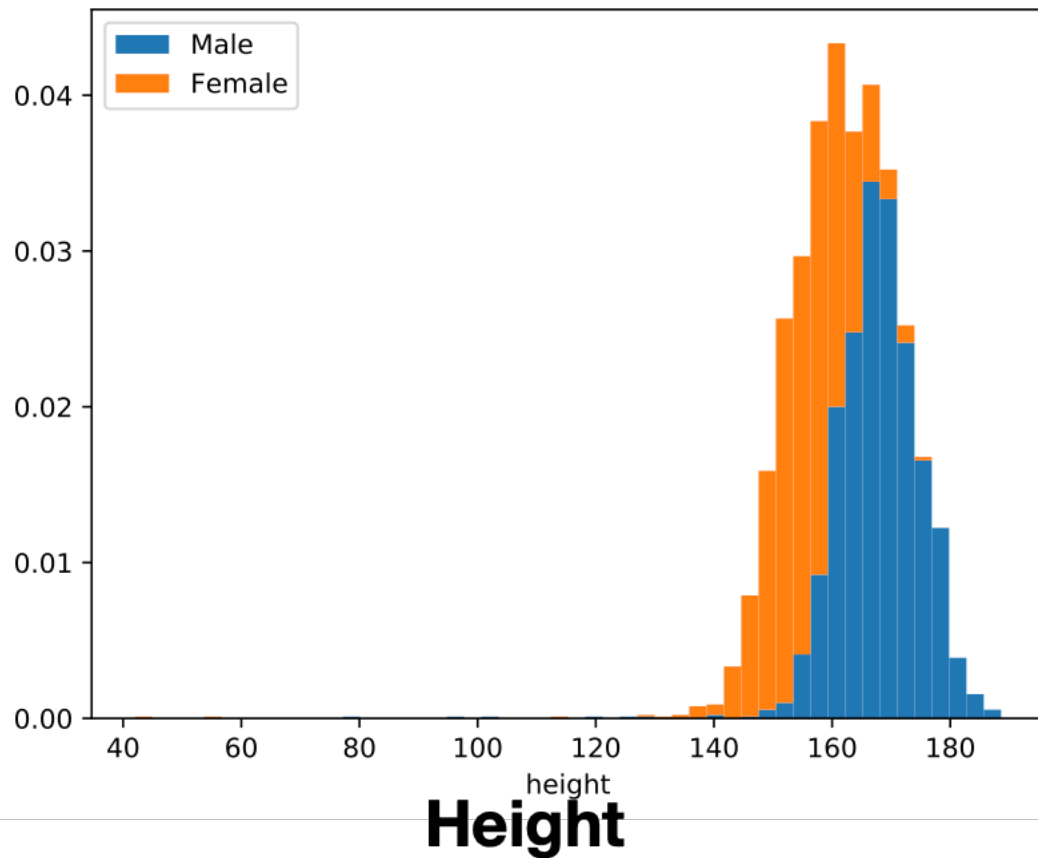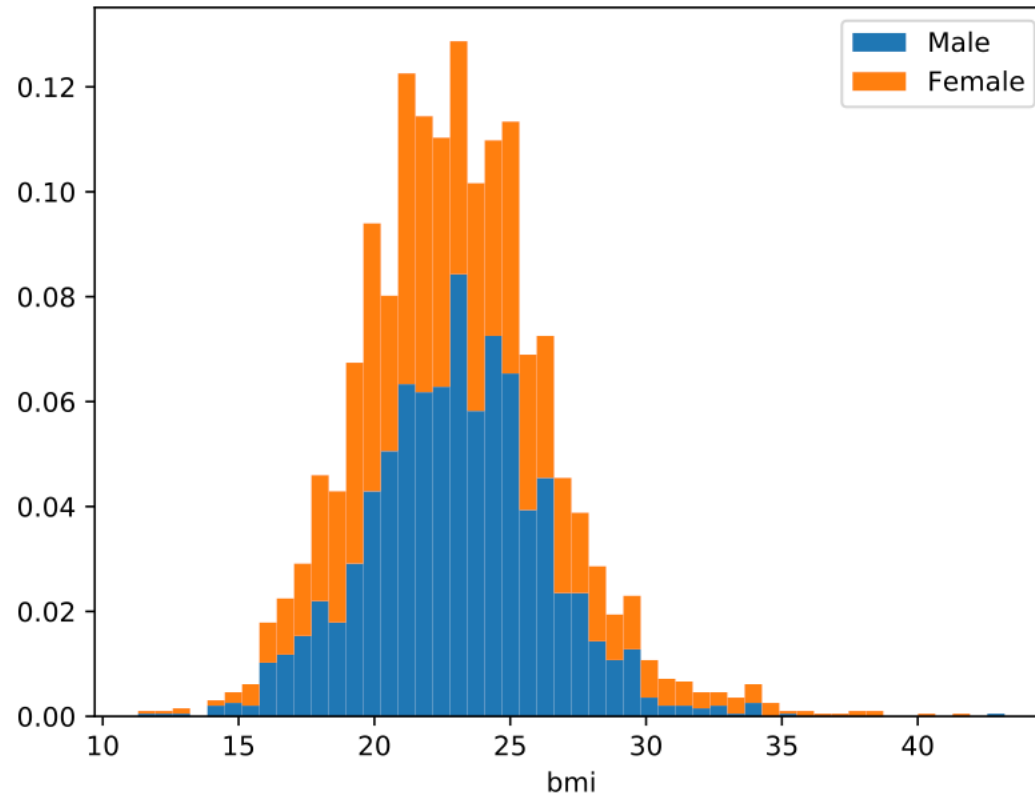- Besides BP and PPG, also contains anthropometric data
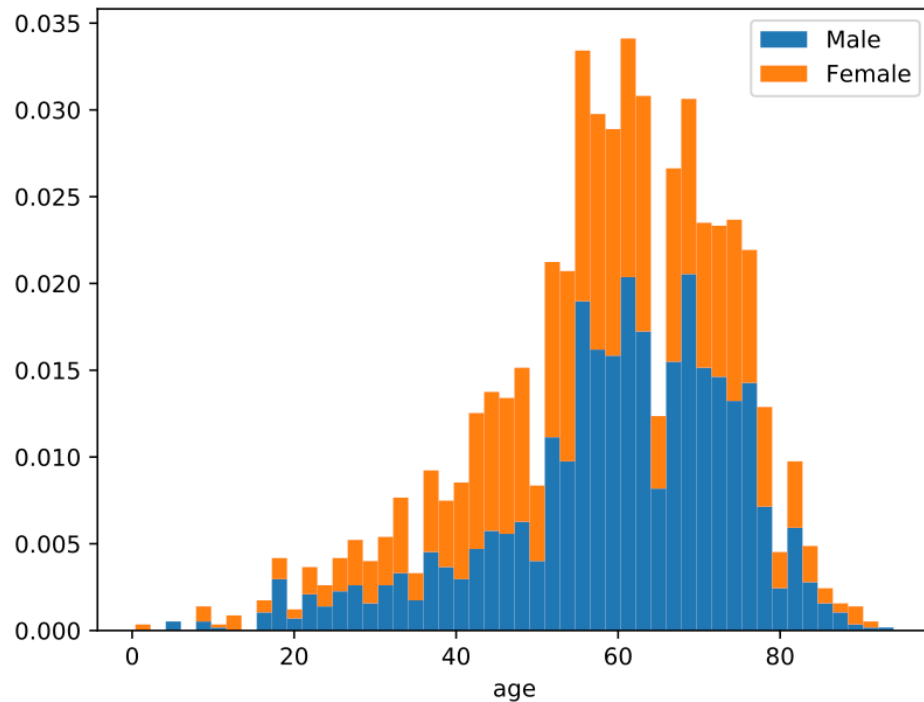
age

