

5G-Energy Consumption Modelling

A Residual LightGBM Predictor for Energy Consumption Prediction

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Problem Statement

Leverage ML/AI to predict the energy consumption of base stations

The dataset provided for this competition was three comprehensive collections of base station basic information cell level data and Energy consumption

The provided data had 92629 training items and 26139 test items. Each item contains the essential information including:

1. Base Station Basic Information:
Base Station ID, Cell Name, RUtype, Mode, Frequency, Bandwidth, Antennas and TXpower
2. Cell Level Data:
Time, Base Station ID, Cell Name, load and ESMODE1-6
3. Energy Consumption:
Time, Base Station ID and Energy Consumption (training set only)

The Task - predict the Energy Consumed during some specific hours

Evaluate - weighted mean absolute percentage error (WMAPE) scores

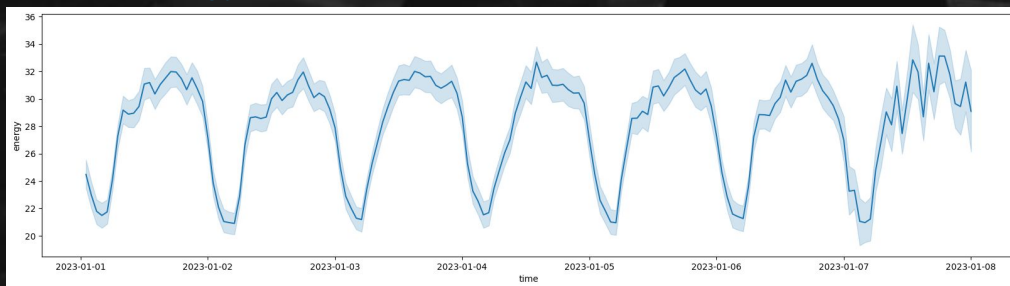
Dataset and EDA

Cell Level Data:

| Time | BS | CellName | load | ESMode1 | ESMode2 | ESMode3 | ESMode4 | ESMode5 | ESMode6 |
|-------------|-------|----------|------------|---------|---------|---------|---------|---------|---------|
| 1/1/23 1:00 | B_0 | Cell0 | 0.48793617 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1/1/23 1:00 | B_105 | Cell0 | 0.0503 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1/1/23 1:00 | B_105 | Cell1 | 0.01674 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1/2/23 0:00 | B_105 | Cell0 | 0.07884 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1/2/23 0:00 | B_105 | Cell1 | 0.02141 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1/2/23 0:00 | B_105 | Cell2 | 0.04605769 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1/2/23 0:00 | B_105 | Cell3 | 0.04680769 | 0 | 0 | 0 | 0 | 0 | 0 |

- The varying number of cells for each base station at different hours poses a challenge for Deep Neural Networks (DNN). This is because DNN requires a consistent input shape.

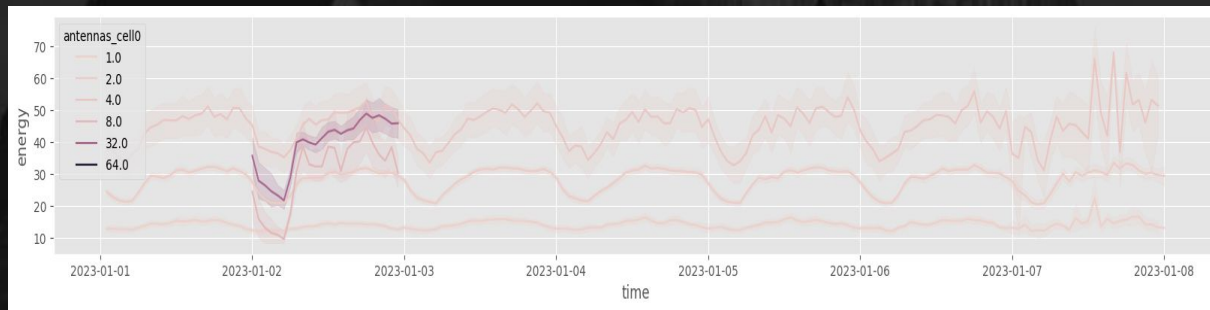
Period Energy:



