Modelling and understanding thermal comfort using self-reporting and interpretable machine learning

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Agenda for the presentation

- ➔ Introduction
- ➔ Why thermal comfort is important?
- ➔ Traditional vs State-of-the-art
- ➔ Modeling Thermal Comfort
- ➔ Understanding the model using interpretable machine learning tools
- ➔ Applications and Future Work
- ➔ Conclusion

Why is thermal comfort important in the built environment?

Productivity and Performance

Important for

- Corporate offices
- Educational institutions
- Other buildings too, of course.

Roelofsen, P. (2002). The impact of office environments on employee performance: The design of the workplace as a strategy for productivity enhancement. Journal of facilities Management, 1(3), 247-264.

Bueno, A. M., de Paula Xavier, A. A., & Broday, E. E. (2021). Evaluating the connection between thermal comfort and productivity in buildings: A systematic literature review. Buildings, 11(6), 244.

Health and Wellbeing

Thermal comfort and Indoor air quality linked with health and wellbeing of occupants

- Sick Building Syndrome (SBS)

Coined by WHO in 1986, as nonspecific symptoms were reported by tenants in newly constructed buildings.

10-30% of newly constructed building had this problem.

Energy efficiency

Occupant behavior, when uncomfortable, can cause them to take actions counterproductive to energy efficiency.

- Opening windows or doors/ keeping them open.
- Increasing/decreasing thermostat to extreme settings

Miscellaneous

Other things include

- Value of a building
- Following compliances and standards such as ASHRAE, BREAM, LEED.
- Decrease absenteeism and increase occupant satisfaction.

Traditional vs State-of-the-art

Traditional

Two most popular thermal comfort models - PMV and Adaptive

State-of-the-art

Machine learning based thermal comfort models.

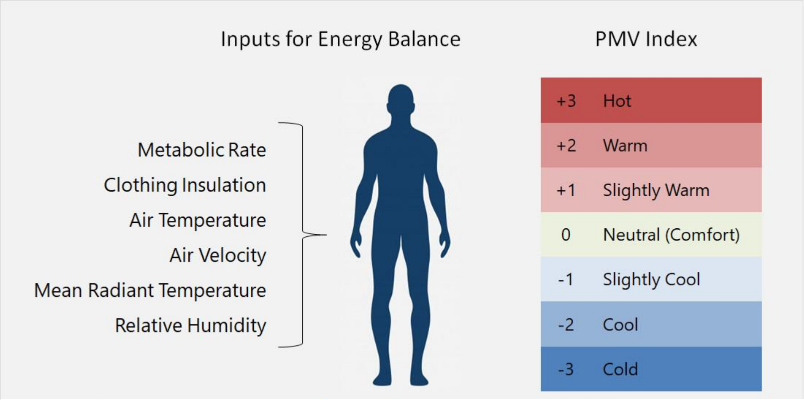
Personalized Comfort Systems (PCS)

Traditional methods (1970s and early 2000s)

Predicted Mean Vote (PMV)

Most widely used thermal comfort model in standards and certifications.

Steady-state equation, mathematical equation.

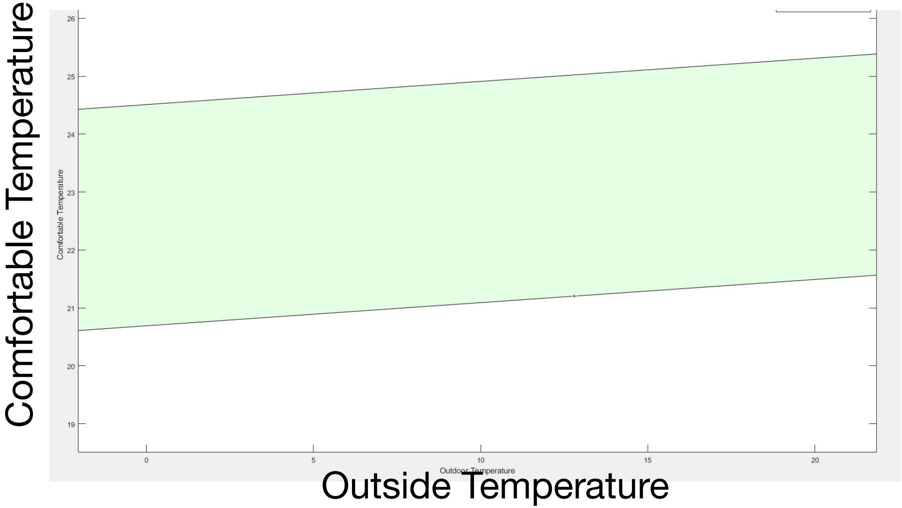


$$PMV = \left[0{,}303 \cdot \exp(-0{,}036 \cdot M) + 0{,}028\right] \cdot \left\{ \begin{array}{l} (M-W) - 3{,}05 \cdot 10^{-3} \cdot \left[5\,733 - 6{,}99 \cdot (M-W) - p_a\right] - 0{,}42 \cdot \left[(M-W) - 58{,}15\right] \\ -1{,}7 \cdot 10^{-5} \cdot M \cdot (5\,867 - p_a) - 0{,}001\,4 \cdot M \cdot (34 - t_a) \\ -3{,}96 \cdot 10^{-8} \cdot f_{cl} \cdot \left[(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4\right] - f_{cl} \cdot h_c \cdot (t_{cl} - t_a) \end{array} \right\}$$

Adaptive Model

Also widely used, especially in countries like Netherlands, Brazil, USA.

Based on the assumption that occupants adapt to their environments.
Only a function of outdoor temperature.



Limitations

Predicted Mean Vote (PMV)

Most widely used thermal comfort model in standards and certifications.

Steady-state equation, mathematical equation.

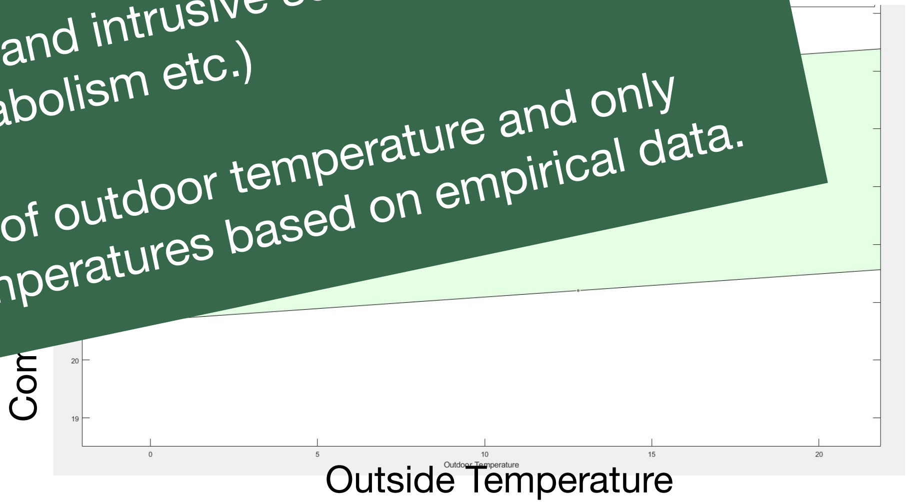
Mean

$PMV = 0.303e$ … $(W - M) - 3.05.$ … $-58.15]$ … -1 … $M(34 - t_a)$ … $-3.96.10^{-}$ … $273)^4 - (\overline{t_r} + 273)^4] - f_{cl}.h_c(t_{cl} - t_a)$

Adaptive Model

Als… razil, USA.

…onments.



- Do not take into account gender, culture, age, and <u>subjectivity</u> of thermal comfort.
- PMV requires many expensive and intrusive sensors for accurate calculations. (air velocity, metabolism etc.)
- Adaptive model is a function of outdoor temperature and only gives a possible range of temperatures based on empirical data.