Sex

*https://vitaldb.net/data-bank/

Dataset

- Besides BP and PPG, also contains anthropometric data

Height

Weight

Dataset

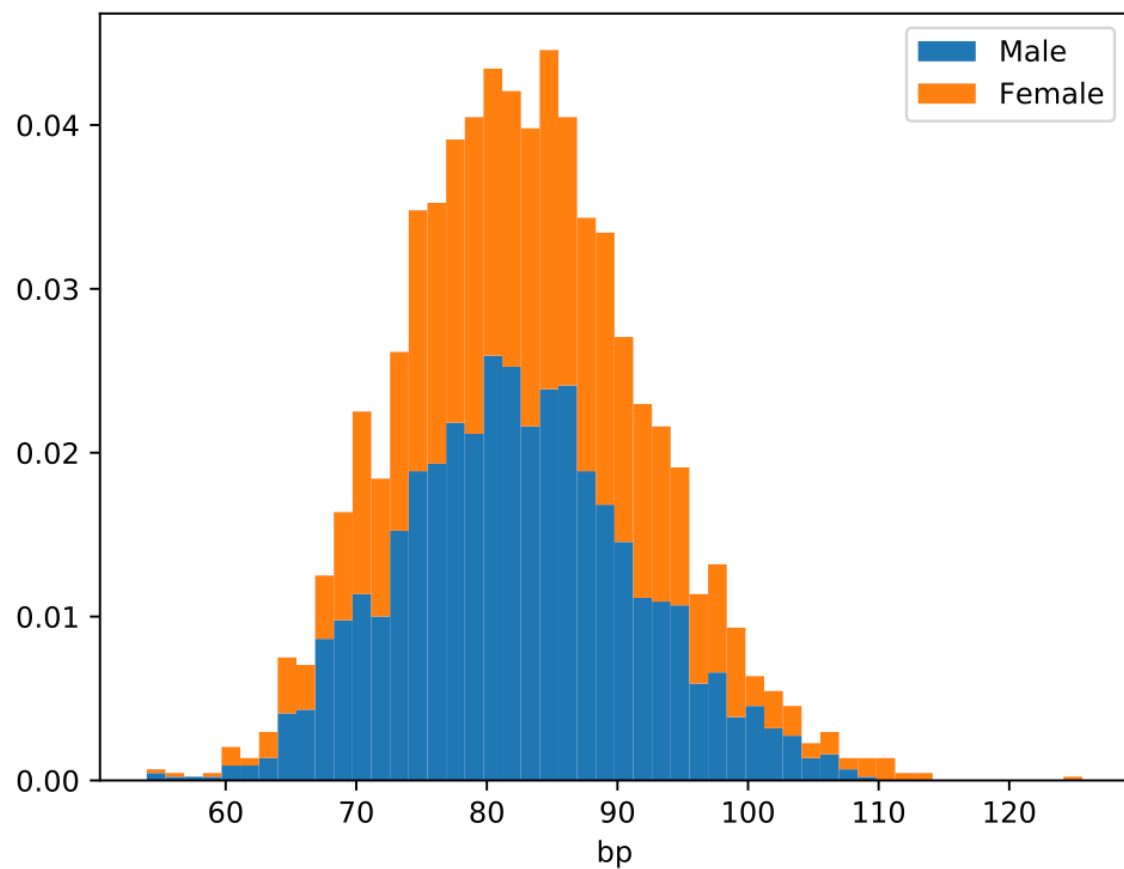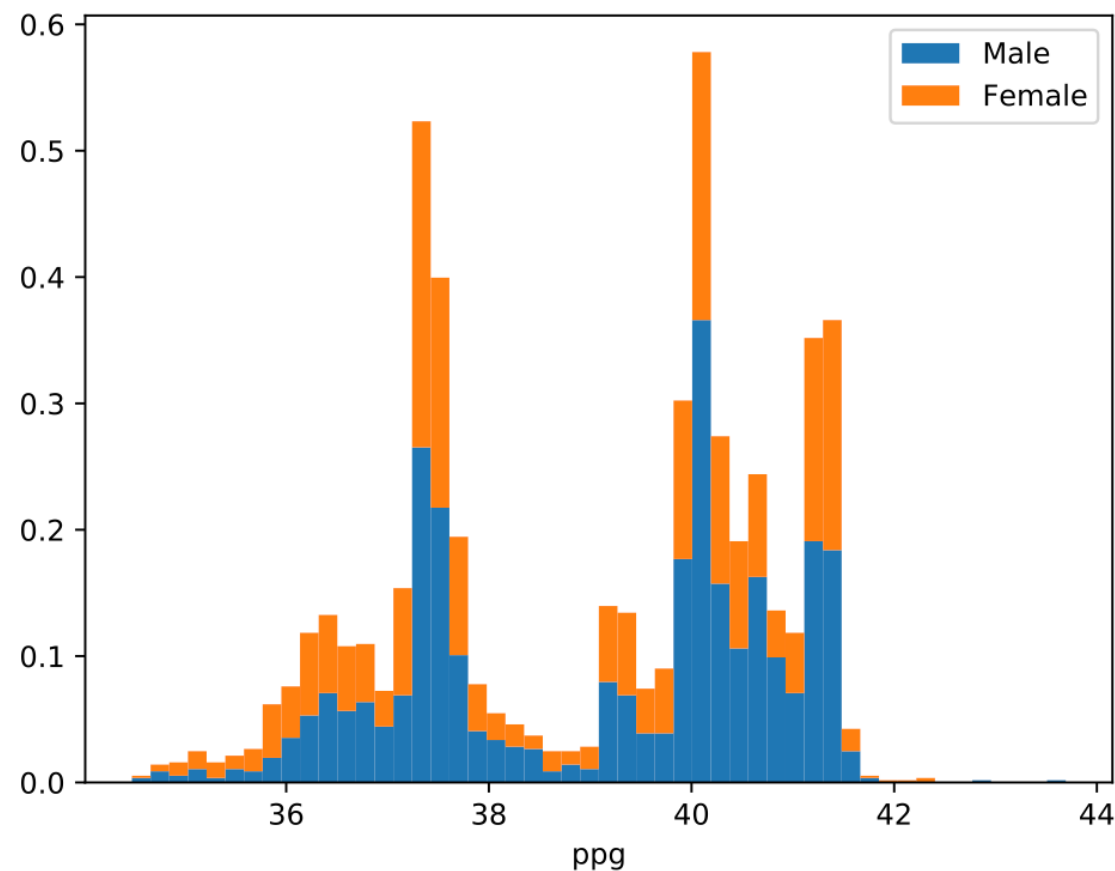- Besides BP and PPG, also contains anthropometric data


