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Probabilistic Machine Learning for Occupancy Prediction based on Sensor Fusion

Amirreza Heidari[1*], Verena Marie Barthelmes [1], and Dolaana Khovalyg[1]

1: Thermal Engineering for the Built Environment Laboratory
Ecole Polytechnique Fédérale de Lausanne (EPFL)
Lausanne, Switzerland
e-mail: amirreza.heidari@epfl.ch

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1. Introduction

A substantial corpus of research has shown that occupancy-related factors, such as presence/absence and movement of occupants, significantly influence energy use and the indoor environmental quality in buildings [1]–[4]. Targeting reliable occupancy information is, therefore, a key to achieving efficient HVAC system operations and building management systems, as they are designed to maintain occupants' comfort [5].

Occupancy prediction has been recognized as one of the most inspiring topics for energy saving in buildings [6]. Different approaches have been used for occupancy prediction, such as statistical models [7] or a combination of statistical and physical models [8]. Another common approach that is state-of-the-art in this context is deep learning [9]. However, typical deep neural networks, which are deterministic models, do not provide any information on the uncertainty of predictions and predict a value confidently. Although studies that have used deterministic deep learning sometimes show an acceptable accuracy [10], [11], it can be seen that the exact number of occupants is not predicted most of the time. Therefore, in such highly stochastic applications, deep learning models can be further enhanced by providing information about how the model is certain about its prediction. The objective of this paper is, therefore, to investigate the use of probabilistic deep learning in the context of occupancy prediction, which is overlooked so far.

2. Methodology

The probabilistic modeling approach in this paper is based on Monte-Carlo Dropout presented by Gal and Ghahramani [12]. In the typical neural networks, the Dropout is used only in the training phase to inactivate some nodes and prevent overfitting. This approach, however, can also be used during the testing phase to account for the uncertainty of predictions. To develop the Monte-Carlo probabilistic model, the following considerations are taken:

I. Using Probabilistic loss function: Negative Log-Likelihood is used, which is calculated as below:

$$-\log \varphi_\theta(x) = \frac{\log \hat{\sigma}_\theta^2(x)}{2} - \frac{(y - \hat{\mu}_\theta(x))^2}{2\hat{\sigma}_\theta^2(x)} \tag{1}$$

In which, y is the true value, $\hat{\mu}_\theta(x)$ is the mean of predicted values, and $\hat{\sigma}_\theta^2(x)$ is the variance of predictions.

II. Activation of Monte-Carlo Dropout during test phase: In the testing phase, multiple passes of input data are performed to obtain the predictions for input data x. In each pass, a different dropout mask is implemented, causing variations in outputs. The final mean and variance are therefore calculated as below:

(2)

(3)

where N is the number of different passes, $\mu_n(x)$ is the prediction of each pass, and $\hat{\sigma}_\theta^2(x)$ is the variance of each pass.

The dataset of this research is provided by the study of Hobson et al. [11] on the occupancy prediction of an academic office building in Ottawa, Canada, including measurements of CO_2 concentration, detected motions, plug and lighting power use, total power use, and the number of connected WiFi devices on 4 floors. The ground truth occupancy data in this building is provided by installing a camera on the entrance and exit points. This study will focus on floors 3 and 4 of the case study building. Figure 1 shows the floor plans and location of different installed sensors on each floor.

Figure 1: Location of different sensors in floors 3 and 4 (plansadopted from [1])

Two probabilistic models are developed in this study, one based on the Feed-Forward Neural Network model and the other based on the Long-Short Term Memory (LSTM) Neural Network, which is developed and then compared to a deterministic LSTM Neural Network model. Figure 2 shows the schematics of the developed models.

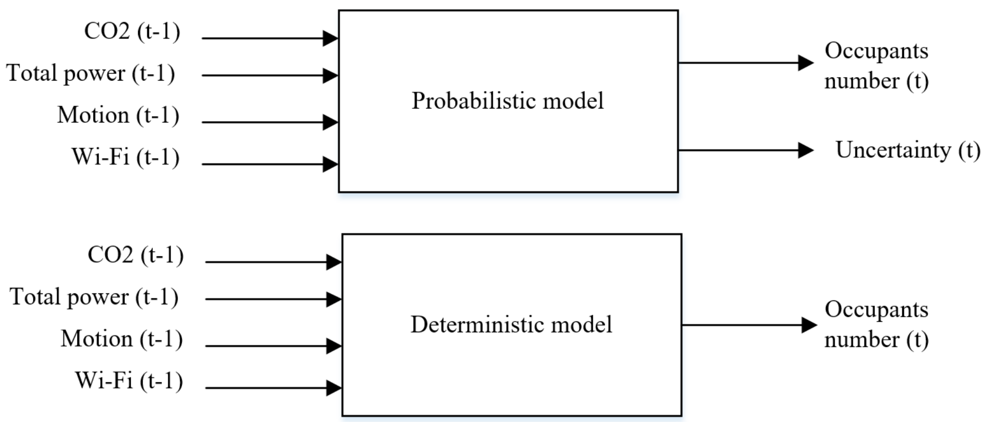

Figure 2: Schematics of models

3. Results and Findings

The accuracy of occupancy predictions by different models is reported in Table 1. It can be seen that the probabilistic LSTM model shows higher accuracy than the other models on both floors. Only on floor 3, the probabilistic Feed-Forward model shows a higher mean squared error than the deterministic LSTM model. This is because the probabilistic models try to minimize negative log likelihood as the loss function, while the deterministic models try to minimize mean squared error. Between the probabilistic models, the model based on LSTM cells shows better accuracy. This is because the LSTM model, due to the gating mechanism, has a better performance in learning long term dependency between the data.