Limitations

Predicted Mean Vote (PMV)

Most widely used thermal comfort model in standards and certifications.

Steady-state equation, mathematical equation.

$PMV = 0.303e$

$(W - M) - 3.05.$ … $-58.15]$

-1 … $M(34 - t_a)$

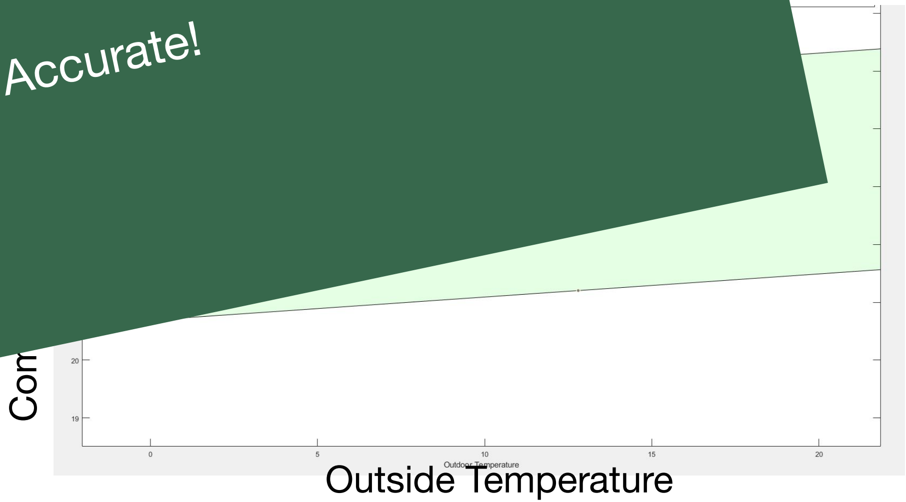
$-3.96.10^{-}$ … $+273)^4 - (\overline{t_r} + 273)^4] - f_{cl}.h_c(t_{cl} - t_a)$

Not Accurate!

Adaptive Model

Als… razil, USA.

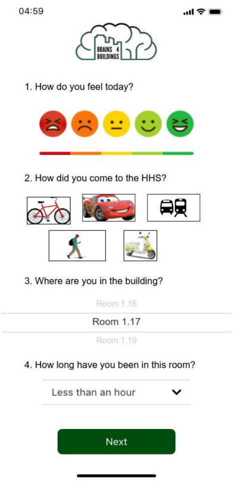
…onments.



State-of-the-art

Self-reporting based ML models

Ask people themselves!



Personalized Comfort systems

Let’s provide comfort to everyone :)

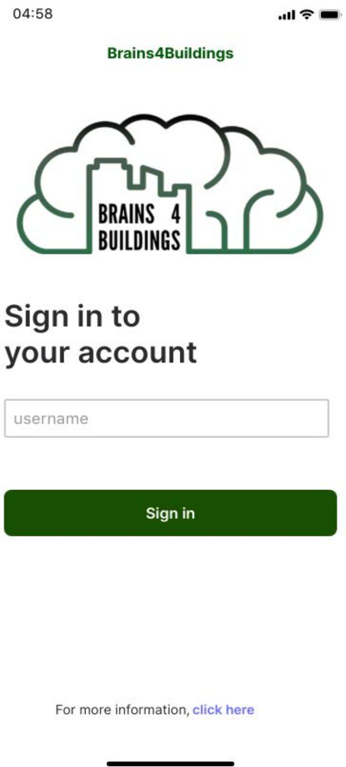
Others

Only for research :p

In this presentation,

Self-Reporting based ML models

Mobile Application



Smartwatch Application

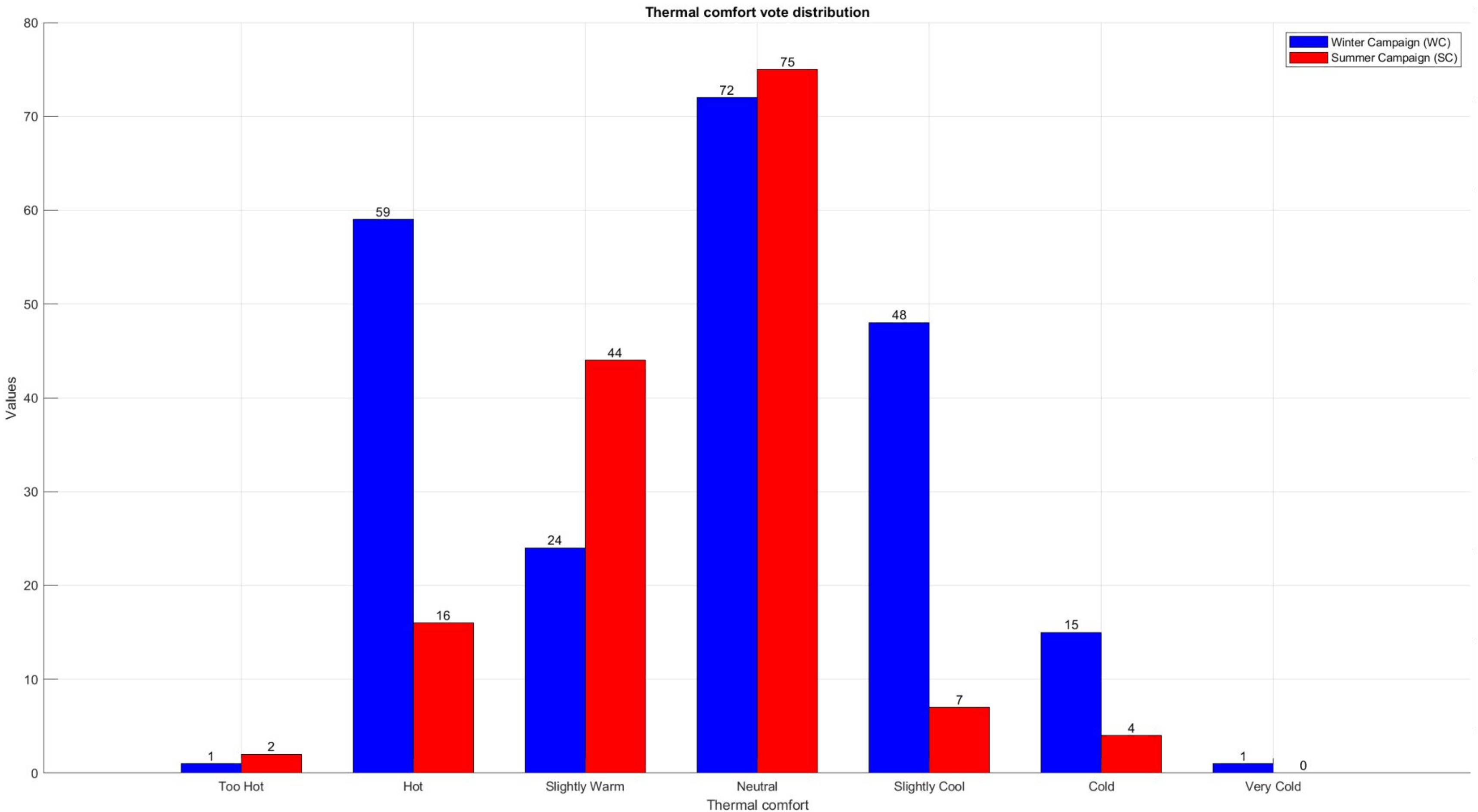
Use-Case

Department of Facility Management Studies, HHS Hague

Types of sensors in every room

- Temperature
- CO_2
- Humidity
- Occupancy (presence)
- Sound/Light
- Window open/closed

Descriptive Statistics - 377 votes over a period of 4 weeks.