BMI

Dataset

- MAP and mean PPG distribution:

MAP   **Mean_PPG**

Input features to the ML model

| Data Type	Feature
Vector	PPG Waveform
Scalar	Age
Scalar	Sex
Scalar	Weight
Scalar	Height
Scaler	BMI

Input features preprocessing

- Settings 1: Normalize PPG & BP **within** each beat for (the scale information is **removed**) No information on MAP and pulse pressure

- Setting2: Normalize PPG & BP **across** all beats (the scale information is still **maintained**)

- **Resample** the input vectors to 100 time steps

- The target BP wave is also resampled to 100 time steps

- **Standardization** of each feature among all samples

- Repeat and **concatenate** other scalars with PPG vector to get the input features

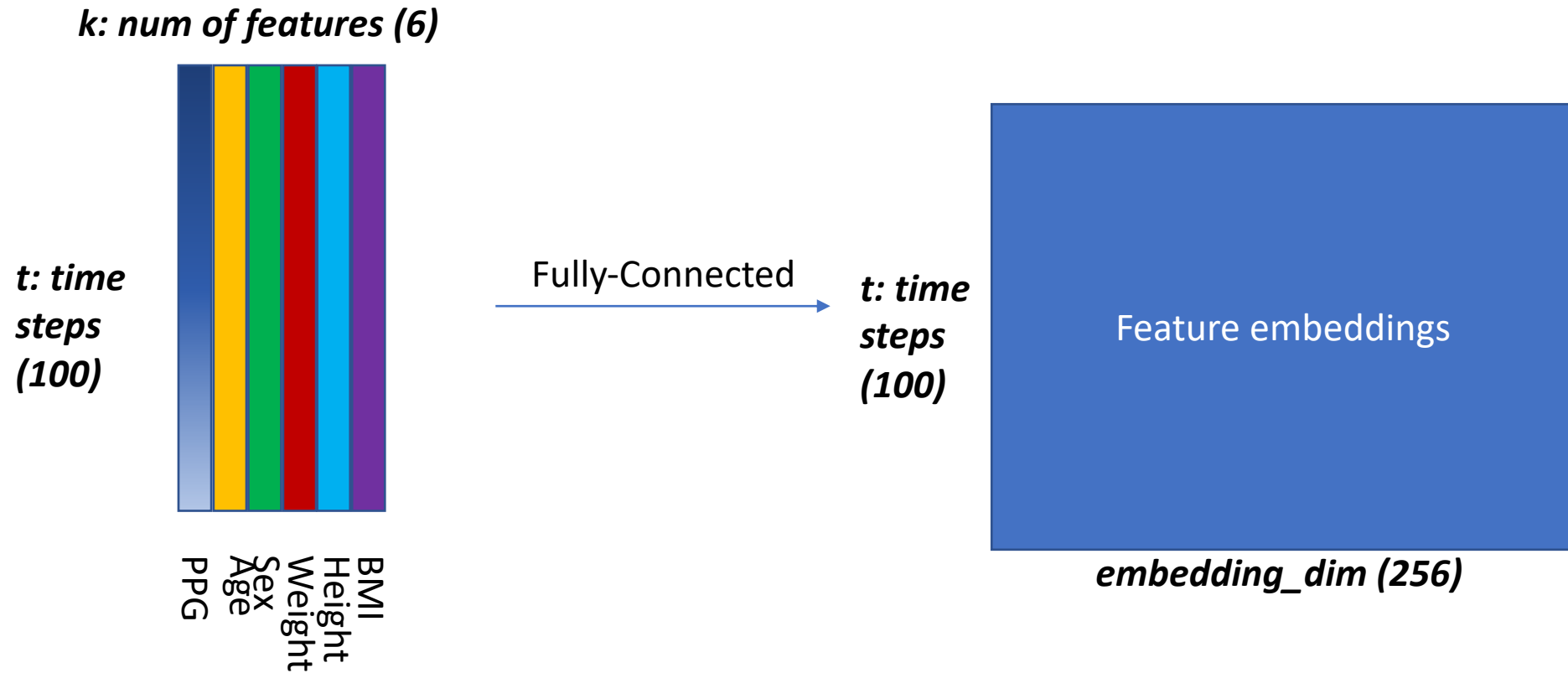Model input shape (PPG)
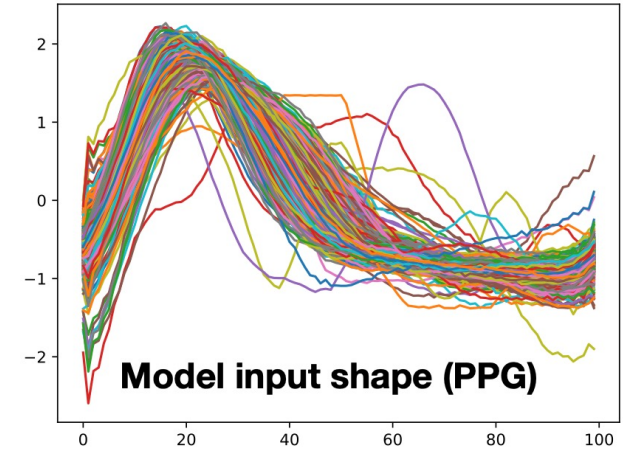
k: num of features (6)

