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Meta-learning of personalized thermal comfort model and fast identification of the best personalized thermal environmental conditions

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ABSTRACT

The model of personalized thermal comfort can be learned via various machine learning algorithms and used to improve the individuals' thermal comfort levels with potentially less energy consumption of HVAC systems. However, the learning of such a model typically requires a substantial number of thermal votes from the considered occupant, and the environmental conditions needed for collecting some votes may be undesired by the occupant in order to obtain a model with good generalization ability. In this paper, we propose to use a meta-learning algorithm to reduce the required number of personalized thermal votes so that a personalized thermal comfort model can be obtained with only a small number of feedback. With the learned meta-model, we derive a method based on the backpropagation of neural networks to quickly identify the best environmental and personal conditions for a specific occupant. The proposed identification algorithm has an additional advantage that the thermal comfort, indicated by the mean thermal sensation value, improves incrementally during the data collection process. We use the ASHRAE global thermal comfort database II to verify that the meta-learning algorithm can achieve an improved prediction accuracy after using 5 thermal sensation votes from an occupant to make adaptations. In addition, we show the effectiveness of the fast identification algorithm for the best personalized thermal environmental conditions with a thermal sensation generation model built from the PMV model.

1. Introduction

Thermal comfort is important for occupants in buildings and thus is a vital consideration for building managers who tune the indoor thermal environment via the heating, ventilation, and air conditioning (HVAC) systems. The existing research works [1,2] have proposed many methods to obtain a thermal comfort model of occupants at a group level based on the predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD). However, different individuals may have different thermal preferences [3]. Thus, it is hard or impossible to find an environmental thermal condition that satisfies every occupant. Fortunately, with the development of personal comfort systems (PCS) [4], we can control the local environmental conditions in the occupied zones of different individuals. On the other hand, the HVAC systems are major energy-consuming units in building systems [5]. Incorporating the personalized thermal comfort model into the HVAC controller design can contribute to more thermal satisfaction and less energy consumption [6–8]. Thus, we focus on the personalized thermal comfort model construction in this paper.

In order to obtain a personalized thermal comfort model, we need to collect the individuals' thermal votes, which reveal the thermal comfort level of occupants under different conditions [9–11]. Based on the thermal sensation feedback, the existing papers used various machine learning techniques to learn a personalized thermal comfort model [12,13]. However, a sufficient, typically not small [12], number of thermal feedback data at various environmental and personal conditions are required to train the model so that a reliable prediction performance can be reached [14]. From the occupants' perspective, the more thermal feedback is required, the more intrusions they encounter. In addition, during the long-time data collection period, the collected data should cover the space of conditions that are of interest to learn a model with good generalization ability. This indicates that the occupants may need to be exposed to some uncomfortable environmental conditions intentionally, which contradicts the motivation of thermal comfort model learning [13], i.e., to make occupants thermally comfortable. Thus, the designed learning algorithm is expected to require only a few thermal sensation feedback votes, of which the environmental conditions are not necessarily undesired for the considered occupants [14,15]. In effect, there exist common structures among the thermal preferences of different individuals [13]. Leveraging this structure information would

