Time Series Forecasting of Appliance Energy Usage

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1 Introduction

This project focuses on forecasting energy consumption using multivariate time series data. It demonstrates both deterministic and probabilistic deep learning approaches and highlights the benefits of modeling uncertainty in forecasting tasks.

Deliverables submitted:

- **Report:** This PDF document explaining the dataset, models, methodology, and conclusions.
- **Jupyter Notebooks:** A modular pipeline with three standalone notebooks:
  1. `1_eda.ipynb` – Exploratory Data Analysis.
  2. `2_training.ipynb` – Training scripts for both RNN and LSTM-VAE models.
  3. `3_evaluation.ipynb` – Evaluation and visualization of results.
- **Python Package:** A production-ready package that includes:
  - Trained model (`model.pkl`)
  - Inference and evaluation utilities
  - CLI and REST interfaces (via `app.py` and Docker)
- **GitHub Repository:** The full source code, notebooks, Dockerfile, and documentation can be found at:

  `https://github.com/username/appliances-energy-forecasting`

The following sections explain the methodology, data preprocessing, model training, and key insights derived from this work.

2 Dataset

The dataset consists of multivariate sensor readings recorded every 10 minutes from a household. It includes 28 input variables (e.g., lights, temperature, humidity) and one target variable: `Appliances`, representing the energy consumed.

3 Forecasting Models

We compare two deep learning architectures:

3.1 RNN (Deterministic)

A classic recurrent neural network trained to produce point forecasts. It is simple, efficient, and suitable for baseline performance.

3.2 LSTM-VAE (Probabilistic)

A variational autoencoder with LSTM encoder-decoder, trained to model uncertainty. The decoder reconstructs 100 future steps conditioned on the latent code, enabling probabilistic forecasting through the reconstruction mean and intervals.

4 Training Setup

Input-output windows: Each sample consists of:

- **X:** A window of 500 past time steps of all variables.
- **y:** The next 100 future steps of the target variable (`Appliances`).

We explore two training regimes:

- **Direct forecasting:** Predict all 100 steps in a single forward pass.
- **One-step autoregressive:** Predict one step at a time recursively.

5 Validation and Evaluation

We split the data into training, validation, and test sets. Evaluation metrics include:

- MAE (Mean Absolute Error)
- RMSE (Root Mean Squared Error)
- R^2 score
- CRPS (Continuous Ranked Probability Score) for probabilistic models

The **LSTM-VAE** consistently provides more stable predictions with tighter confidence intervals and competitive RMSE/MAE, making it favorable for deployment.

6 Conclusions

The probabilistic approach using an LSTM-VAE offers significant advantages:

- Captures uncertainty in long-term forecasts.
- Produces more informative predictions (intervals, distributions).
- Robust to noisy or incomplete data.

Adapting an image-focused architecture (VAE) to time series required careful reshaping of data and replacing convolutional layers with LSTM cells. This allowed the latent representation to encode temporal dynamics rather than spatial patterns.

7 Final Remarks

Probabilistic forecasting is essential in energy modeling and many real-world domains where uncertainty matters. This project demonstrates how modern deep generative models can be adapted and applied effectively to sequential problems.