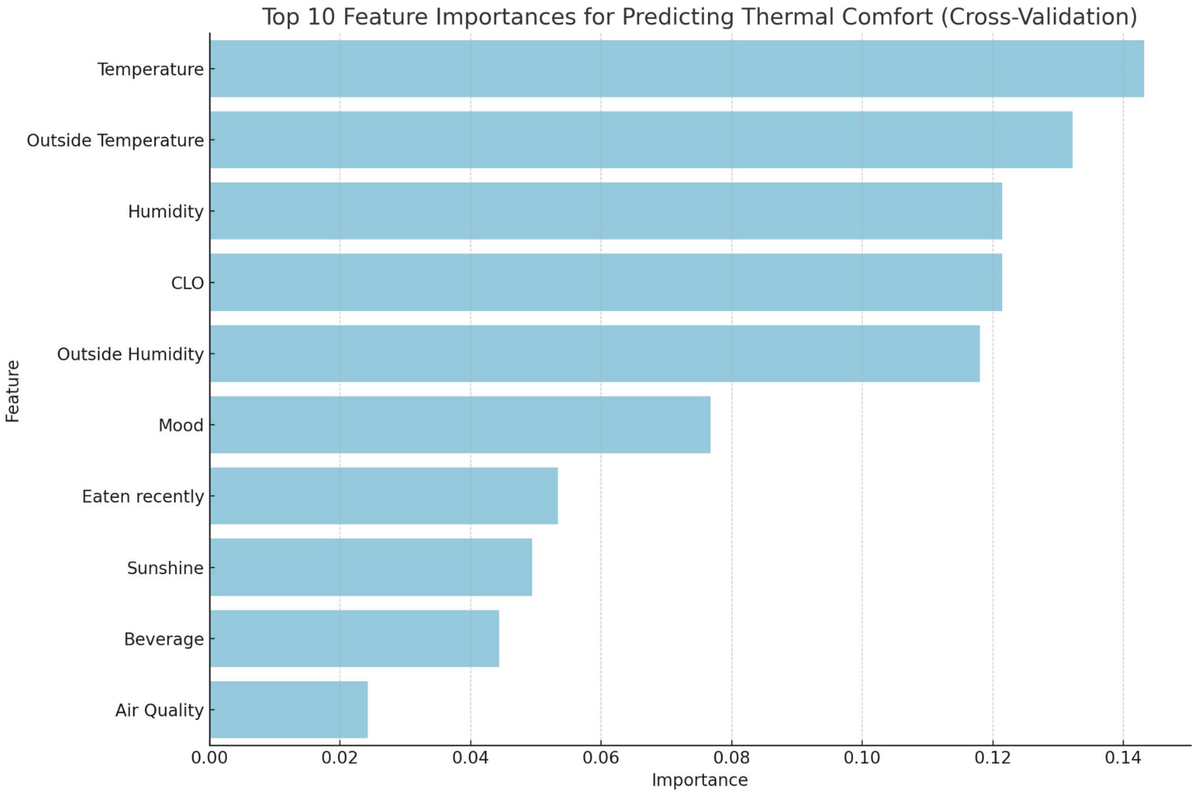
Modeling Thermal Comfort

We treat modeling thermal comfort as a regression problem and approach it in the following steps.

- Feature Selection – A tree-based feature importance method with cross-validation.
- Model Selection – Run a preliminary test on all possible models and see which one performs the best.
- Train-test split – 70-30 split training and testing data. Stratified sampling.
- Training – For training the dataset with different models, a 10-fold cross validation was used to avoid overfitting and allow all parts of the dataset in the training process.

Feature Selection

Consider all parameters in a tree-based model, like random forest classifier. Then choose top features.



Top 6 features selected for modeling

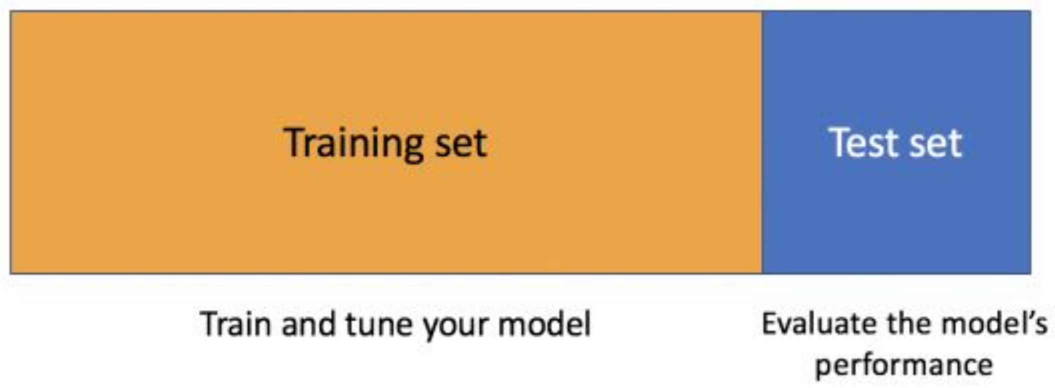
- Temperature (Indoor)
- Temperature (Outdoor)
- Humidity
- Clothing Levels
- Outside Humidity
- Mood

Model Selection

Preliminary comparing all models without hyperparameter tuning.

Model	MAE	MSE	RMSE	R2
Random Forest Regressor	0.6566	0.8199	0.8959	0.3574
Gradient Boosting Regressor	0.6842	0.8249	0.8985	0.3503
Extra Trees Regressor	0.6322	0.8553	0.9159	0.317
Extreme Gradient Boosting	0.633	0.8896	0.931	0.3022
Light Gradient Boosting Machine	0.713	0.888	0.9287	0.2955
AdaBoostRegressor	0.8275	0.9738	0.9835	0.2275
Linear Regression	0.8373	1.0415	1.0151	0.185

Train-test Split



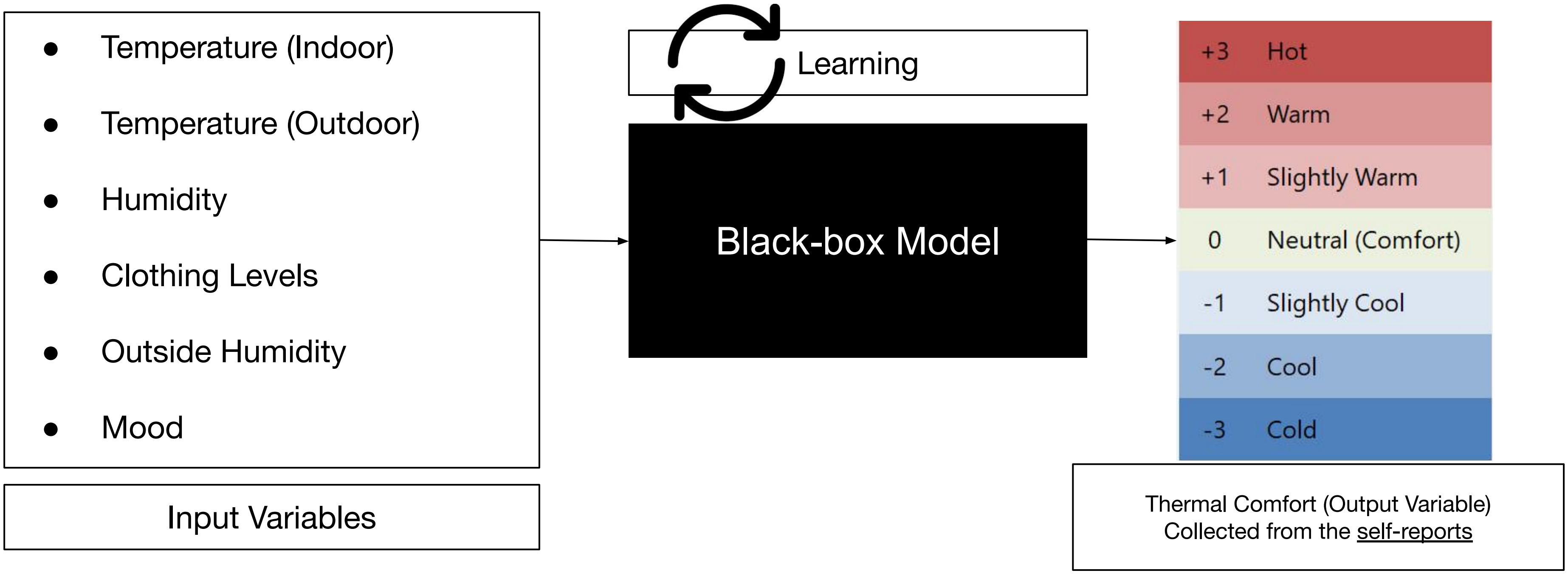
Stratified Sampling

When choosing the 70% (or 30%) population, it is made sure that the split is proportional to the entire population.