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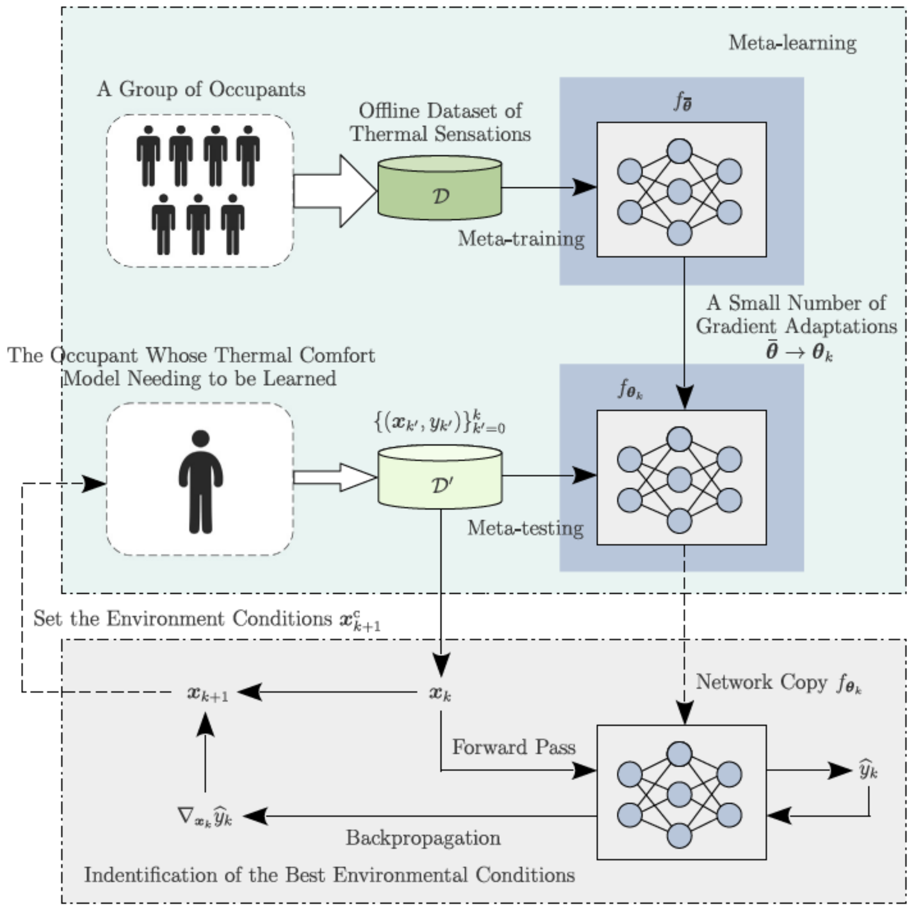


Fig. 1. The architecture of the algorithms.

(iii) In the remaining data after preprocessing step (ii), we obtained 25,113 data from 4256 occupants with the numbers of thermal votes from different occupants varying from 1 to 23. Fig. 2 shows the histogram of thermal sensation vote numbers of different occupants. We only keep those data with the associated occupants having at least 8 thermal sensation votes since multiple thermal sensation data are required to learn a thermal preference model for a specific occupant. Fig. 2 indicates that the number of occupants in the preprocessed dataset will be reduced significantly if we require at least 10 thermal sensation votes per occupant. In addition, for the occupants with more than 8 thermal sensation votes, we use only the first 8 raw data when evaluating the performance of Algorithm 1.

(iv) Before training and validation for the meta-model, the feature vector $\boldsymbol{x} \triangleq [T_{\text{air}}, MRT, Vel, RH, M, I_{\text{cloth}}]^{\text{T}}$ is normalized with

$$\boldsymbol{x}^{\text{norm}} \triangleq \frac{\boldsymbol{x} - \text{mean}(\{\boldsymbol{x}\})}{\text{std}(\{\boldsymbol{x}\})}, \tag{6}$$

where mean($\{\boldsymbol{x}\}$) and std($\{\boldsymbol{x}\}$) denote the elementwise mean and standard deviation of the feature vector $\boldsymbol{x}$ across the dataset after preprocessing steps (i)–(iii), respectively. Similarly, the thermal sensation votes are also normalized with

$$y^{\text{norm}} \triangleq \frac{y}{3}, \tag{7}$$

after which we have $y^{\text{norm}} \in [-1, 1]$ for all data.
The meta-model is directly trained and tested with 8 tuples $(\boldsymbol{x}^{\text{norm}}, y^{\text{norm}})$'s from each occupant.