t: time steps (100)
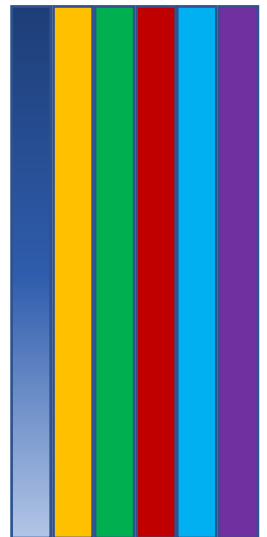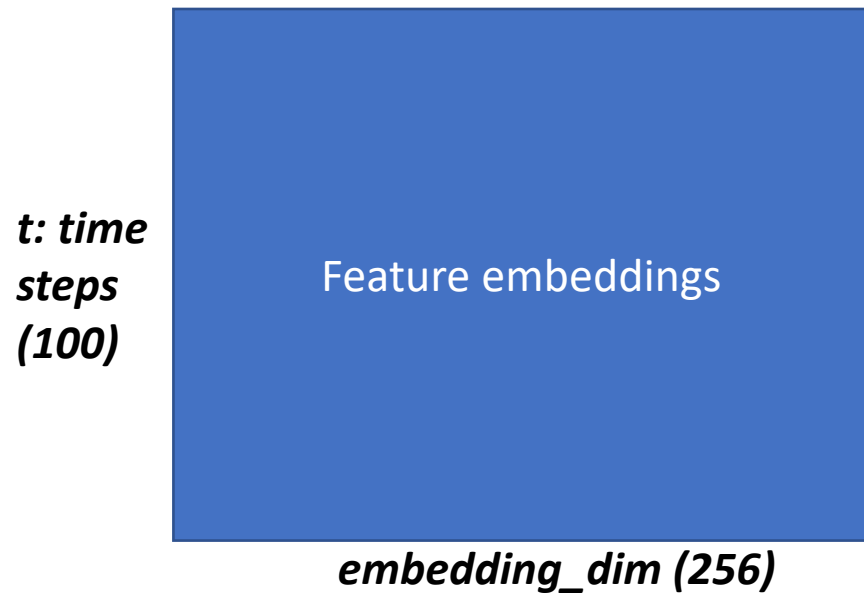
BMI
Height
Weight
Sex
Age
PPG

Input features preprocessing

- FC to project the input features to a **higher dimension** embedding (from 6 to 256)
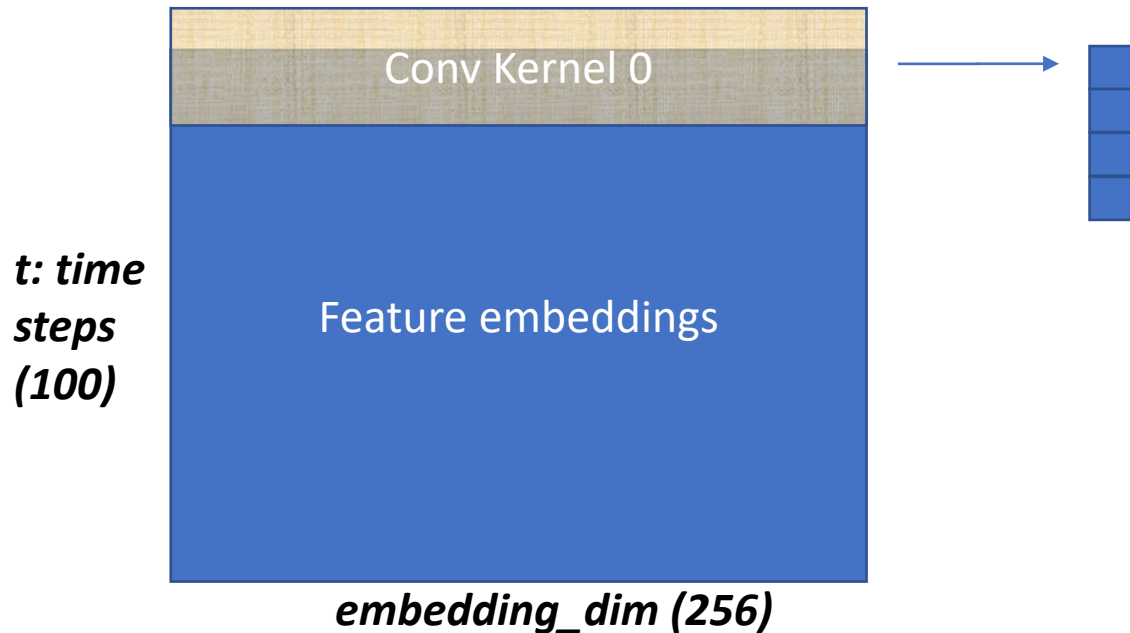
ML model