For example, if 10 people voted as being too hot, 7 of the data points should be in the training set, and 3 in the testing set.

Training

Uses 10-fold cross validation to avoid overfitting, but also to ensure every part of the data is included for training.

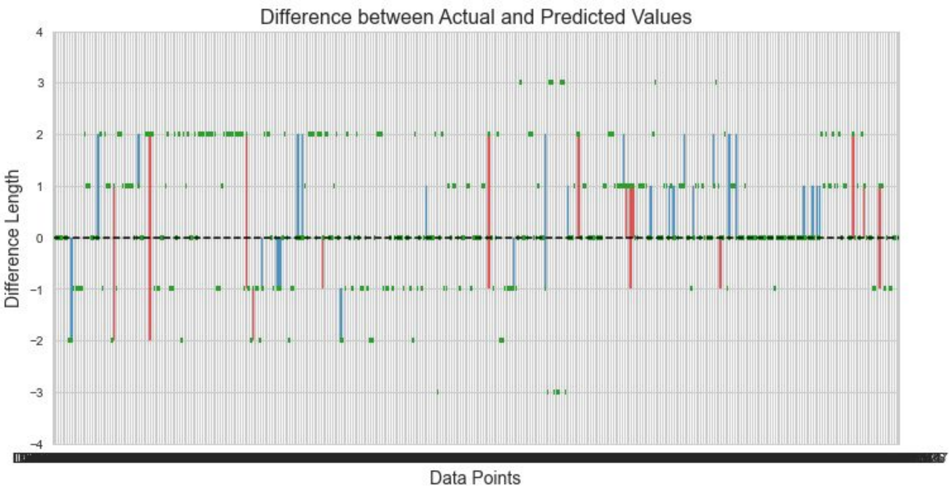


k-fold cross validation

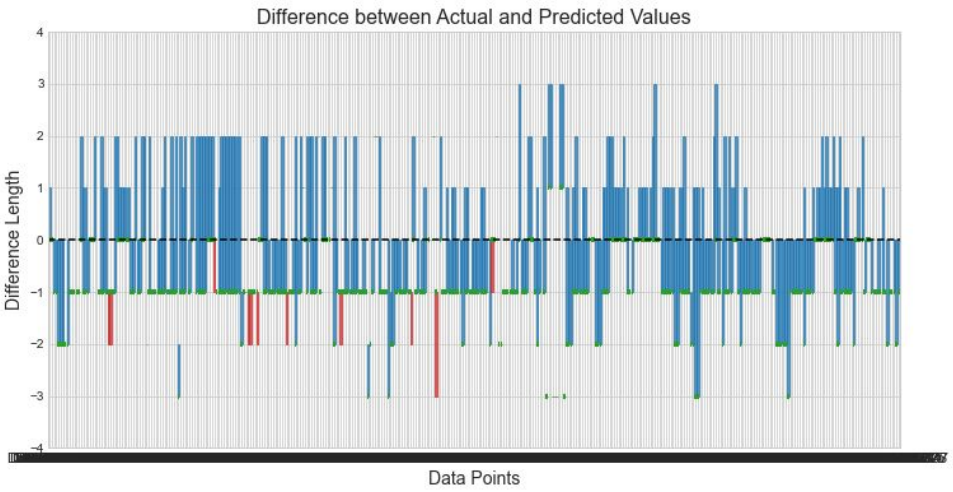
Performance of SRTCM vs PMV Model

Model	Correct Prediction	Margin error = ±1	Margin error = ±2	Final accuracy	Error = ±1 Accuracy
SRTCM	271	360	376	72%	95.49%
PMV	88	211	304	25%	79.31%