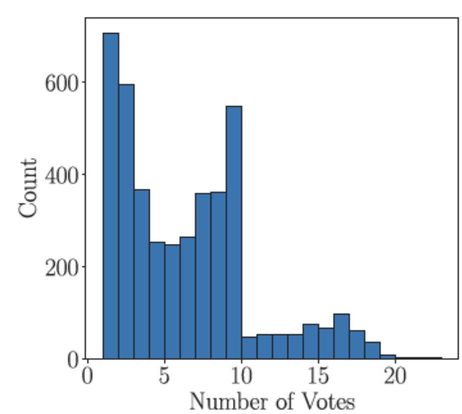
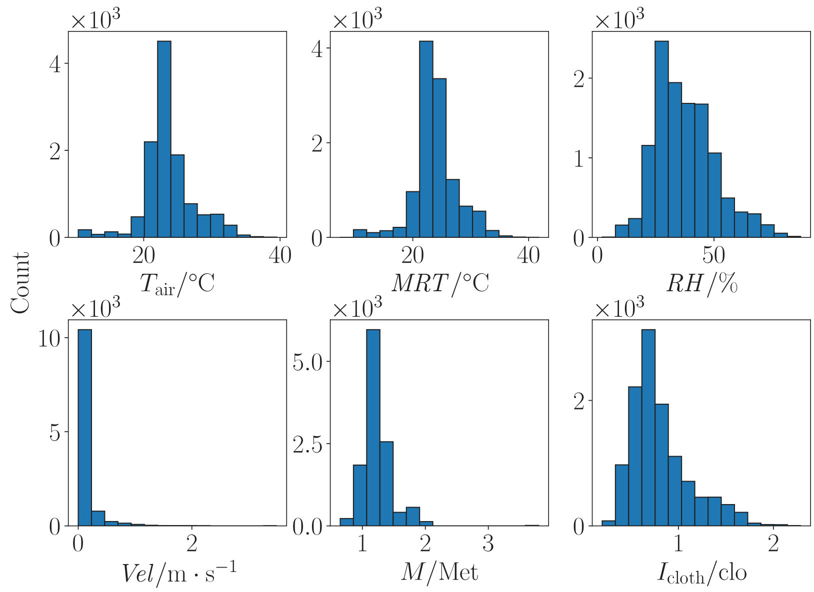


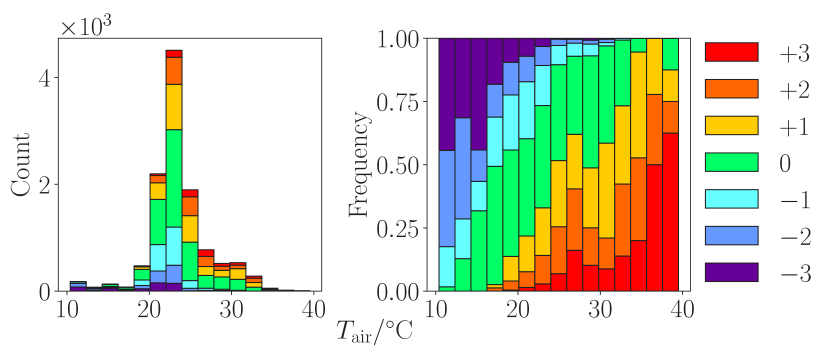
Fig. 2. Histogram of thermal sensation vote numbers of different occupants.

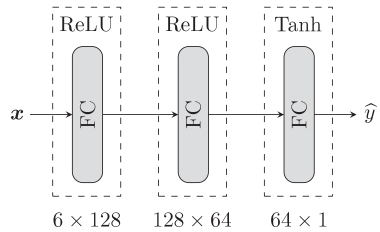
Remark 1. The reason why the Z-scores, instead of the min–max normalization, are used to standardize the feature vector $\boldsymbol{x}$ in (6) is that the Z-score can handle outliers better than the min–max normalization. This is important in the following two senses.