- Convolution + Attention
- Pure convolution

t: time steps (100)
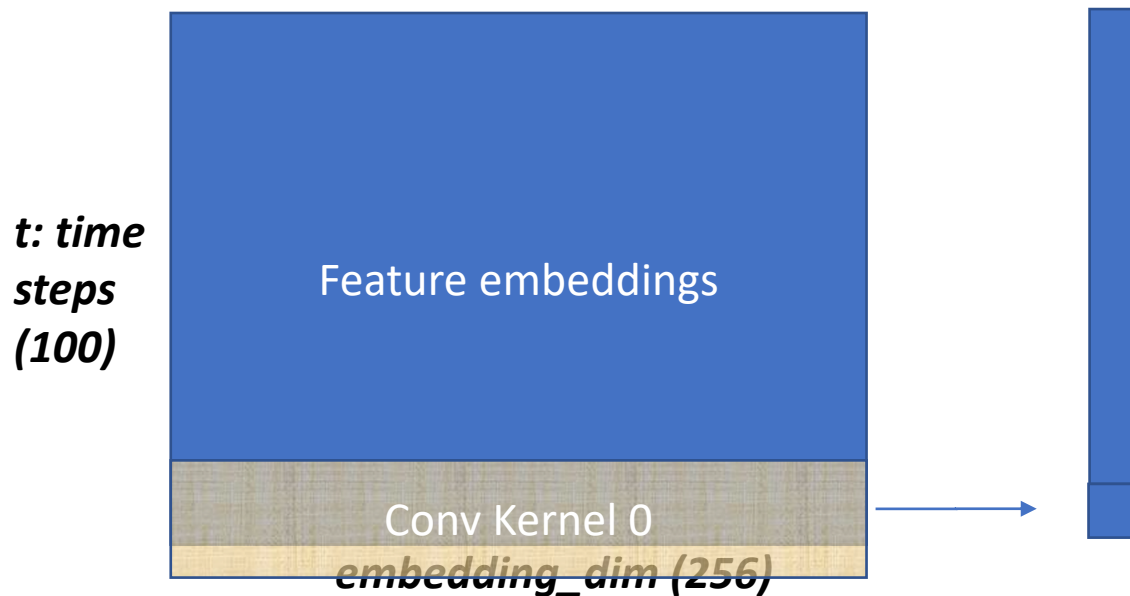
Feature embeddings

embedding_dim (256)

ML model: Convolution + Attention

- Firstly apply **1D convolution**, stride=1, kernel_size=3, padding=1
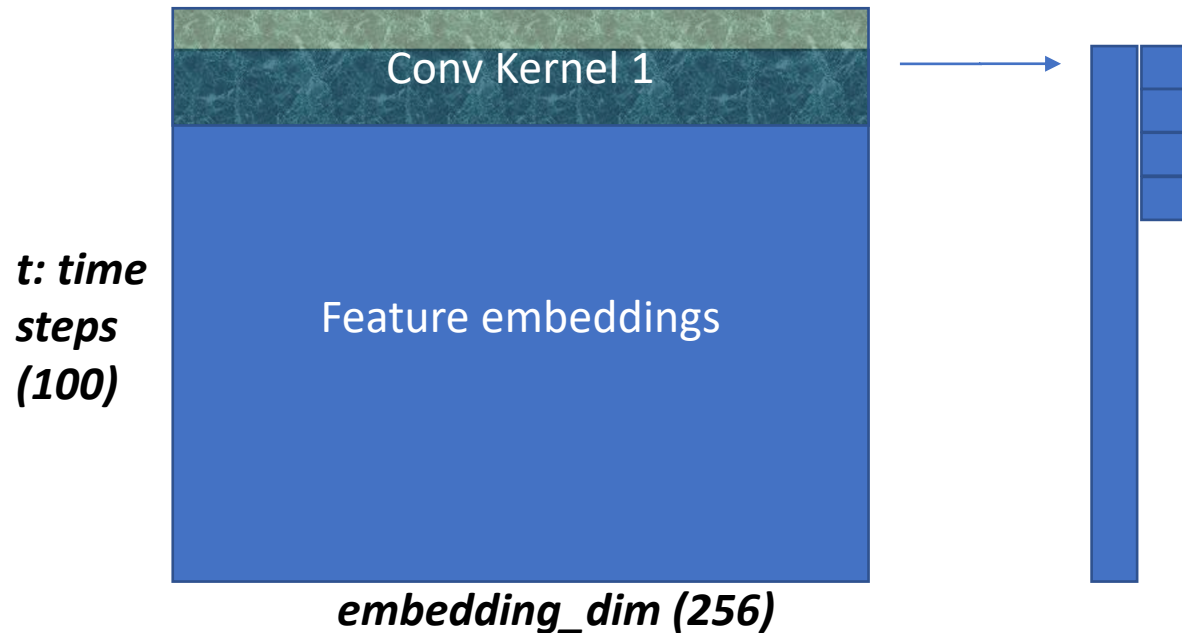- Output feature_dim = embedding_dim = 256

