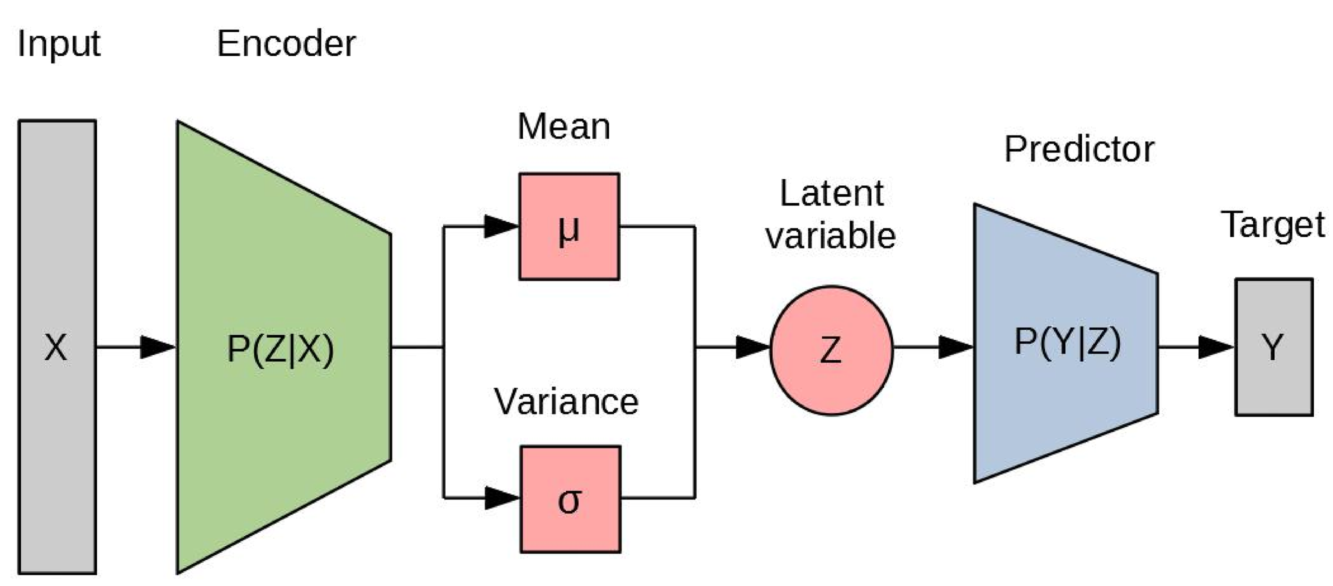
VARIATIONAL INFORMATION BOTTLENECK MODEL FOR ACCURATE INDOOR POSITION RECOGNITION

Weizhu Qian,[1] and Franck Gechter, [1,2]
[1]CIAD UMR 7533, Université Bourgogne-Franche-Comté, UTBM, 90010, Belfort, France
[2]Mosel LORIA UMR CNRS 7503, Université de Lorraine, 54506, Vandœuvre-lès-Nancy, France.

ABSTRACT

In this work, we aim to calculate accurate indoor location with WiFi fingerprints. This task is tricky because the input are high dimensional and noisy. To deal with these issues, we propose a Variational Information Bottleneck-base model. The proposed model consists of an encoder used to find a representation of the input and a predictor used to predict the final output using the latent representation. Finally, we test the proposed model on a real-word dataset and the obtained results show the effectiveness of our method.

FIGURE 1



Overview of the VIB-based model.

PROBLEM STATEMENT

In our task, the input are received signal strength values and the target are the corresponding user coordinates. This task can be regarded as a high dimensional regression task.

PROPOSED METHOD

Key Idea: We assume that there exists a latent variable Z governing both the input X (WiFi fingerprints) and the target Y (user coordinates). Then we have the following information Markov chain:

$$X \to Z \to Y$$

- **Assumption 1:** There exists a statistic of the input X which is solely sufficient enough to learn the posterior of Z, i.e., $\mathbb{P}(Z|X,Y) = \mathbb{P}(Z|X)$;
- **Assumption 2:** The learned representation Z is solely sufficient enough to learn the likelihood of Y, i.e., $\mathbb{P}(Y|X,Z) = \mathbb{P}(Y|Z)$.