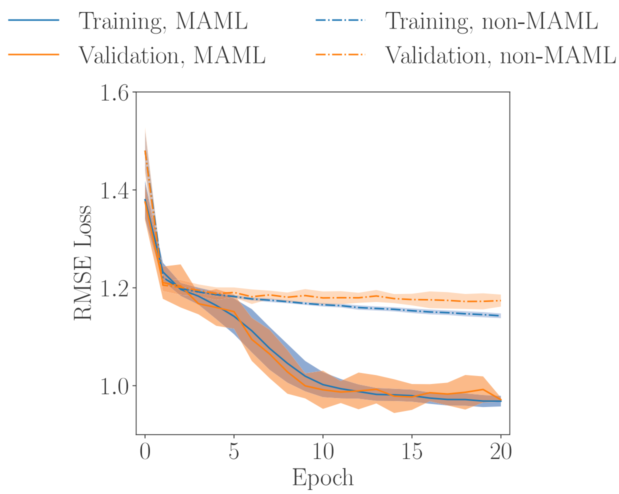
(i) For the experiment in this section, we use a static offline dataset, for which the minimum and maximum values of each feature can be obtained. When putting the meta-trained model into practice, we cannot guarantee that the conditions are in the pre-calculated min–max ranges if we use the min–max normalization. This is not an issue for the Z-score, which is not intended to normalize features to the same scales.

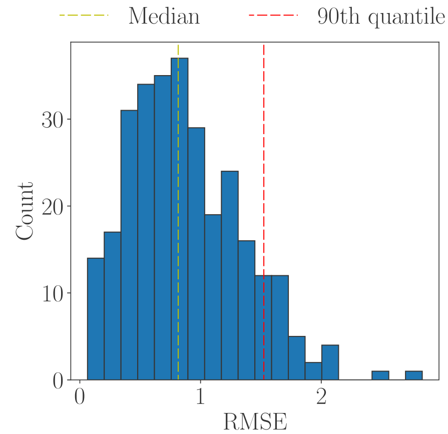
(ii) As shown in Fig. 3, the histogram of air velocity is highly right-screwed, with the support $[0, 3.3941]$ but mean 0.1108. In this case, if the min–max normalization is used, then most normalized