Residuals

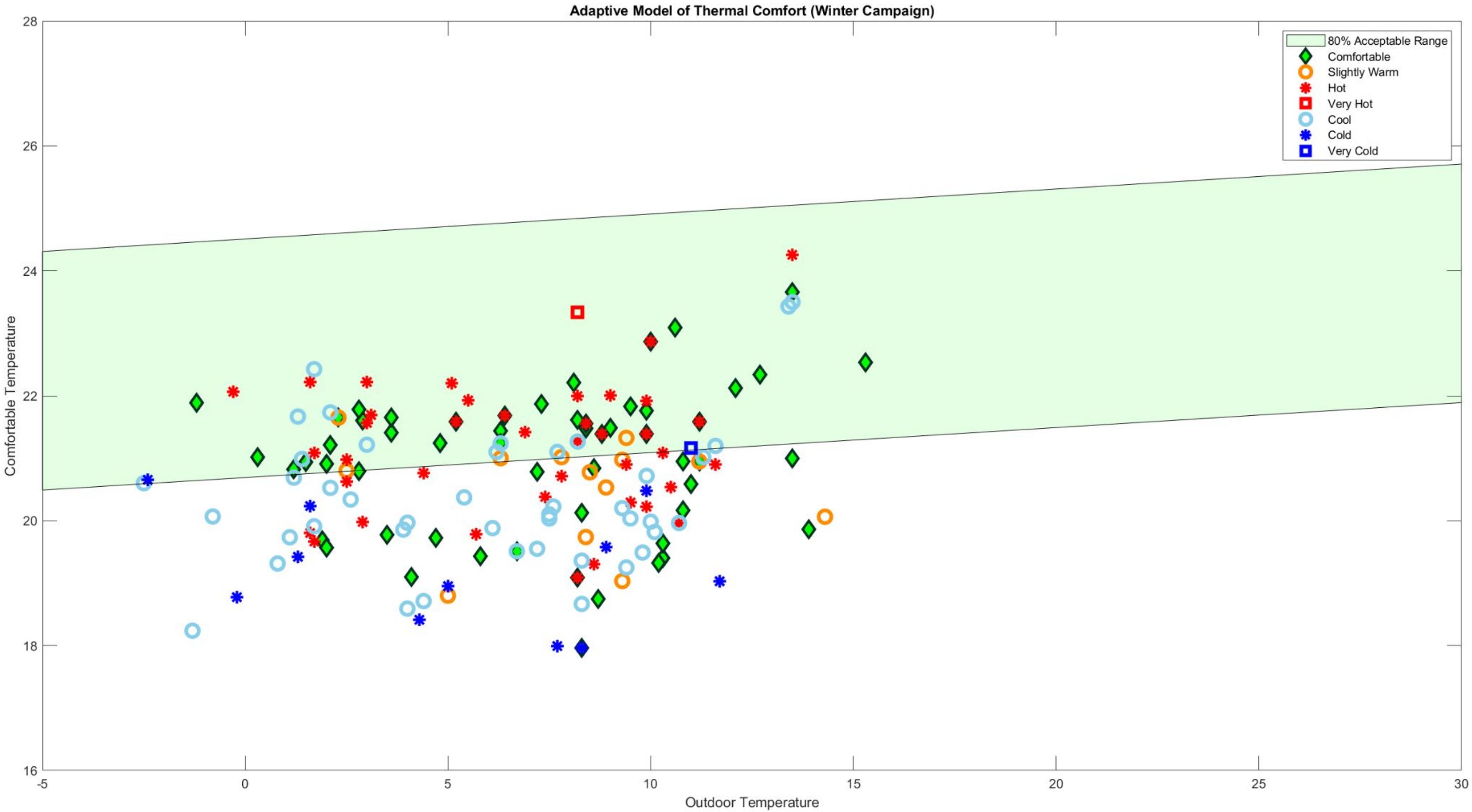


SRTCM

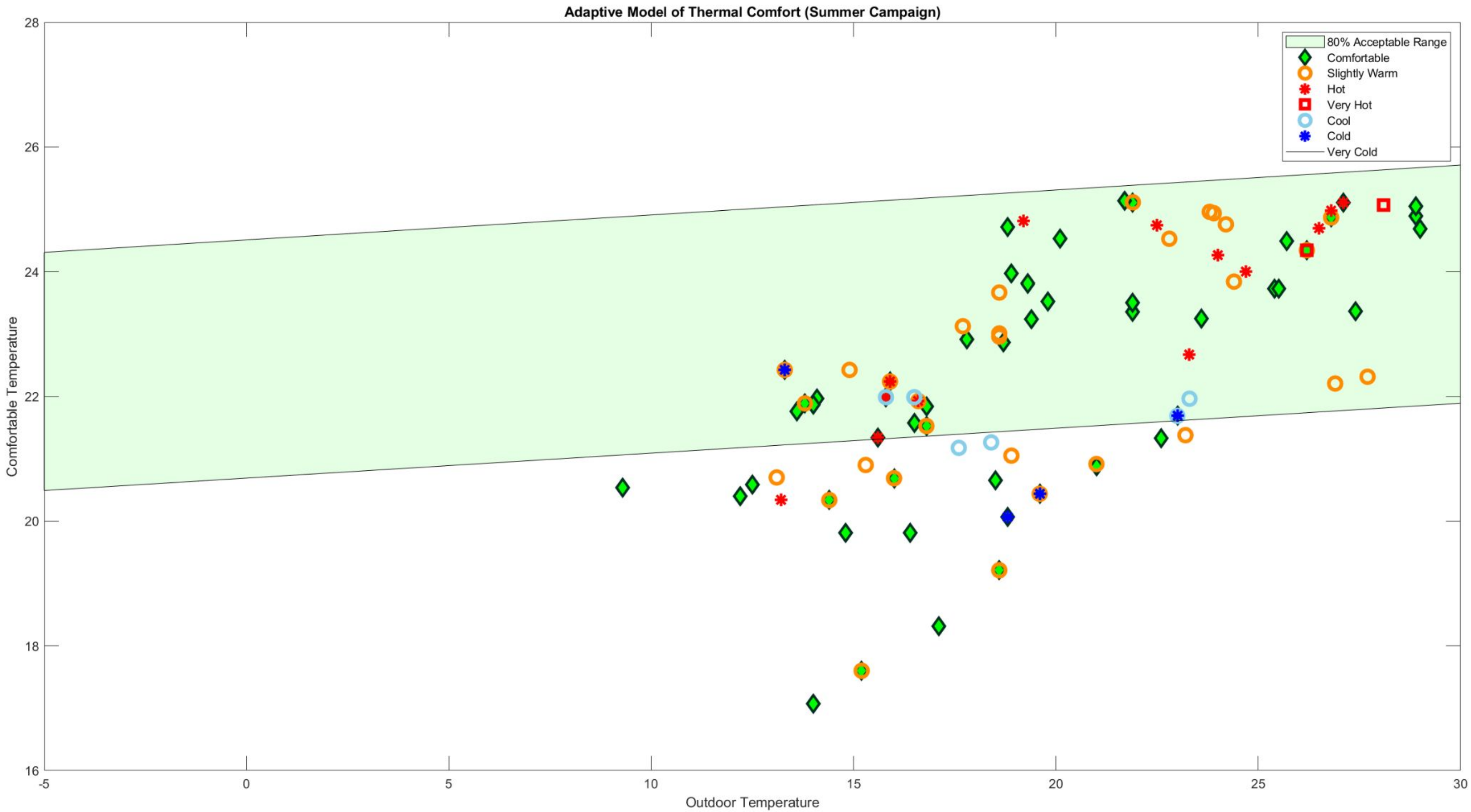


PMV Model

Comparison of self-reporting votes with Adaptive Model (Winter campaign)



Comparison of self-reporting votes with Adaptive Model (Summer campaign)



Conclusions from Modeling

Performs better than traditional empirical models like PMV and the Adaptive model, but …

Still a black-box!

- Temperature (Indoor)
- Temperature (Outdoor)
- Humidity
- Clothing Levels
- Outside Humidity
- Mood

Input Variables

Thermal Comfort Model

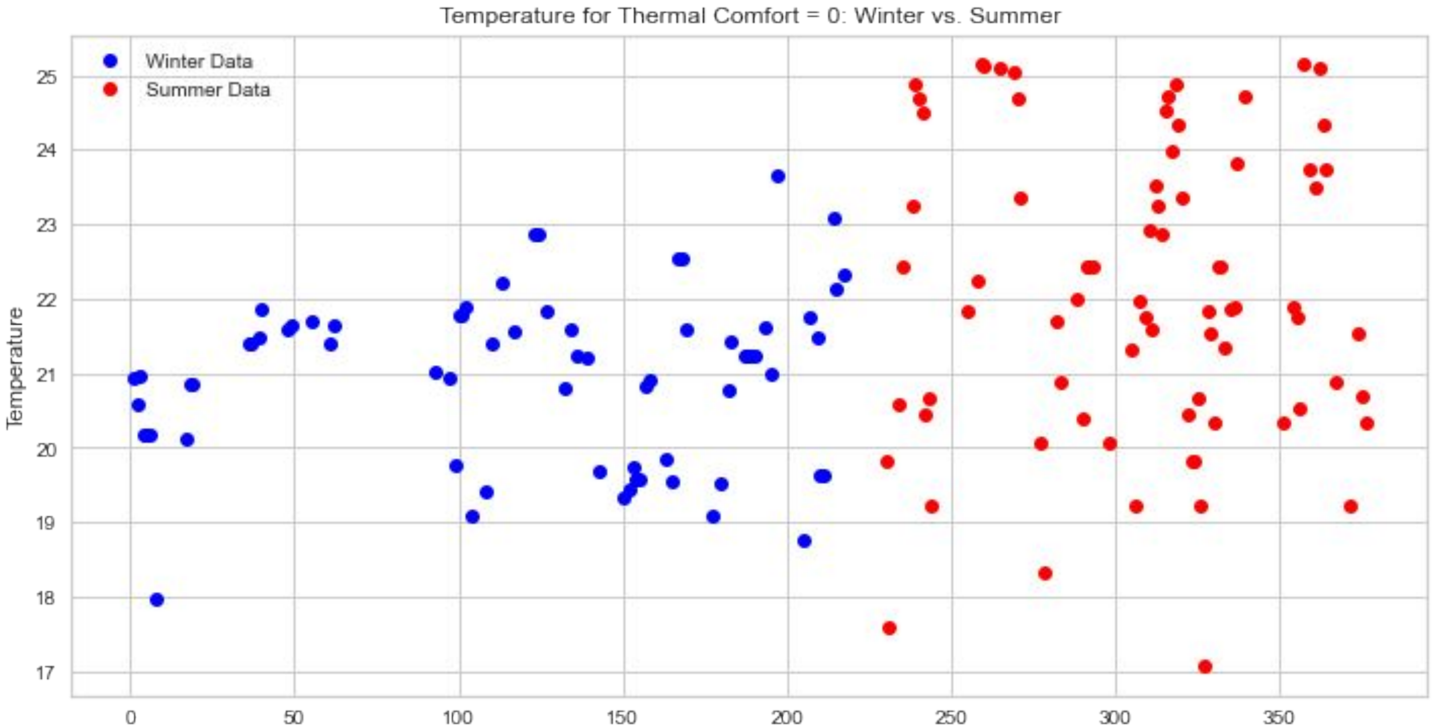
Black box Model

+3	Hot
+2	Warm
+1	Slightly Warm
0	Neutral (Comfort)
-1	Slightly Cool
-2	Cool
-3	Cold