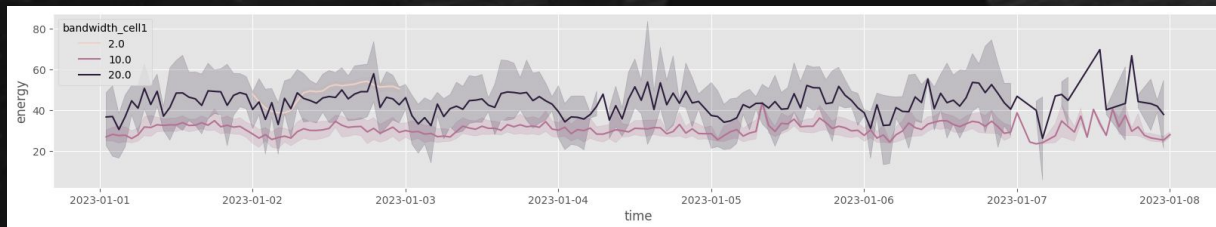
- The energy consumption of a base station exhibits periodic patterns with a 24-hour cycle. This observation led me to consider that feature data and energy consumption at the same hours of the day might be a valuable feature.

Dataset and EDA

Noise:



The energy data exhibits noise, which can have a negative impact on the decision trees algorithms like LightGBM.



Algorithms based on decision tree are iterative, and they adjust sample weights based on predictions from previous iterations. Consequently, as the iterations progress, errors tend to decrease, leading to a reduction in the model's bias [1].

However, this competition's data is marked by significant noise. Minimize the bias with noise may cause overfitting.

[1] Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., ... & Liu, T. Y. (2017). Lightgbm: A highly efficient gradient boosting decision tree. Advances in neural information processing systems, 30.

Feature Engineering

Feature set 1:

we combine these three files based on timestamps and base station id. There are 11 basic features which are listed in the following table. This is a part of basic inputs.

| features and cell | cell0 | cell1 | cell2 | cell3 |
|-------------------|-----------------|-----------------|-----------------|-----------------|
| load | load_cell0 | load_cell1 | load_cell2 | load_cell3 |
| esmode1 | esmode1_cell0 | esmode1_cell1 | esmode1_cell2 | esmode1_cell3 |
| esmode2 | esmode2_cell0 | esmode2_cell1 | esmode2_cell2 | esmode2_cell3 |
| esmode3 | esmode3_cell0 | esmode3_cell1 | esmode3_cell2 | esmode3_cell3 |
| esmode4 | esmode4_cell0 | esmode4_cell1 | esmode4_cell2 | esmode4_cell3 |
| esmode5 | esmode5_cell0 | esmode5_cell1 | esmode5_cell2 | esmode5_cell3 |
| esmode6 | esmode6_cell0 | esmode6_cell1 | esmode6_cell2 | esmode6_cell3 |
| frequency | frequency_cell0 | frequency_cell1 | frequency_cell2 | frequency_cell3 |
| bandwidth | bandwidth_cell0 | bandwidth_cell1 | bandwidth_cell2 | bandwidth_cell3 |
| antennas | antennas_cell0 | antennas_cell1 | antennas_cell2 | antennas_cell3 |
| txpower | txpower_cell0 | txpower_cell1 | txpower_cell2 | txpower_cell3 |

Feature set 2:

- Energy of past 5 days in the same hours(We will call this Previous Energy from now)
- Features of past 6 days in the same hours
- Difference on features of past 6 days in the same hours
- Percentage on features of past 6 days(We will call this Percentage of Features from now)

Feature Engineering

Feature set 3:

- Difference of Features
- Product of Features
- This is the other part of basic inputs