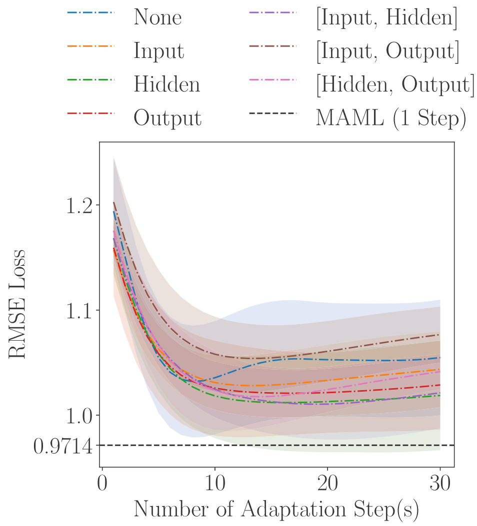

×10^3
Count
T_{air}/°C
MRT/°C
RH/%
Vel/m · s^−1
M/Met
I_{cloth}/clo

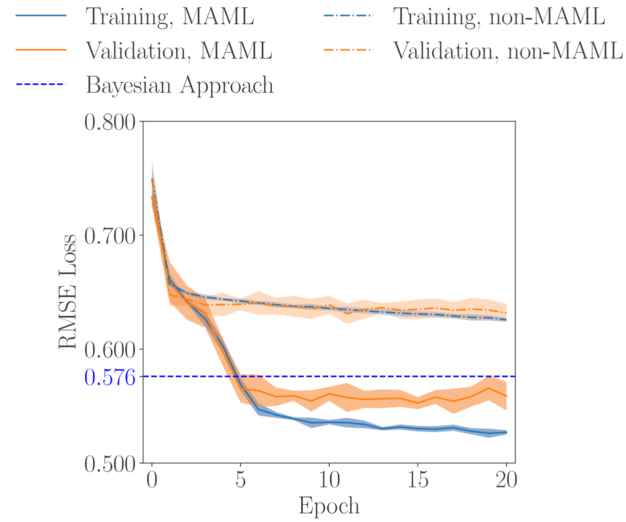

×10^3
Count
Frequency
T_{air}/°C
+3
+2
+1
0
−1
−2
−3

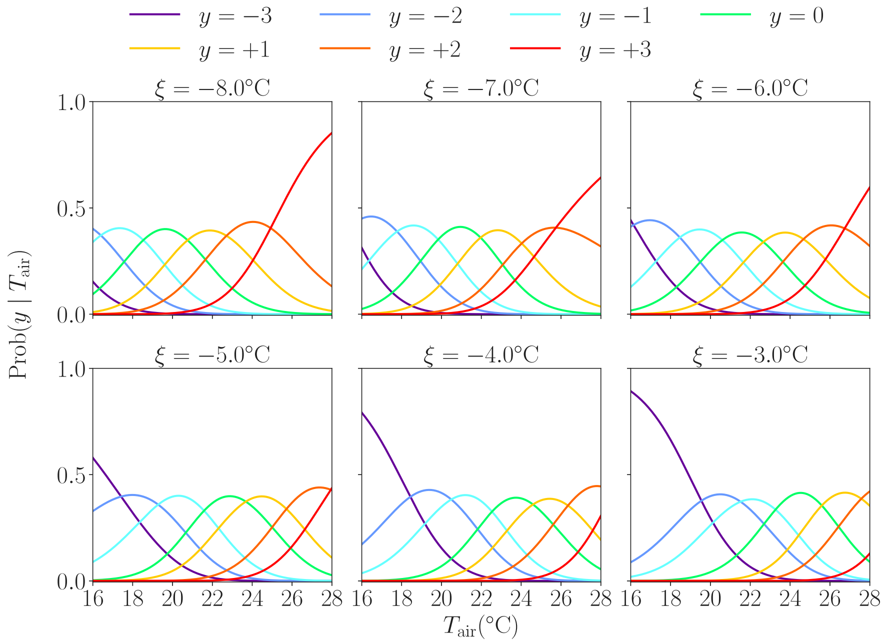

ReLU
ReLU
Tanh
FC
FC
FC
6 × 128
128 × 64
64 × 1

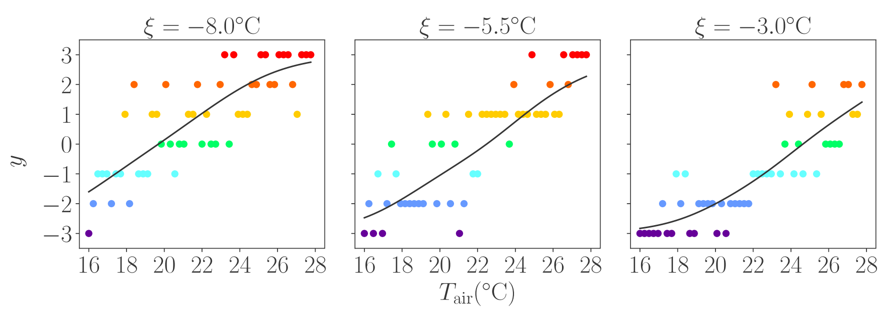

Training, MAML
Validation, MAML
Training, non-MAML
Validation, non-MAML
RMSE Loss
Epoch


