SmartHome Savant: Optimizing Living Spaces with LLM Innovation

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1 Background and motivation

The landscape of smart home technology is evolving and there is a growing need for personalized and efficient household management solutions. Smart devices need to be used wisely by homeowners to save money by consuming less energy and to reduce pressure on smart grids, thus promoting sustainability for the environment. With the increasing proliferation of connected appliances and devices, homeowners face problems for which they seek solutions with minimal effort. Firstly, they struggle to identify appliances that cause spikes in energy consumption and exhibit anomalous behavior. Secondly, there is no one-stop solution for their smart home appliances where they can find answers to queries related to smart usage. Thirdly, homeowners often neglect reading user manuals on how to use appliances properly, resulting in decreased appliance lifespan and increased energy consumption. Lastly, they may seek suggestions on how to change the electrical layout of their room to enhance energy efficiency. We aim to address these problems and provide a one-stop solution in the form of a smart home assistant. While numerous studies have explored AI/ML approaches, recent advancements in language understanding and multi-modal techniques have opened new avenues. In this project, we intend to leverage the latest technology of Language and Layout Models (LLMs) over traditional AI/ML methods due to their progress in Natural Language Understanding (NLU), Document Understanding, Multi-Modal Capabilities, Flexibility and Adaptability, and State-of-the-Art Performance. Importantly, we aim to utilize the generalization language generation capabilities offered by LLMs. Traditionally, solutions in this field are black box with little explanation of feature contributions. Our goal is to achieve feature-wise explainability, enhancing understanding of the model's intuition.

2 Project Statement/Objective

Develop a Smart Home Assistant leveraging **Language and Layout Models (LLMs)** to optimize energy usage, manage appliances, and provide real-time information. The goal is to detect excessive energy consumption in advance, prevent increased usage fees, and predict future energy consumption and generation through weather data integration for energy supply optimization. By offering explainable insights, personalized recommendations, and a centralized platform for user queries, the project aims to enhance smart home interaction, promote efficiency, and foster sustainability.

3 Proposed Solution

The proposed solution encompasses leveraging Language and Layout Models (LLMs) across multiple usage scenarios to enhance user experience and optimize smart home power consumption usage.

- Firstly, we intend to develop an **anomaly detection model and forecasting model** for smart home power usage using tree-based modeling integrated with [3] **SHAP (SHapley Additive exPlanations)** for feature explainability and importance analysis. This model, utilizing local LLMs, will give tailored recommendations for the smart homeowner on best device usage patterns.
- Secondly, we plan to **fine-tune a local model** using various FAQ datasets to address user queries and facilitate access to knowledge base documents efficiently. Leveraging LLMs in this context enhances the accuracy and relevance of responses, enriching user interaction. Further, we propose utilizing the [2] **Retrieval-Augmented Generation (RAG)** model to extract insights from manuals and instructional materials, enabling users to understand device usage and functionalities effectively.
- Lastly, we aim to implement **multi-modal techniques** to identify devices within room images and offer personalized suggestions for optimization. By harnessing the capabilities of LLMs across these diverse usage scenarios, our Smart Home Assistant endeavors to provide intelligent, context-aware assistance tailored to the needs of users, fostering efficiency, convenience, and sustainability within the smart home environment.

4 Project Deliverables

4.1 Anomaly Detection Model with SHAP Integration:

- Develop two models based on a user's historical energy usage data: one to detect anomalies in device power usage and another to predict total energy consumption.
- Integrate SHAP models into each of these models to explain feature importance.
- Utilize tailored suggestions from LLM to recommend ideal energy usage practices based on the user's historical data using the top SHAP feature values.

4.2 Fine-Tuned FAQ Model for User Queries:

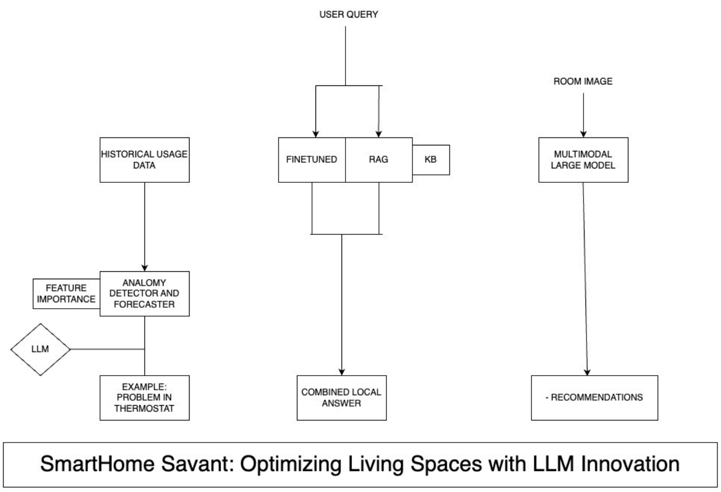
- [1]Fine-tune a local LLM model using FAQ datasets to address user queries and facilitate access to knowledge base documents on the consumer device.
- Implement the Retrieval-Augmented Generation (RAG) model to extract insights from manuals and instructional materials.

4.3 Optimal device placement recommendations:

- Utilize multi-modal models such as Layout LM, [4] GPT-4 V, and Gemini Turbo to recommend optimal device placement within a room.

4.4 Evaluation Methodology:

For the anomaly detection and forecasting model, we employ random data point masking to compute precision, accuracy, and recall. We also verify if the output in natural language form adheres to language rule integrity. For the fine-tuned model, we will utilize a human evaluation methodology to rate the response from the fine-tuned model on a scale of 1 to 5, depending on how well the question was answered. The knowledge base for this can be compiled by aggregating the output from commercially available LLM models and other internet resources. For the RAG model, we will employ cosine similarity to compute the similarity between the output from the RAG model and our FAQ dataset. For the last model, the only available evaluation methodology is human intervention.



(a) Architecture diagram

5 Task allocation among team members

- Abhilash - Anomaly Detection Model with SHAP Integration
- Aditya - Scraping FAQ datasets, EDA on datasets and front-end of the application.
- Ankith - Fine-Tuned FAQ Model for User Queries
- Snigdha - Optimal device placement recommendations

6 Dataset

- Appliances Energy Consumption
- Smart Home Energy Data
- Hourly energy demand generation and weather

References

[1] Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. Qlora: Efficient finetuning of quantized llms, 2023.

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[3] Scott M. Lundberg and Su-In Lee. A unified approach to interpreting model predictions. *CoRR*, abs/1705.07874, 2017.

[4] OpenAI. Gpt-4 technical report, 2024.