ML model: Convolution + Attention

- Firstly apply 1D convolution, stride=1, kernel_size=3, padding=1
- Output feature_dim = embedding_dim = 256

ML model: Convolution + Attention

- Firstly apply 1D convolution, stride=1, kernel_size=3, padding=1
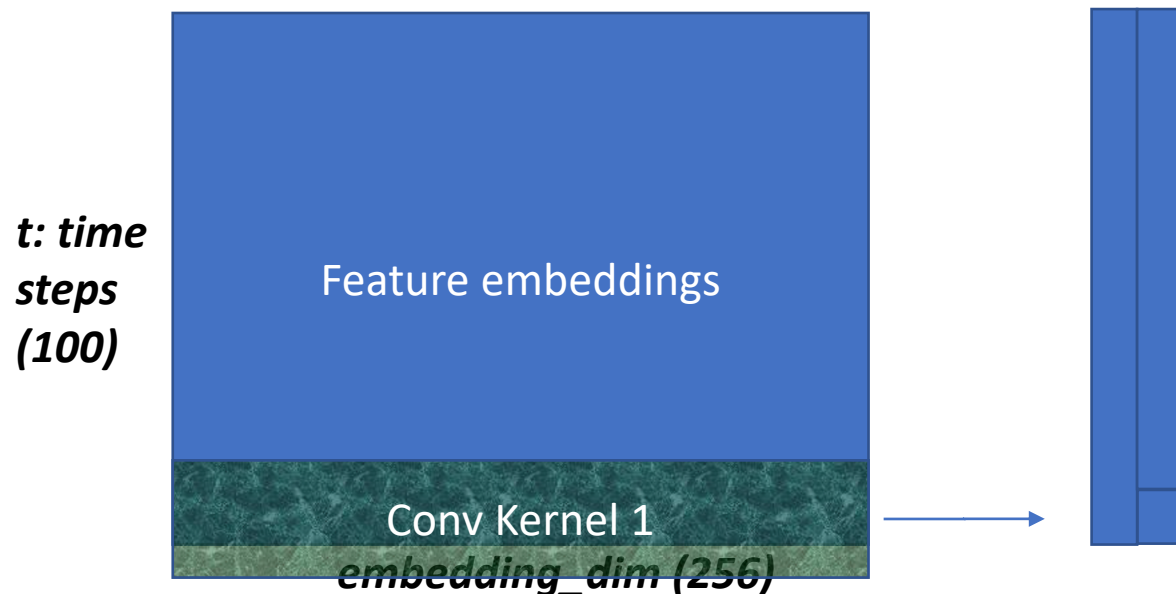- Output feature_dim = embedding_dim = 256

ML model: Convolution + Attention

- Firstly apply 1D convolution, stride=1, kernel_size=3, padding=1
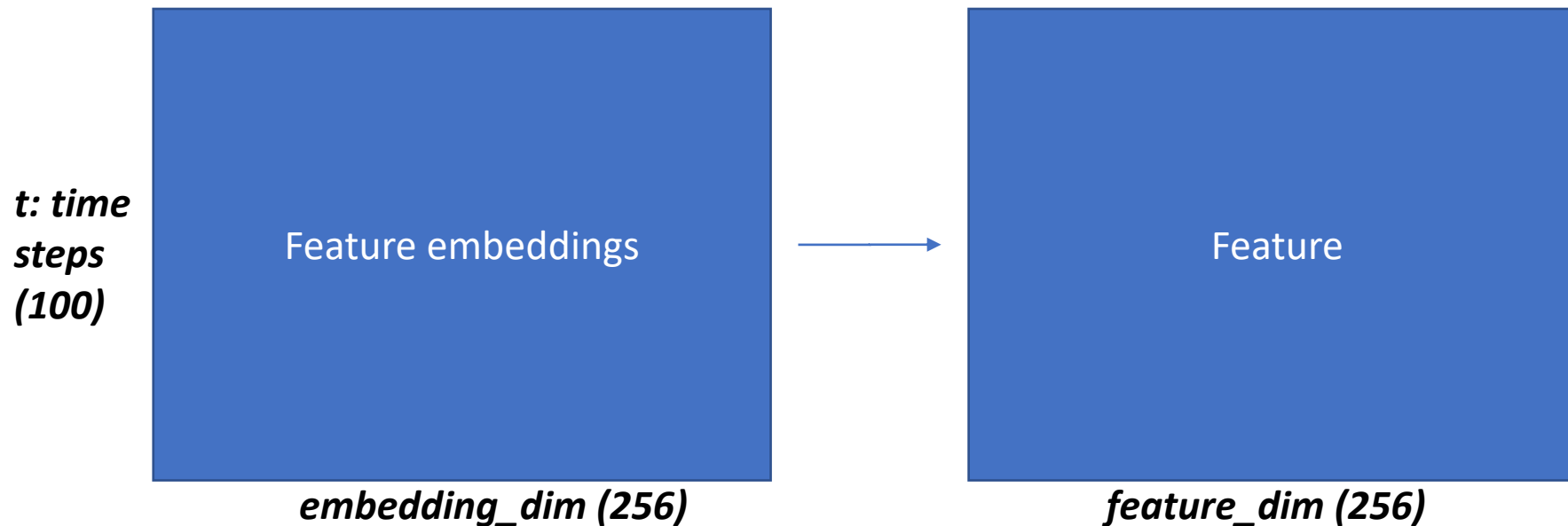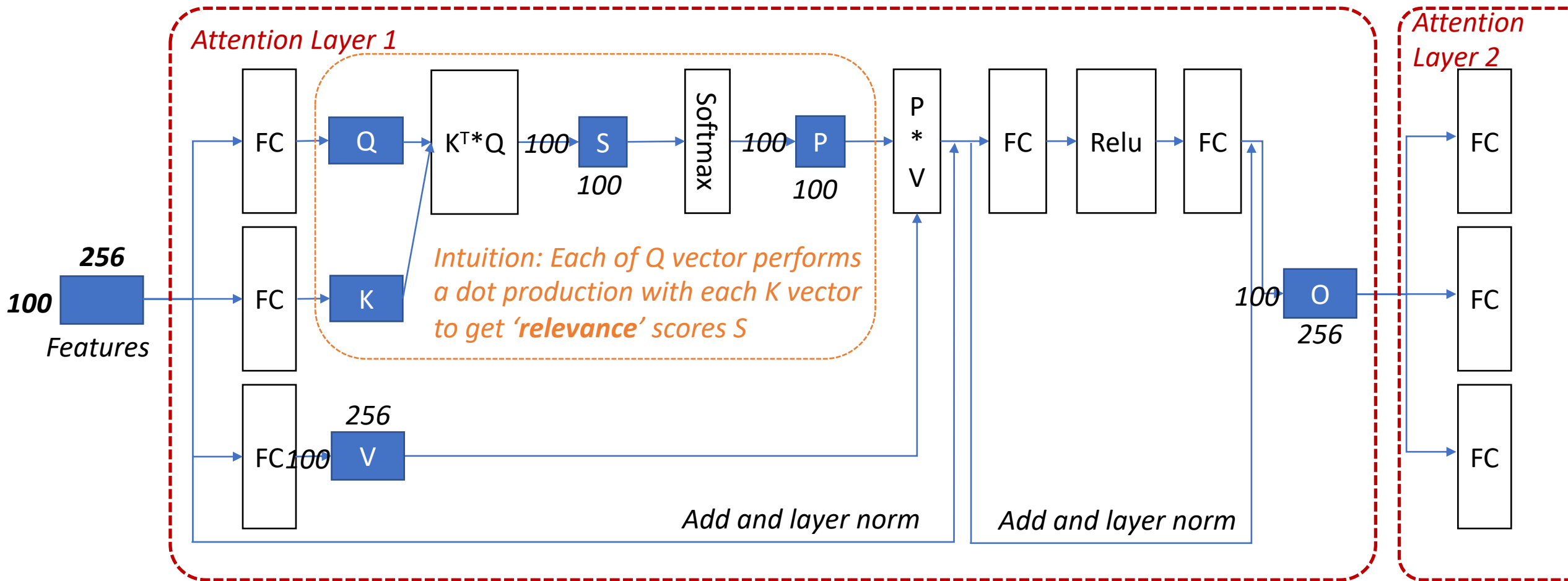- Output feature_dim = embedding_dim = 256