Median
90th quantile
Count
RMSE

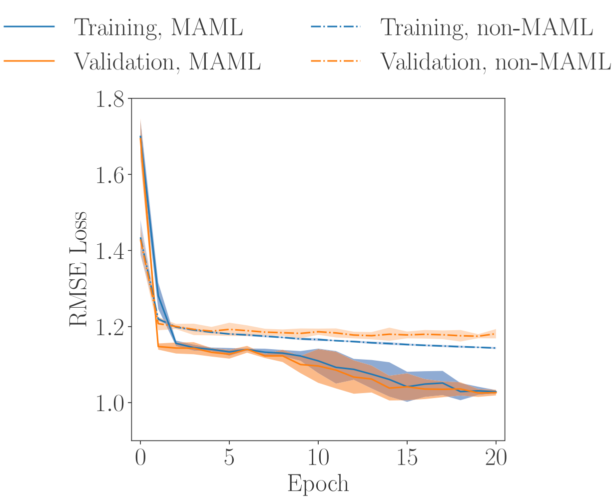

None
Input
Hidden
Output
[Input, Hidden]
[Input, Output]
[Hidden, Output]
MAML (1 Step)
RMSE Loss
1.2
1.1
1.0
0.9714
0
10
20
30
Number of Adaptation Step(s)

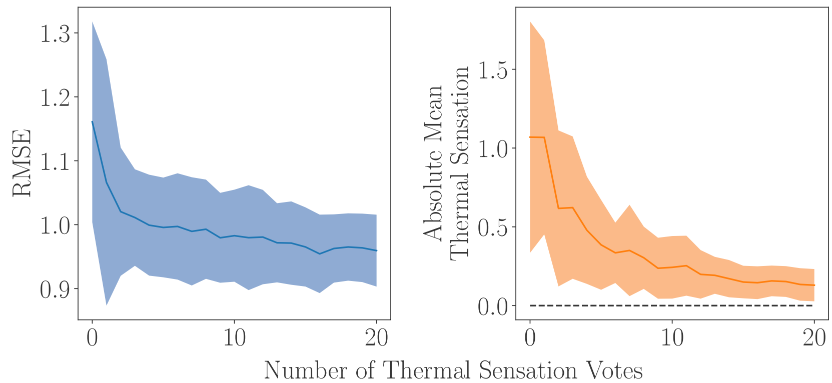

Training, MAML
Validation, MAML
Bayesian Approach
Training, non-MAML
Validation, non-MAML
RMSE Loss
0.800
0.700
0.600
0.576
0.500
0
5
10
15
20
Epoch


$y = -3$
$y = -2$
$y = -1$
$y = 0$
$y = +1$
$y = +2$
$y = +3$
$\xi = -8.0$°C
$\xi = -7.0$°C
$\xi = -6.0$°C
$\xi = -5.0$°C
$\xi = -4.0$°C
$\xi = -3.0$°C
Prob(y | T_{air})
T_{air}(°C)

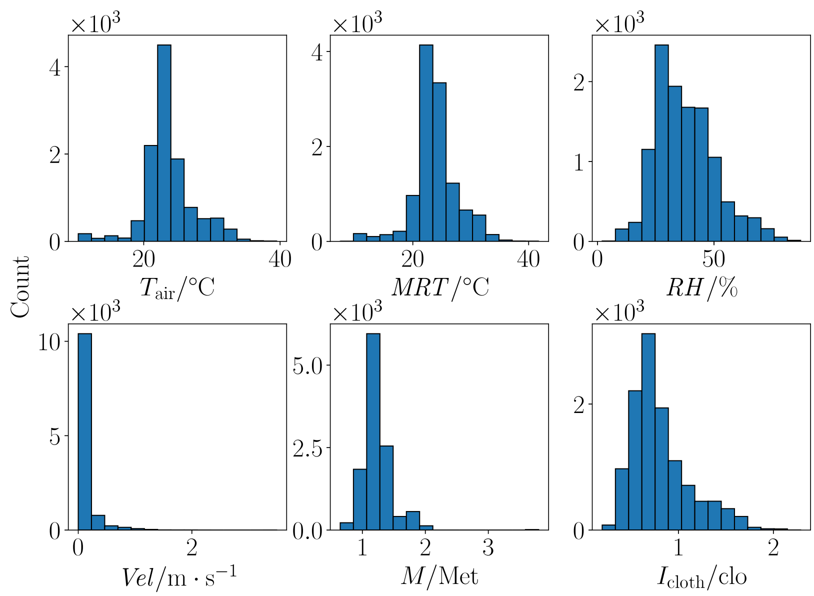

$\xi = -8.0$°C
$\xi = -5.5$°C
$\xi = -3.0$°C
y
T_{air}(°C)

