ABSTRACT
High-resolution data are desired in many data-driven applications; however, in many cases only data whose resolution is lower than expected are available due to various reasons. It is then a challenge how to obtain as much useful information as possible from the low-resolution data. In this paper, we target interval energy data collected by Advanced Metering Infrastructure (AMI), and propose a Super-Resolution Reconstruction (SRR) approach to upsample low-resolution (hourly) interval data into higher-resolution (15-minute) data using deep learning. Our preliminary results show that the proposed SRR approaches can achieve much improved performance compared to the baseline model.

CCS CONCEPTS
• Computing methodologies → Neural networks.

KEYWORDS
Super-resolution, neural network, interval energy data

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1 INTRODUCTION
Interval energy data (a.k.a. interval data) are fine-grained records of energy consumption captured by Advanced Metering Infrastructure (AMI); the readings are made at regular time intervals. Each measurement represents the total energy consumption (in kWh) during the corresponding time interval.

Interval data contains rich information on energy consumption of different users and can be useful in many cases. First, interval data can identify energy use peaks and trends, which can be used as a diagnostic tool for anomaly detection [5]. Second, it can inform and evaluate energy efficiency policies. Researchers evaluated the performance of policies, such as electricity subsidies and peak electricity pricing, by analyzing the variations in electricity consumption informed by interval data [3, 6].

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2 PROBLEM FORMULATION
We consider an integer factor S for upsampling each interval of time length τ into S intervals each with length S/τ. Let us denote by \( \{s_k\} = s_1 s_2 \ldots s_K \) a low-resolution signal of K τ-intervals, and by \( \{r_k\} = (r_1^1 r_2^2 \ldots r_K^K) (r_1^2 r_2^2 \ldots r_K^K) \ldots (r_1^K r_2^K \ldots r_K^K) \) the corresponding high-resolution signal. Each entry in sequences \( \{s_k\} \) and \( \{r_k\} \) represents the energy consumption during the corresponding interval. To achieve SRR, we aim to learn a function
We tested the above methods on the publicly available Pecan Street data [7] from 73 households across three U.S. states, New York (NY), California (CA), and Texas (TX). We used 15 CA households and 18 NY households for training, and the rest for testing.

The performance of the three methods (baseline, CNN and GAN) in terms of MSE and WPE is shown in Table 1. From the results we can see that both CNN and GAN approaches lead to slightly increased MSE on test set data, but achieve much better performance in terms of the WPE metric, which indicates that our proposed methods can more faithfully recover the peaks in the original, high-resolution data. The displayed WPE results are for window size \( W = 3 \); we also evaluate the performance for other window sizes and the results are similar.

We also show a few SRR results in Fig. 1. As can be seen, the GAN-based method excels at capturing the peak consumption events, despite sometimes missing the accurate occurrences of the peaks. The misalignment of the peaks results in increased errors under the MSE metric, but will not be penalized by our proposed peak consumption error metric if the temporal misalignment is not significant. The CNN method can also capture some of the peak events; however, the resulting load profile is overly smooth and cannot predict well the magnitude of the peaks. This demonstrates the benefits of incorporating a discriminator in the GAN approach: the discriminator encourages the generator to produce more authentic load profiles besides lowering the MSE.

### 5 SUMMARY

The presented results have several implications. First, we have shown that by using deep learning approaches we can recover to a good extent the important information of high-resolution (15-minute) interval data that are missing from lower-resolution (hourly) data. The reconstructed high-resolution data can be potentially useful for household energy management applications such as peak shaving and battery dispatch. In addition, the findings motivate us to rethink potential privacy issues associated with low-resolution interval data. For future work, we plan to further explore the design space for better performing models.

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