Thermal Comfort
(Output Variable)

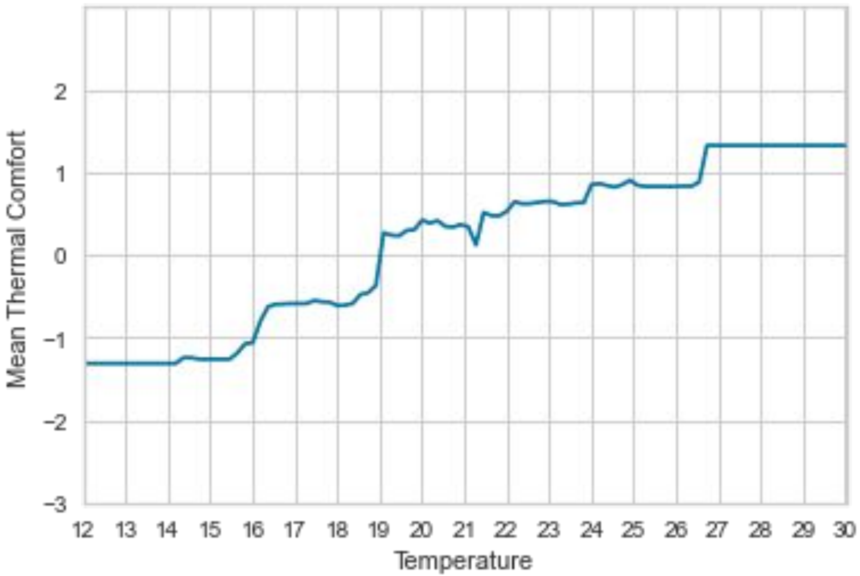
Difficult to understand how the output is calculated, which features affect the output and when

Indoor Temperatures when occupants voted TC as Comfortable



Very difficult to set temperature as the range is big! > 8°C

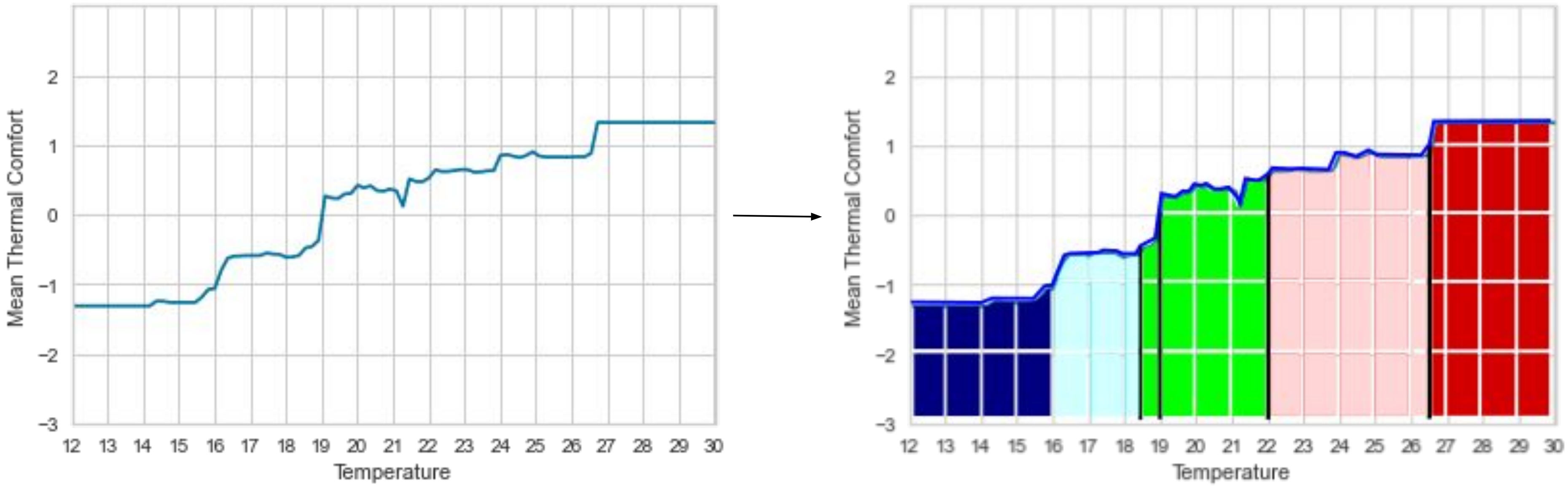
Understanding the SRTCM (BLACK BOX) Model



- A PDP is a tool used to visualize the importance of a feature on the output of a complex model
- It is calculated by averaging out the effects of all other features except the feature in consideration for the PDP (in this case, temperature).
- Can be used for any (thermal comfort) model, even PMV.