Figure 3 also shows the predictions by probabilistic Feed-Forward, probabilistic LSTM, deterministic LSTM as well as ground truth data. The visual comparison shows that the predicted mean by probabilistic models is very close to the predicted value by the deterministic model, and both of them rarely matches the ground truth data. However, in the case of probabilistic models, the uncertainty of predictions well covers the ground truth data, which can be very useful information for decision making.

Table 1: Accuracy of different models

Model	Mean Squared Error	Mean Absolute Error	Negative Log-Likelihood
Floor 3			
Probabilistic LSTM	**18**	**2.53**	**4.84**
Probabilistic Feed-Forward	18.95	2.67	2.43
Deterministic LSTM	18.03	2.86	-
Floor 4			
Probabilistic LSTM	**8.2**	**1.9**	**3.4**
Probabilistic Feed-Forward	9.72	2	3.29
Deterministic LSTM	10.24	2.17	-

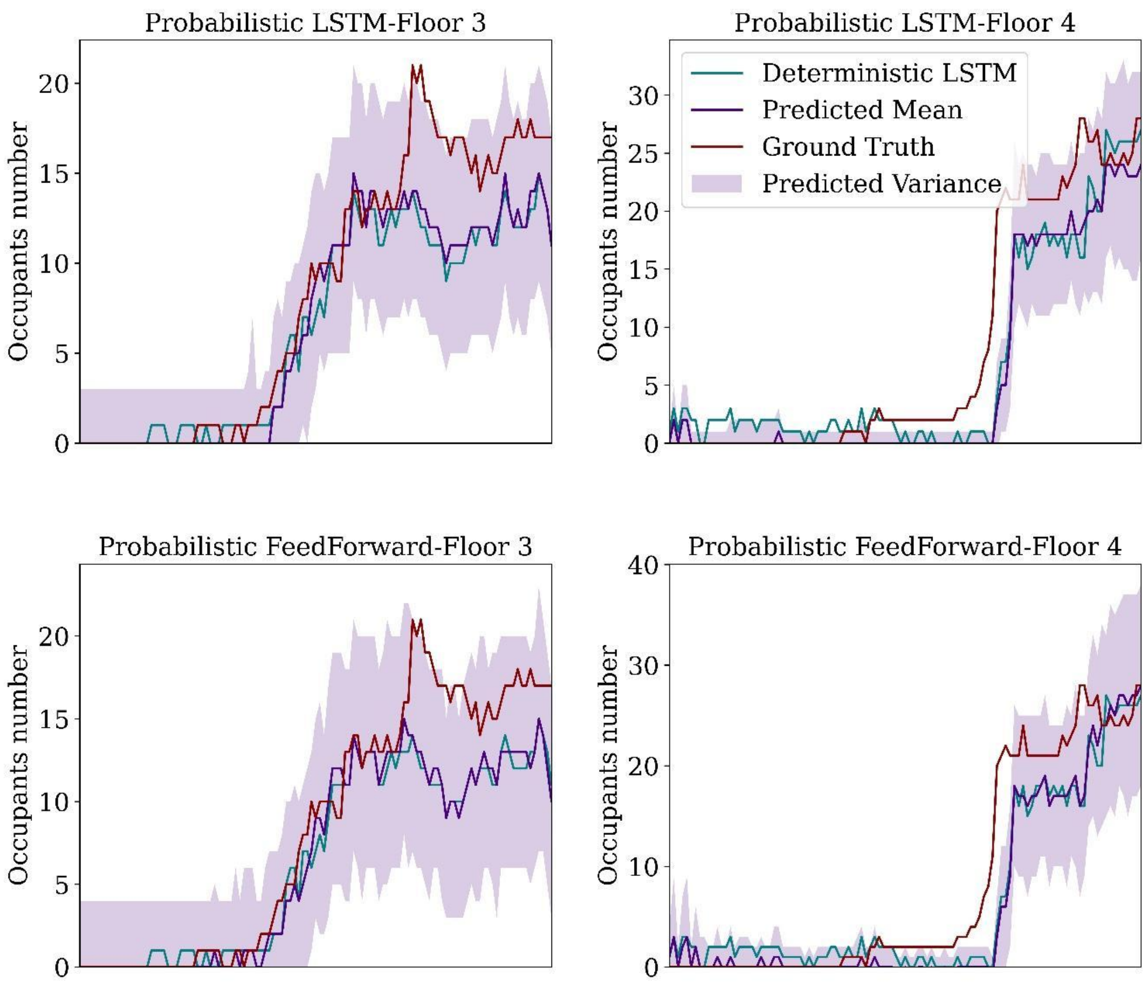

Figure 3: Predictions by different models versus ground truth data

4. Discussions and Conclusions

The following conclusion can be drawn based on the results:

- The predictions by deterministic models usually underestimate the occupancy and therefore is not reliable for decision making. However, the variance of the probabilistic models well covers the real occupancy number and therefore is very useful for the decision-making level.
- The probabilistic models not only provide uncertainty as additional information but also show higher accuracy in the case of mean squared error and mean absolute error.

In general, it can be concluded that for highly stochastic phenomena like the occupancy of buildings, the MC Dropout probabilistic models, which estimate the uncertainty of prediction, are more reliable than deterministic models that predict a certain value.

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