ML model: Convolution + Attention

- Firstly apply 1D convolution, stride=1, kernel_size=3, padding=1
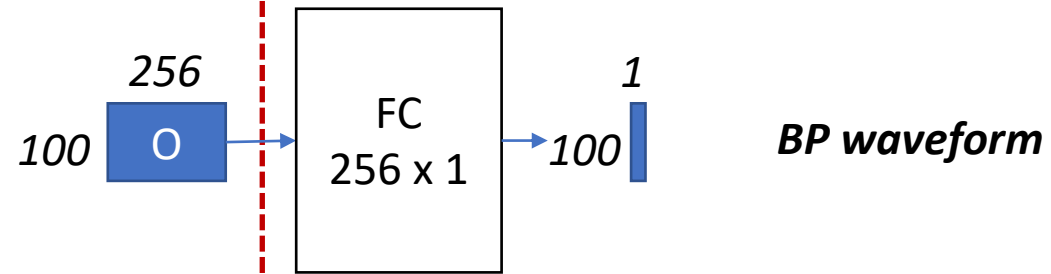- Output feature_dim = embedding_dim = 256
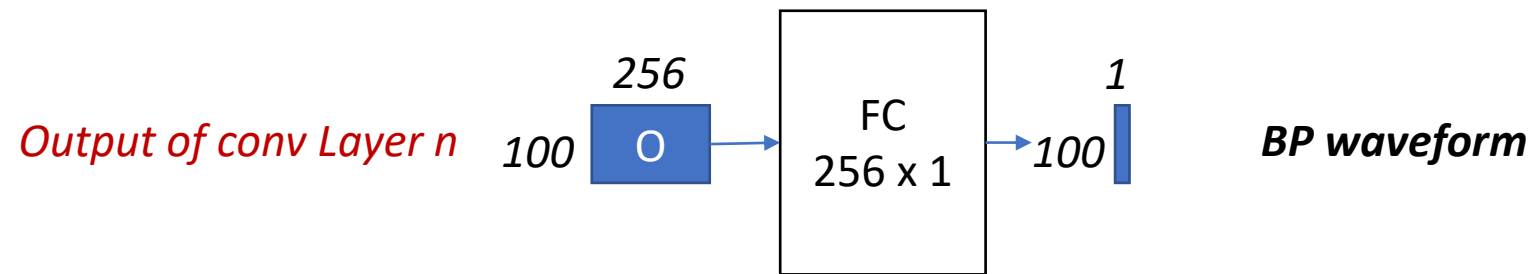
ML model: Convolution + Attention

ML model: Convolution + Attention

ML model: Pure Convolution

Output of conv Layer n   *100* **256** O   **FC**
256 x 1 *100* **1** ***BP waveform***

Model training settings

- Model Architecture
  - Conv+attention: 3 conv layers + 3 attention layers
  - Pure convolution: 6 conv layers
  - Hidden dim and embedding dim = 256
  - In the last layer, feature of each time step goes through a regressor to get one time-step of the BP
- Training on 2400 subjects, validation on 300 and test on 300
  - Train:validation:test=8:1:1
- For each subject, we use 10 beats
- Train for 300 epochs with Adam optimizer

Experimental Results

- Settings 1: regress the BP shape

	MSE (normalized)	Scale back to mmHg
Conv+Attention	0.212	3.45
Pure Conv	0.224	3.66