TABLE 4
NEW FEATURES CREATED

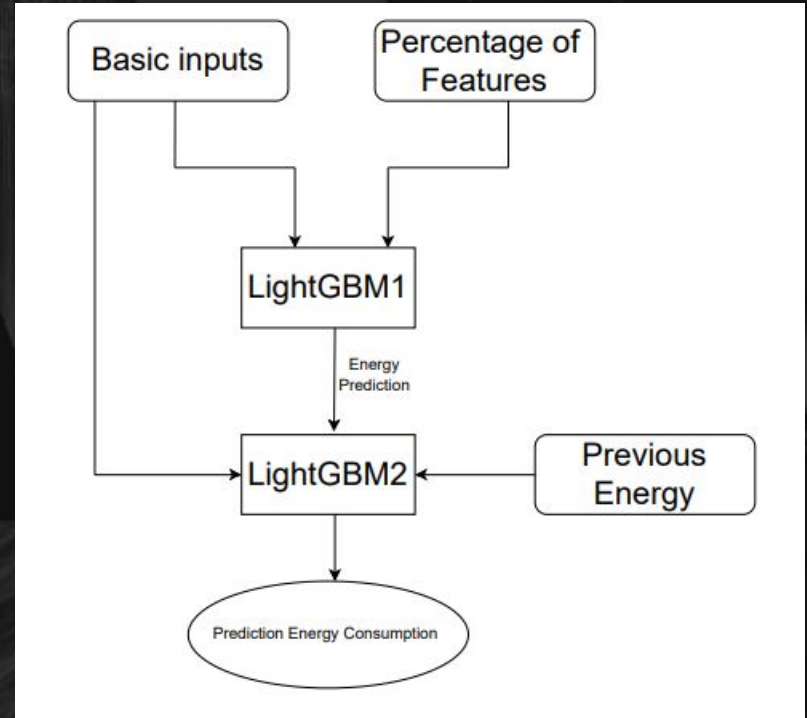
| Type | Features |
|------------|-----------------------------|
| difference | load_minus_frequency |
| | load_minus_bandwidth |
| | load_minus_txpower |
| | frequency_minus_bandwidth |
| | frequency_minus_antennas |
| | frequency_minus_txpower |
| | bandwidth_minus_antennas |
| | bandwidth_minus_txpower |
| product | antennas_minus_txpower |
| | load_product_frequency |
| | load_product_bandwidth |
| | load_product_txpower |
| | frequency_product_bandwidth |
| | frequency_product_antennas |
| | frequency_product_txpower |
| | bandwidth_product_antennas |
| | bandwidth_product_txpower |
| | antennas_product_txpower |

Model

Residual LightGBM:

- Two LightGBM structures are implemented: LightGBM1 and LightGBM2
- The Inputs of LightGBM1 are: Basic inputs and Percentage of Features
- The Inputs of LightGBM2 are: Basic inputs, Energy Prediction of LightGBM1 and Previous Energy.