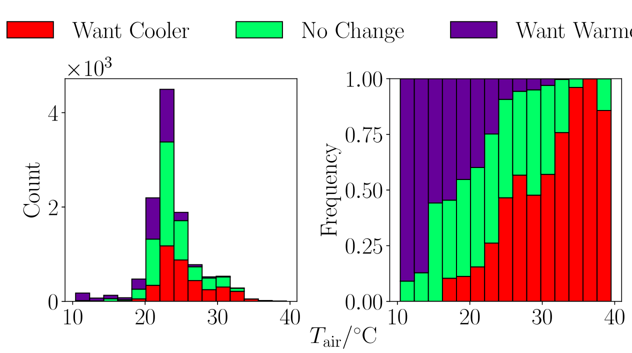
$\mathbb{E}$


Training, MAML
Validation, MAML
Training, non-MAML
Validation, non-MAML
RMSE Loss
Epoch

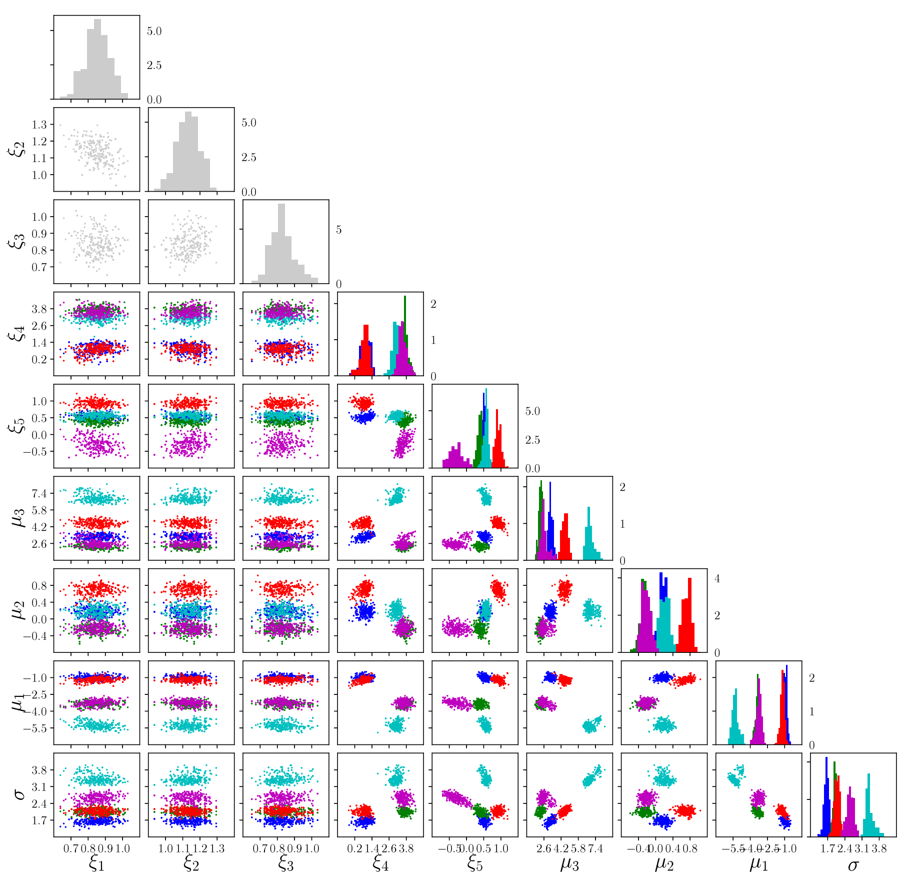

RMSE
1.3
1.2
1.1
1.0
0.9
0
10
20
Absolute Mean
Thermal Sensation
1.5
1.0
0.5
0.0
0
10
20
Number of Thermal Sensation Votes