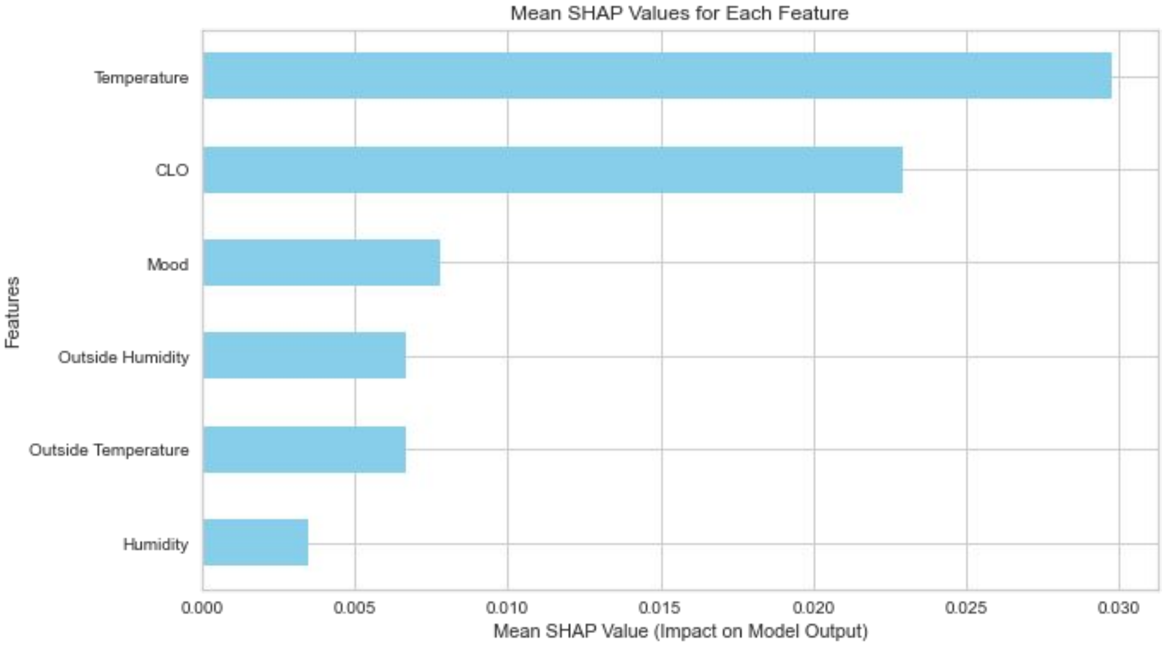
Partial Dependence Plots

Understanding the SRTCM (BLACK BOX) Model



Partial Dependence Plots

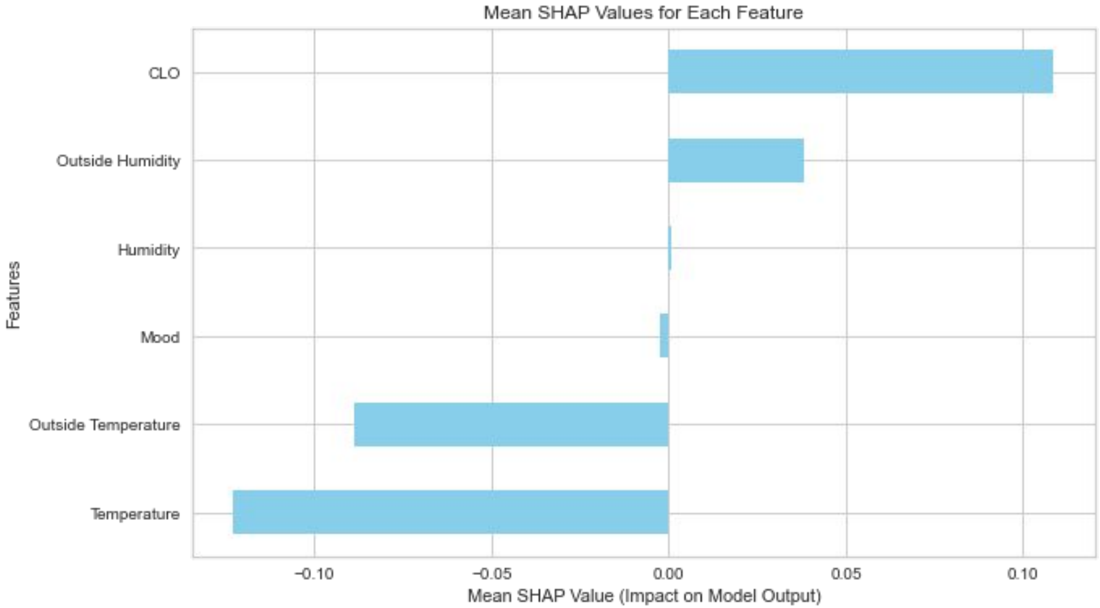
Understanding the SRTCM (BLACK BOX) Model



SHAP Values

- SHAP values can be calculated for any data point, are model agnostic.
- For any specific prediction, SHAP values precisely calculate the contribution of each feature to the final result.
- For a localized dataset, can be seen as feature importance for the local data.

Understanding the SRTCM (BLACK BOX) Model



SHAP Values for Winter data

- Baseline prediction is important to interpret the SHAP values! (Here, the baseline is 0.325 - slightlyyyy warm)
- In winters, clothing values are contributing to occupants feeling even warmer.
- Indoor temperature is contributing negatively for the winter data. (Negative from the baseline, i.e. 0.325)

Learnings

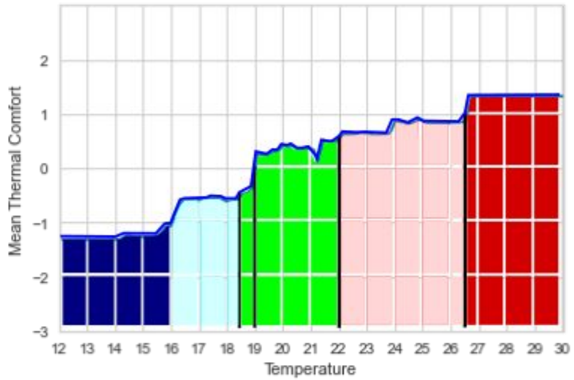
- How to model thermal comfort - Encoding variables, preprocessing, scaling and transforming variables.
- Most important features in predicting thermal comfort.
- More data needed for accurate modeling.
- Subjectivity of thermal comfort - human variables very important.

Applications

Energy Flexibility

Better control strategies

More comfortable environments, Autonomy



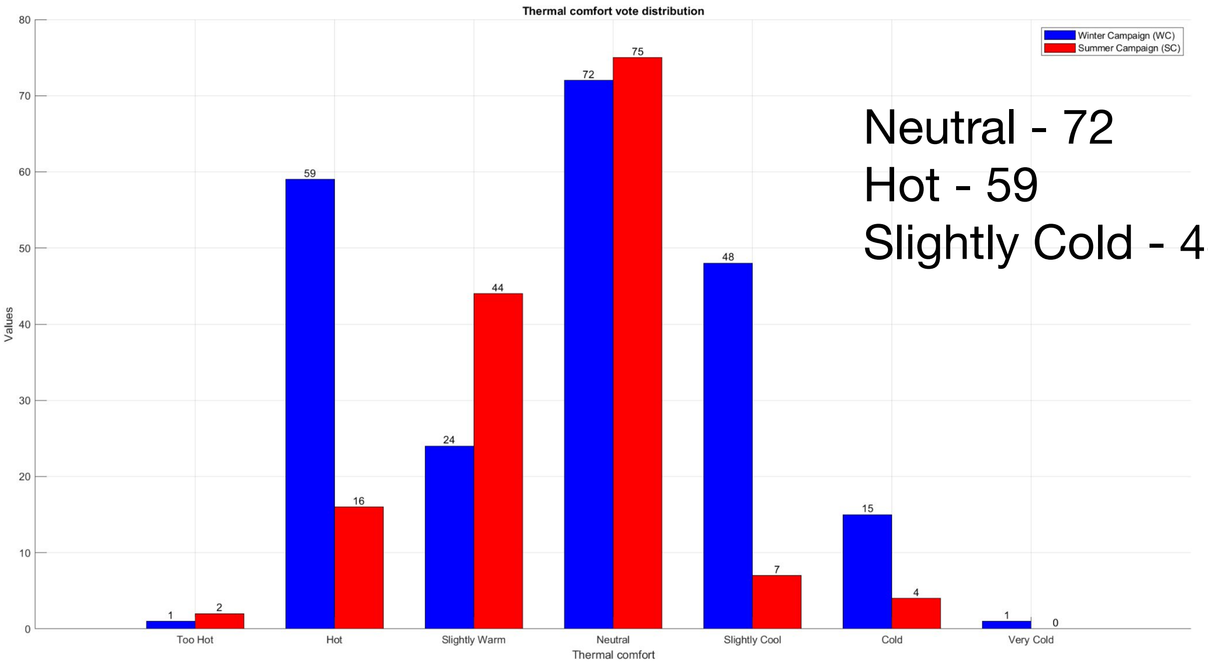
Fault Detection & Diagnosis

Additional input to the HVAC FDD.

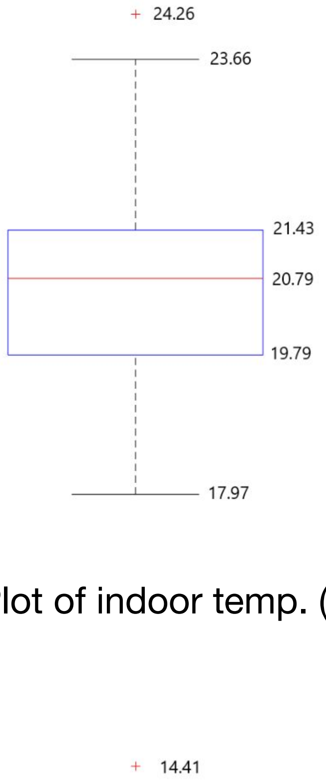
(How?)