The original optimization problem of Information Bottleneck (Tishby, Pereira, and Bialek, 2000) is

$$\max I(Z;Y) \quad (1)$$

$$\text{s.t. } I(Z;X) \leq I_C \quad (2)$$

where I denotes the mutual information, I_C is the information constrain.
We apply the KKT condition to the above optimization problem, then its corresponding Lagrangian yields

$$I(Z;Y) - \beta I(Z;X) \quad (3)$$

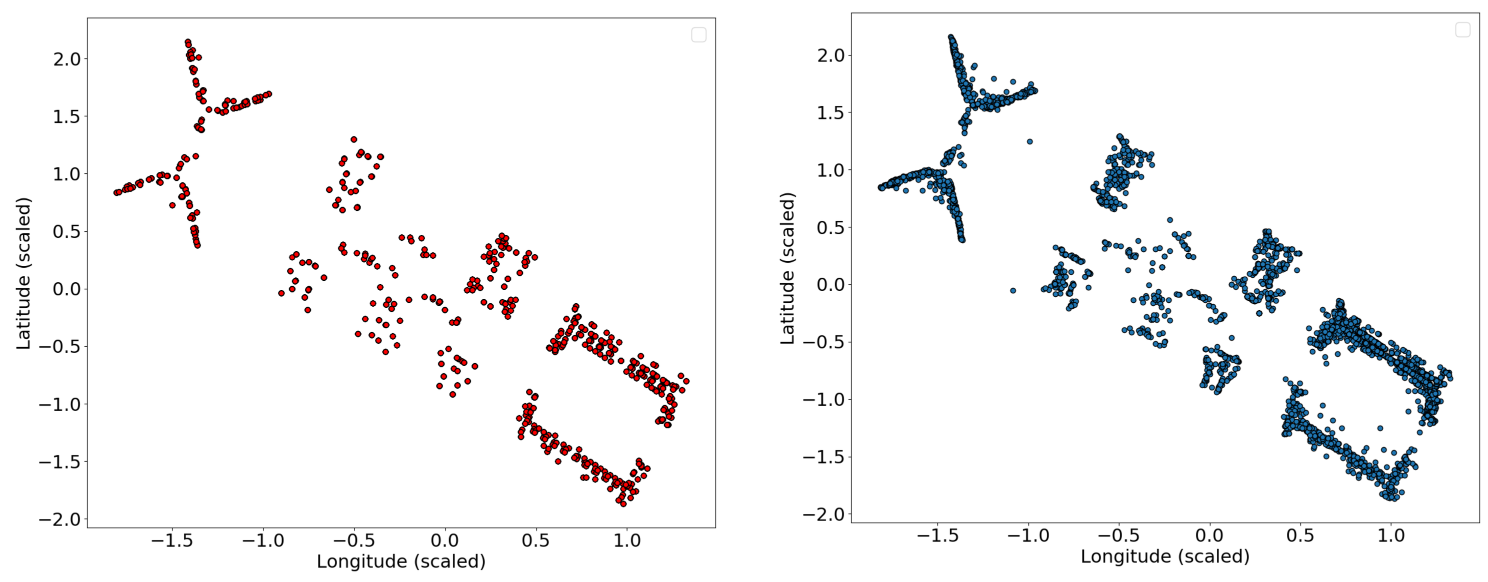
where β is a positive Lagrangian multiplier governing the optimization trade-off.

IB can be implemented via a supervised deep latent model, i.e., **Variational Information Bottleneck (VIB)** (Alemi et al., 2016). The final loss function of the VIB-based model solved by the re-parameterization trick and Monte Carlo sampling is

$$\mathcal{L}(D,\theta,\phi) = \frac{1}{N}\sum_{n=1}^{N}\mathbb{E}_{\epsilon_z\sim p(\epsilon_z)}[p_\theta(y_n|f_\phi(x_n,\epsilon_z))] - \beta D_{KL}[p_\phi(z|x_n)||q(z)] \quad (4)$$