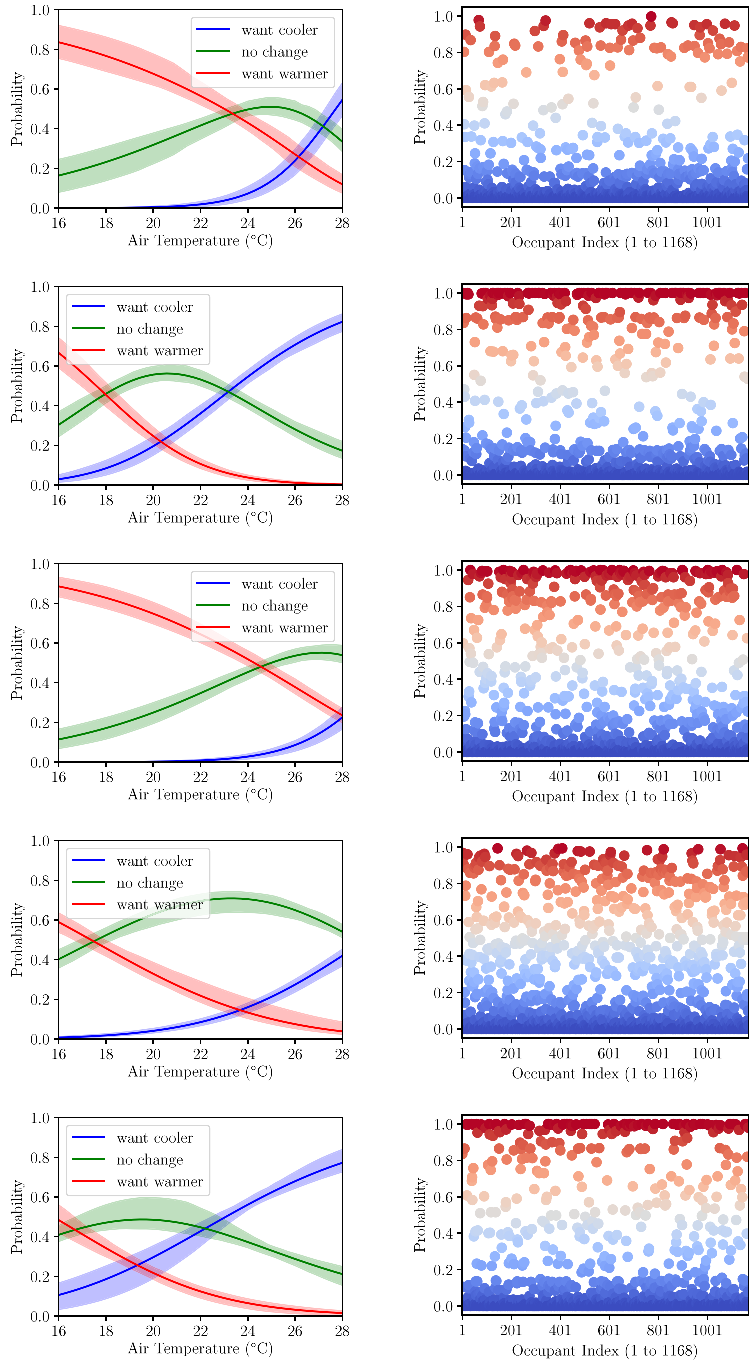
0 9714	**0 0044**


Count
$T_{\mathrm{air}}/°\mathrm{C}$
$MRT/°\mathrm{C}$
$RH/\%$
$Vel/\mathrm{m \cdot s^{-1}}$
M/Met
$I_{\mathrm{cloth}}/\mathrm{clo}$


Want Cooler
No Change
Want Warmer
Count
Frequency
$T_{\mathrm{air}}/°\mathrm{C}$

0 9714	**0 0044**
0 9714	**0 0044**
0 9714	**0 0044**
0 9714	**0 0044**




want cooler
no change
want warmer
Probability
Air Temperature (°C)
Occupant Index (1 to 1168)