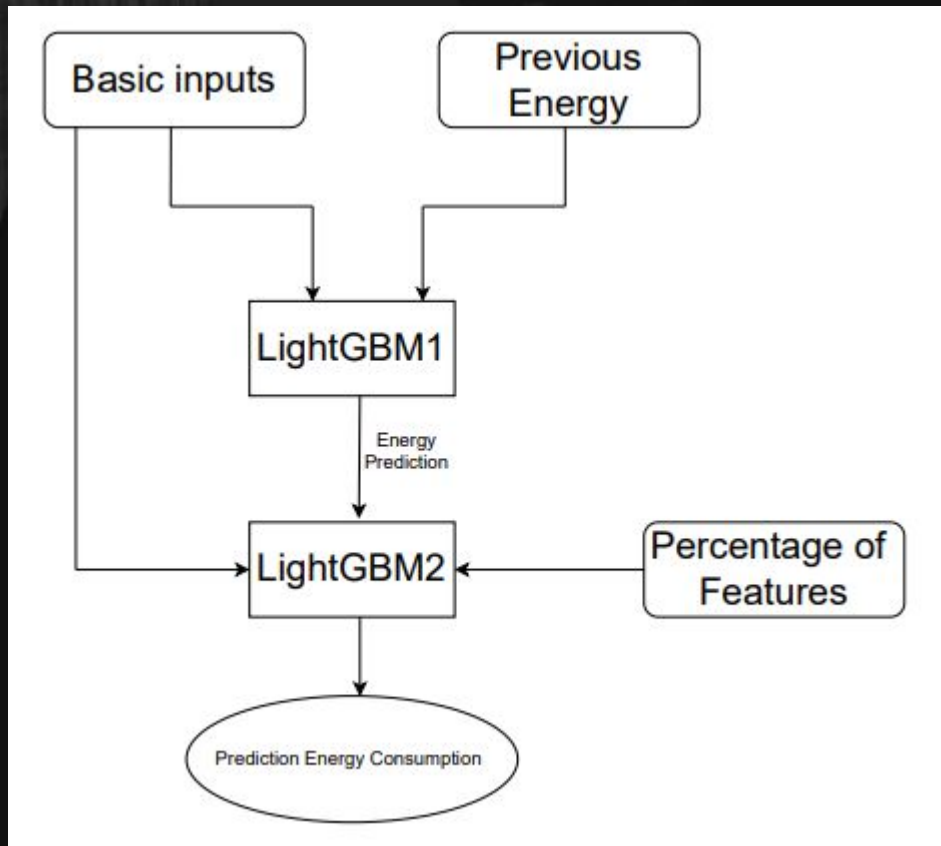
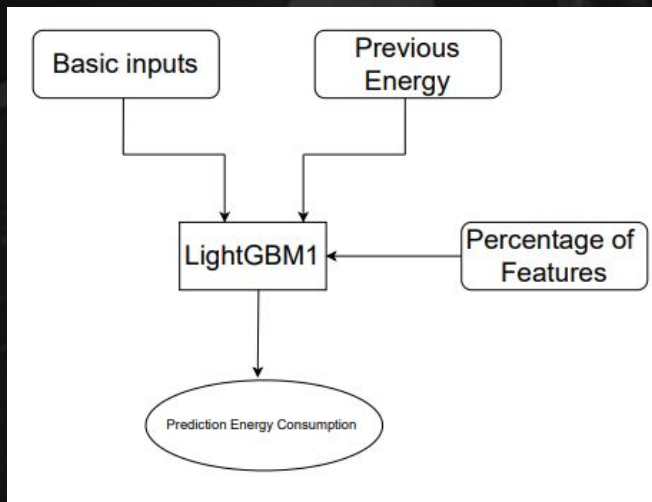
Residual LightGBM use the prediction as input. Because the basic inputs are used as input twice, it can alleviate the impact of noise.



Baseline:

Baseline:

- Other shape of Residual LightGBM
- LightGBM



Submission:

Submission Scores of different Features:

In order to compare the performance, we use LightGBM to evaluate the efficiency of different features.

| features | Public Scores | Private Scores |
|--|---------------|----------------|
| Basic features only | 0.124709515 | 0.123136091 |
| Differences + Basic features | 0.113376462 | 0.111411138 |
| Product + Basic features | 0.118879751 | 0.117040871 |
| Percentages of Features + Basic features | 0.111652422 | 0.109514682 |
| Previous Energy + Basic features | 0.110787858 | 0.109594089 |

Submission Scores of different Models:

| Structure | Public Scores | Private Scores |
|--------------------|---------------|----------------|
| Residual LightGBM | 0.093204536 | 0.092276470 |
| Residual LightGBM2 | 0.101277934 | 0.100985862 |
| LightGBM | 0.105140196 | 0.104014936 |

Conclusion and Future works:

Conclusion:

In this competition, we proposed a Residual LightGBM to solve the noise problem. We also provide some data processing and feature engineering. Finally, we got 0.093 on Public Scores and 0.092 on Private Scores.

Future Works:

- RUType and Mode are not used as our inputs. Because they cannot increase scores. In the future, we will explore more on how to use these two features.
- Deeper Residual LightGBM may helpful.

Q & A