- Setting 2: regress the BP absolute values

	MSE (normalized)	Scale back to mmHg
Conv+Attention	0.86	69.3
Pure Conv	0.89	71.7

*Typically, less than 7mmHg can be considered accurate

Visualizations for Setting 1: BP shape regression
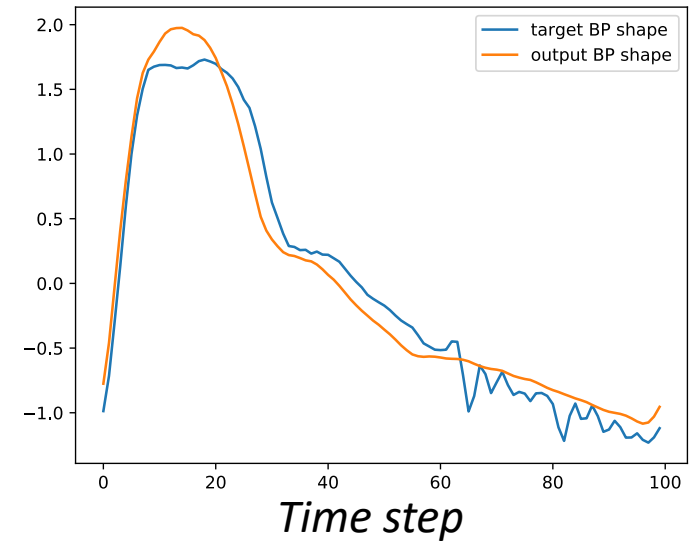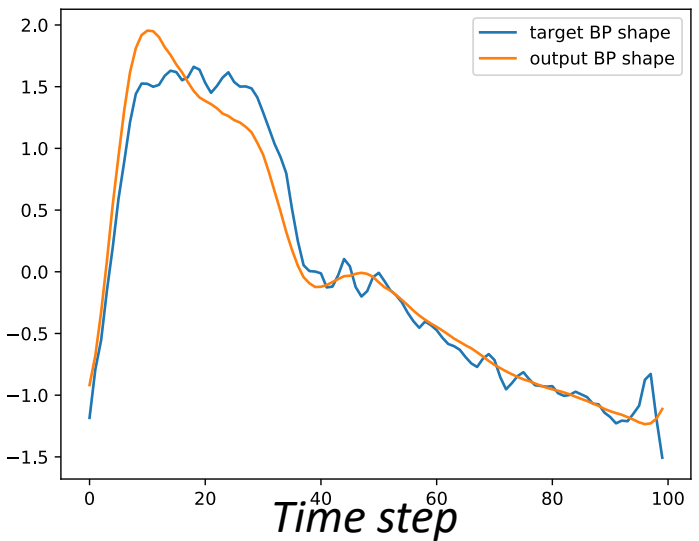
- Conv + Attention
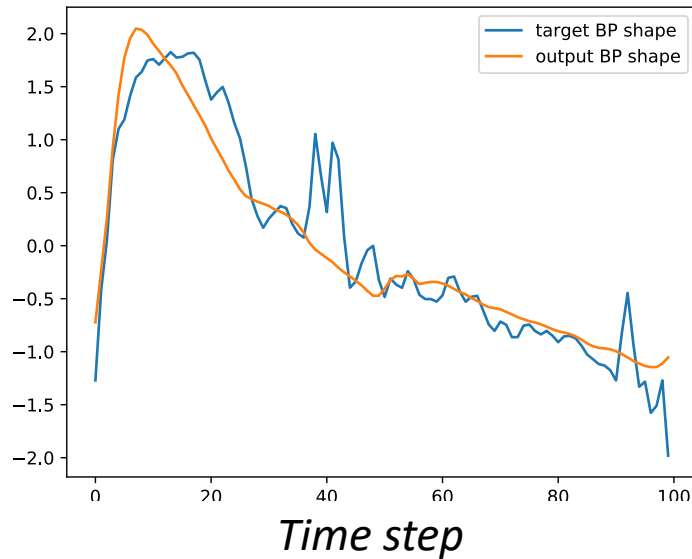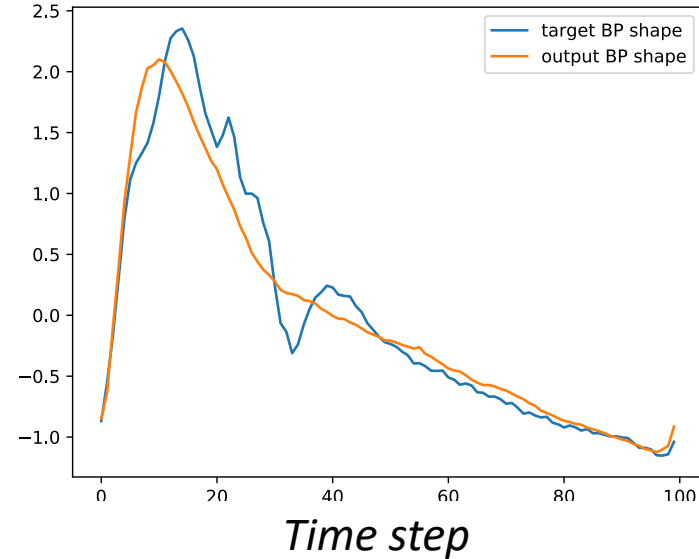
Conclusion and Next Steps

- Attention and convolution based ML models can provide accurate prediction of BP shape from PPG shape; but the prediction for absolute BP values is not good enough.

- Try to regress the shape, mean and std **separately** to improve accuracy

- Try **different** models (LSTM, pure attention, etc)

- Deployment:
  - Reduce model size with pruning and quantization
  - Hardware aware architecture search with HAT*
  - On the raspberry pi or microcontrollers with TinyEngine*

Wang, Hanrui, et al. "Hat: Hardware-aware transformers for efficient natural language processing." arXiv preprint arXiv:2005.14187 (2020).

Lin, Ji, et al. "Mcunet: Tiny deep learning on iot devices." arXiv preprint arXiv:2007.10319 (2020).

Thank you!