A neural network approach to predicting urban building energy consumption

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Cities account for over 75% of all primary energy usage and over 80% of greenhouse gas emissions, with a large majority of each coming from the built environment [1]. Because 90% of urban buildings are estimated to be energy inefficient and 30% of a building’s energy consumption is wasted, buildings represent a great opportunity to enhance the sustainability of cities [2]. Building energy modeling (BEM) is a tool widely used in building design and construction to understand and predict the energy performance of buildings. However, these tools are largely inaccurate when predicting energy consumption because they are unable to account for a building’s “urban context” - both surrounding buildings and its urban microclimate.

This project explores multilayer perceptrons (MLP) and ResNets to integrate deep learning into an urban building energy simulation to more accurately predict the energy consumption of urban buildings. We drew data from three sources:

- NREL: Weather data
- EnergyPlus: building energy simulations (kWh/interval)
- Southern California: university buildings

Our project studies a dense grouping of 22 buildings at a university in southern California. We draw data from three sources:

- EnergyPlus: building energy simulations (kWh/interval)
- NREL: Weather data
- University: metered building energy use (kWh/interval)

The energy data comes in the form of 15-minute interval time series, where each feature represents one of the 22 buildings - each with two years of interval data (~70,080 observations). The inputs vary. For the MLP do we include the hourly weather data as part of the input space, resulting in 25 features. And for the ResNet model, we one-hot encode day of the week and month into our input space, resulting in 41 initial input features.

The above results show that overall, the ResNet significantly outperformed the MLP, as expected. Because of the residual network’s local convolutions, we believe it did the better job of correctly understanding the spatial-temporal relationships between urban context and energy usage. We were surprised that weather had little impact on the performance of the MLP and plan to explore this more for our final deliverable. And finally, while adding additional residual blocks and output channels improves train set performance, it also makes the dev set performance more unstable.

Our future work on this project aims to reduce the mean squared error further and evaluate it against other simulation-based approaches to predicting energy consumption. We would also like to evaluate these errors at different time intervals (e.g., hourly, yearly) and spatial scales (e.g., individual building scale, city-wide scale) to further test its prediction ability.

REFERENCES