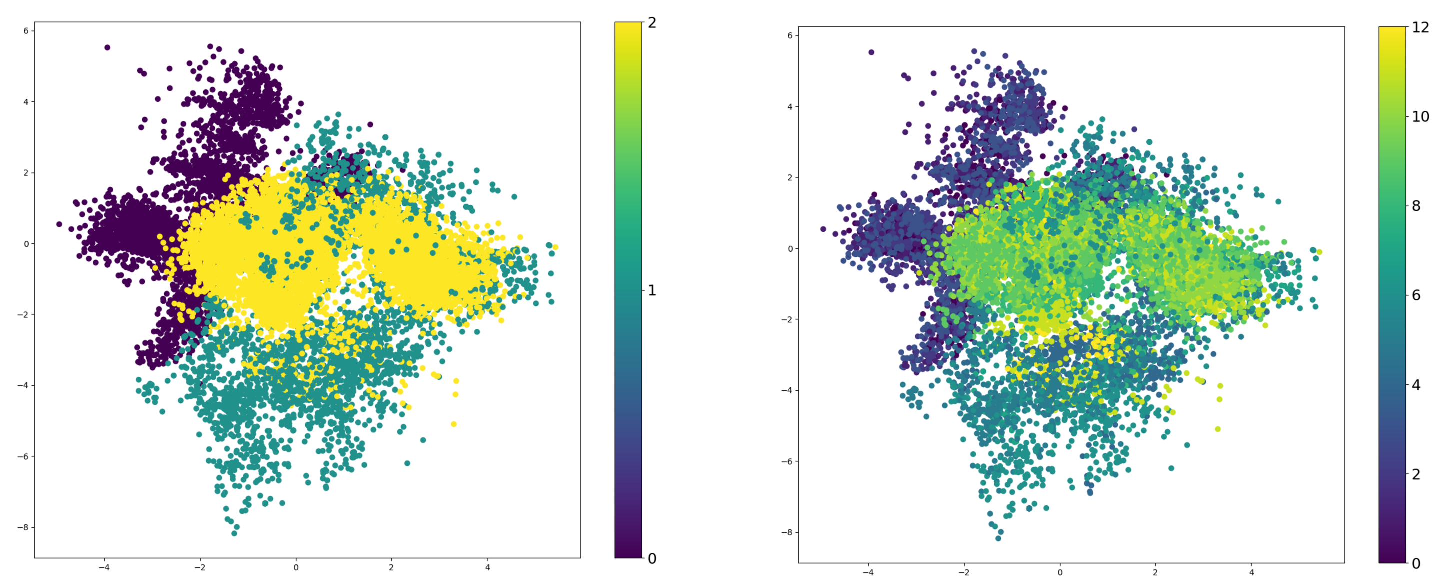
We conduct a series experiments on a real world dataset.

FIGURE 2



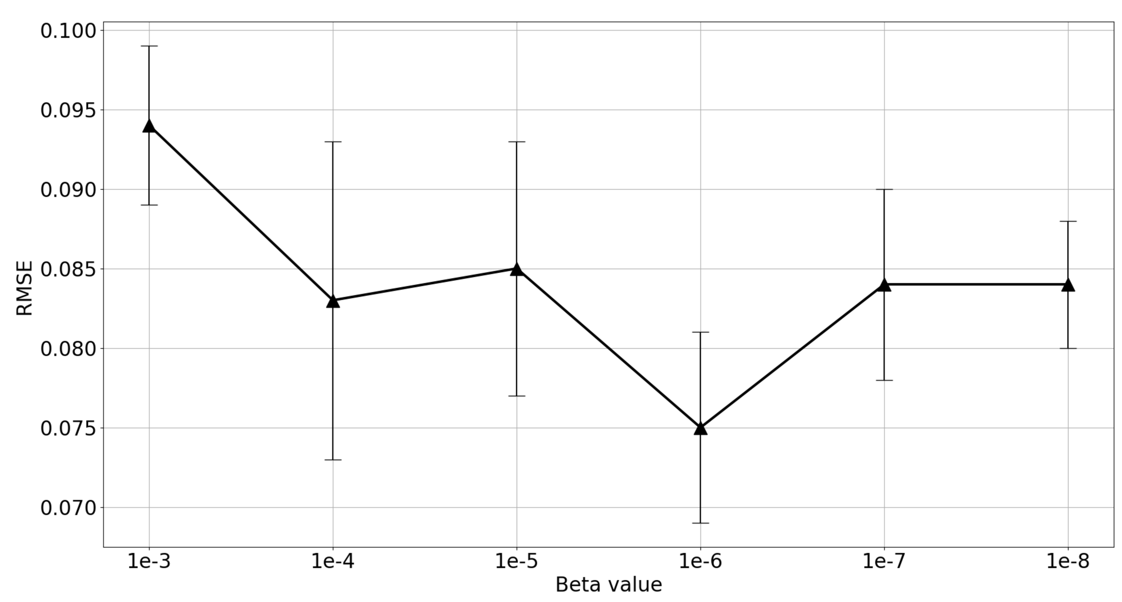
Ground truth. Testing result.

FIGURE 3



Latent distribution labeled with building IDs. Latent distribution labeled with floor IDs.

FIGURE 4



Results with respect to different β values.

TABLE 1

Comparison results.

Method	k-NN	GP	MDN-2	MDN-5	BNN	Semi-VAE	Proposed
RMSE	0.092	0.252	0.099	0.103	1.033	0.088	0.075

REFERENCES

Alemi, Alexander A et al. (2016). "Deep variational information bottleneck". In: *arXiv preprint arXiv:1612.00410*.

Tishby, Naftali, Fernando C Pereira, and William Bialek (2000). "The information bottleneck method". In: *arXiv preprint physics/0004057*.