Energy flexibility and efficiency

According to the PDP, mean comfortable temperature ranges from 18.5-22 °C



Neutral - 72
Hot - 59
Slightly Cold - 48



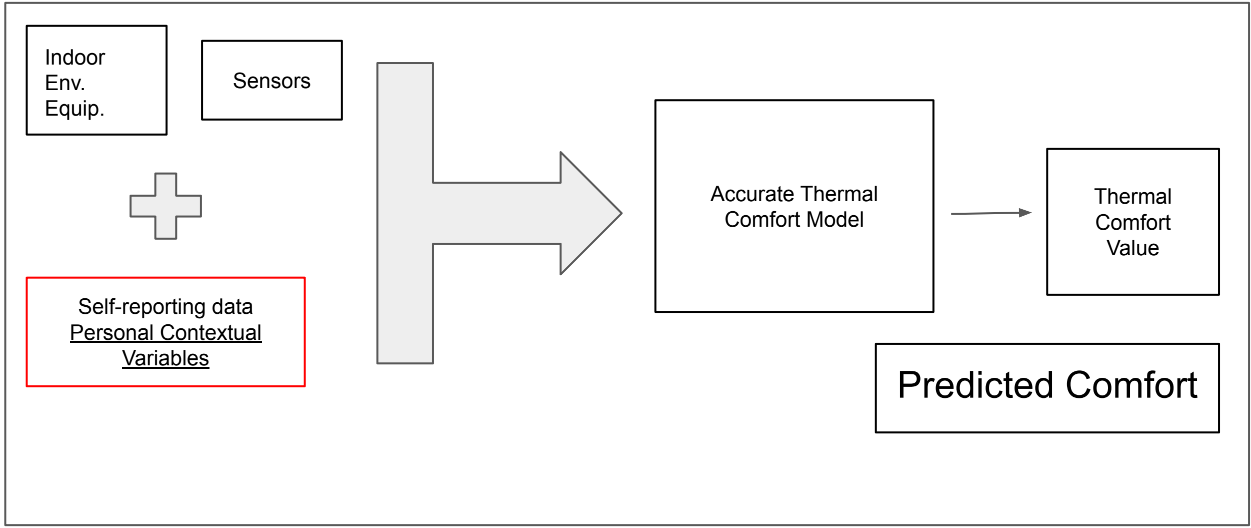
Box Plot of indoor temp. (WC)

Fault Detection & Diagnosis

At any point in time, occupants might feel:

+3	Hot
+2	Warm
+1	Slightly Warm
0	Neutral (Comfort)
-1	Slightly Cool
-2	Cool
-3	Cold

Actual Comfort



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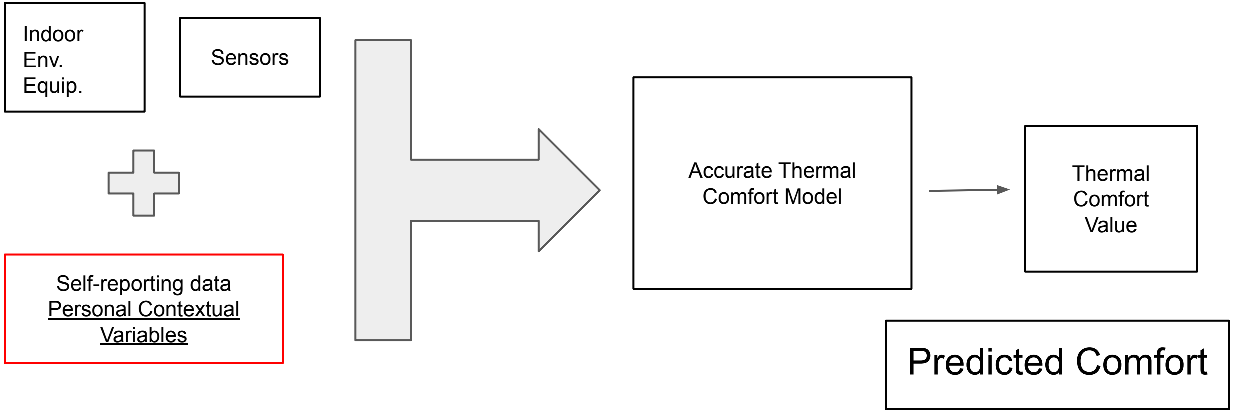


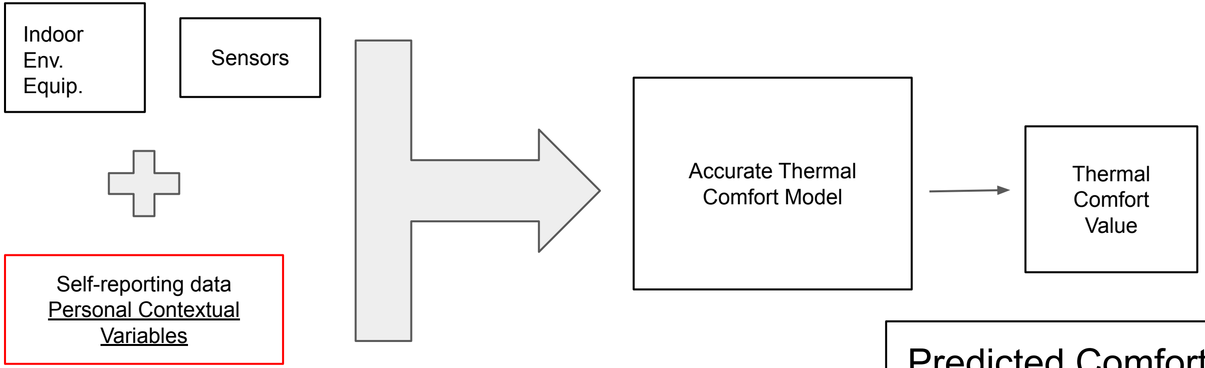
Case 1

No difference between Actual and Predicted, both values indicate **COMFORT**.

No probable fault

+3	Hot
+2	Warm
+1	Slightly Warm
0	Neutral (Comfort)
-1	Slightly Cool
-2	Cool
-3	Cold

Actual Comfort



Predicted Comfort

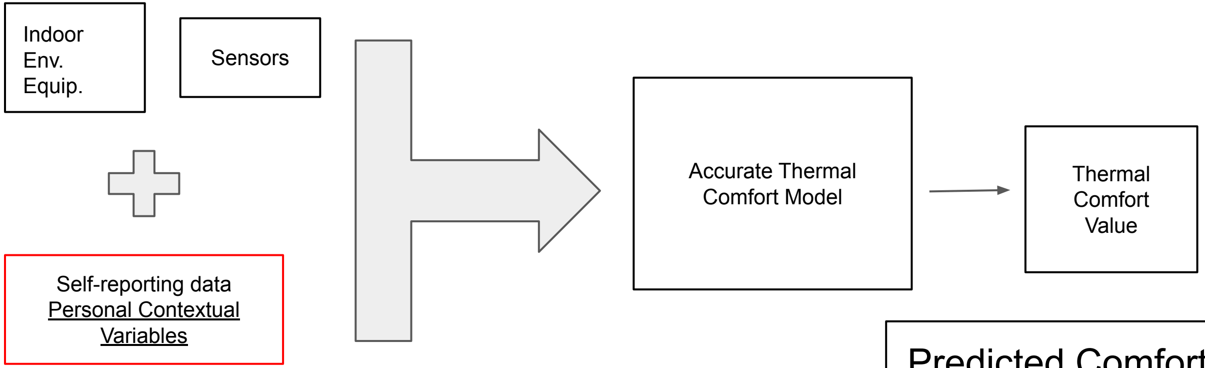
Case 2

No difference between Actual and Predicted, both values indicate **DISCOMFORT**.

Probable fault in the indoor env. equipment **OR** *It's Planned! Eg. Building's still heating up.*

+3	Hot
+2	Warm
+1	Slightly Warm
0	Neutral (Comfort)
-1	Slightly Cool
-2	Cool
-3	Cold

Actual Comfort



Predicted Comfort

Case 3

Difference between Actual and Predicted.

Probable fault in the sensors

Fault Detection & Diagnosis

- Similar rule-based deductions can be made for air quality etc.

- Using the same app/question, self-reporting models can also be of aid in FDD of ventilation systems.

Conclusions

- Importance of thermal comfort for the built environment.
- Self-reporting based thermal comfort models perform better than existing traditional thermal comfort models.
- We can use interpretable machine learning to get actionable insights even from black-box ML-based models.
- Applications in energy flexibility and fault detection and diagnosis (FDD).

Thank you! Questions?

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