Deployed Short Term Energy Forecasting Service

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OVERVIEW

Day ahead energy forecasts are predictions of the expected energy consumption or generation over the next 24 hours. They guide energy traders, grid operators, and generation stations as an integral part of the electrical grid infrastructure.

This project investigates predicting day ahead energy demand for each hour of the day using an LSTM. It also develops a data pipeline for the automatic ingestion, processing, inference, and display.

DOMAIN BACKGROUND

Electrical markets rely on stability and the balance between demand and generation. Part of this balance is achieved by being able to plan resources. This means know how much energy to produce, and when to produce it. Forecasting forms an integral part of predicting how much electrical capacity to have ready to produce.

Forecasting is used in the energy markets for both demand and generation. Demand is the consumption of a country, region, or energy trading zone predicted over timescales of 1 second, 1 minute, 15 minutes, 1 hour, 1 day, 1 week, and so on. The timescale depends on the application.

Generation also uses forecasting in the case of intermittent energy supply (i.e. solar, wind, tidal). These models forecast how much energy is expected to be generated on the basis of weather, time of day, and other features.

Traditional models used in forecasting are the autro-regressive moving average (ARIMA) and its integrated and seasonal variants. With the proliferation of deep learning, other approaches are also being introduced, such as the Long-Short Term Network (LSTM).

PROBLEM STATEMENT

Design and implement an engineer solution to make daily predictions of the energy consumption in Spain.

Sub-Questions

- What model architecture and configuration improves prediction performance over the baseline?
- What configuration of auto-regressive and categorical features deliver the lowest error in terms of mean absolute percentage error?
- How can the model make predictions on new data and display the delivered interece data to end-users?

DATASETS AND INPUTS

This project will narrow its focus to predicting electrical consumption demand in Spain. A dataset for this is available on kaggle. Additional data is available from the ENTSO-E transparency platform and may be downloaded directly or accessed via API.

Model inputs will be limited in order to simplify the problem and focus on the engineer pipeline. The following inputs will be used:

- Historical consumption up to the last 365 days
- Day of the week and hour of the day

SOLUTION STATEMENT

The objectives of this project are twofold:

1. Design and implement a serverless data pipeline that each 24 hours automatically retrieves consumption data, processes the data, stores the data, makes inference for the next 24 hour period, and displays both prediction and historical results on a small web application.
2. Implement an LSTM neural network that predicts energy consumption 24 hours in advance.

BENCHMARK MODEL

Two models will be used as a benchmark for performance. The first is a persistence model, and the second is the daily consumption predictions (i.e. day ahead forecasts) from the Red Española Electrica available via the ENTSO-e platform.

1. Persistence Model: A persistence model uses a previous time step as the prediction for the future timestep. It is a direct mapping of the previous period to the predicted period. Three persistence models will be calculated
    a. Demand from the same hour of the previous day. I.E. Hour 5 from today is used as the prediction for hour 5 tomorrow.
    b. Traditional three day moving average
    c. Three day moving average of each hour in the day. I.E. calculate 24 moving averages of the last 3 days, for hours 0 to 23 and use this set as the prediction.
2. Red Española Electrica Predictions: These are available on a per 24 hour basis.

Note: With the persistence model we can not use a previous period method less than 24 hours because our assumption is that our minimum prediction window is 24 hours.

Evaluation Metrics

All models will be evaluated using the mean absolute percentage error (MAPE). This metric is chosen because it is intuitive for those not familiar with the energy sector to understand (I.E 2% error as opposed to normalized error of 0.5 MWh). Two variants of the MAPE will be used.

- MAPE calculated for each hour of the day. This will indicate the hours where the model is predicting poorly/well.
- MAPE as the cumulative model error. This will be used to compare models against the baselines.

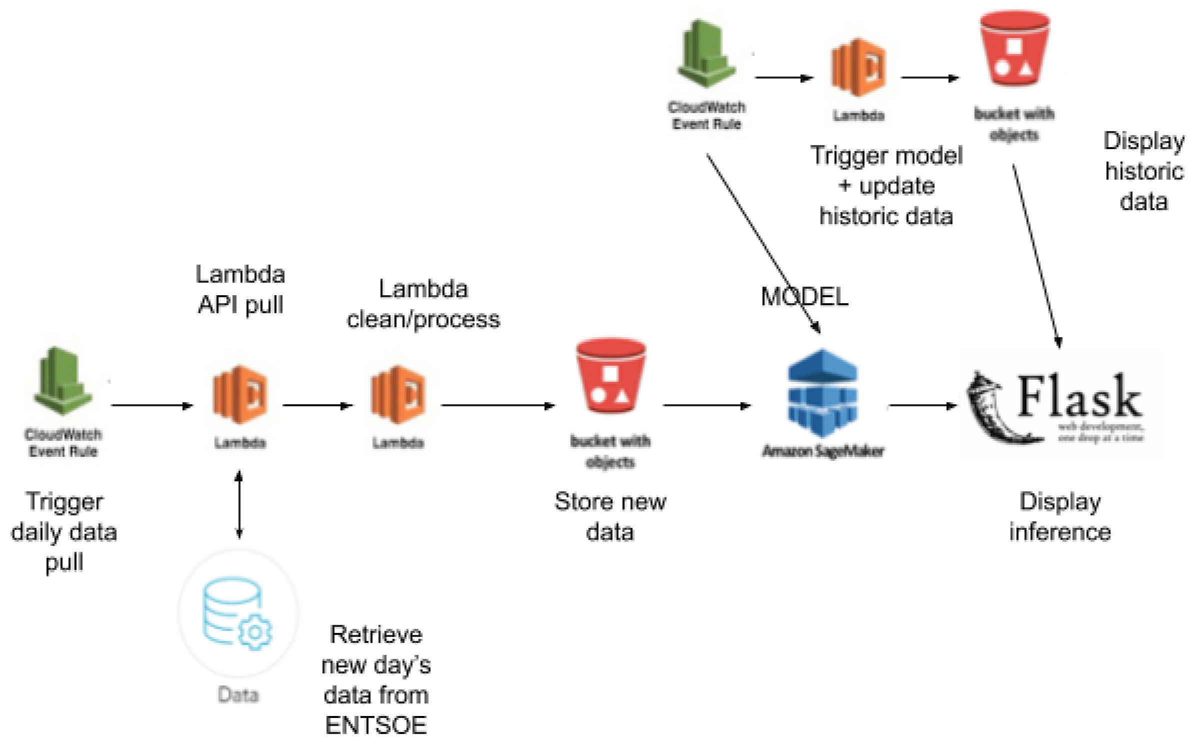
LEARNING OBJECTIVES

My primary learning objective is to understand the end to end process of productionizing a model. The focus will be on setting up the infrastructure and data pipeline to make inference. As such I have identified the following learning goals.

1. Deploy a Tensorflow LSTM model for inference in Sagemaker.
2. Configure AWS cloud watch and Lambda to automatically download historical data and make inference calls to the model.
3. Configure a flask web app to display the daily predictions.

PROJECT DESIGN

This following the learning objectives this project is a MVP of a live time series prediction model. The design can be roughly explained by the following diagram.



This will be broken down into several sub-tasks and steps described in milestones.

MILESTONES

1. Flask front end with a single graph that shows the last 7 days of historic energy consumption data
2. Automate connecting to and downloading from ENTSOE database with cloud watch and lambda.
3. Automate historic dataflow updating.
4. Data analysis, feature selection (time lags), model training, and deploy model artifact.
5. Integrate model inference with historic prediction to front end

NOTES

This project will use a tensorflow model I previously built. An example can be found in [this kaggle notebook](#).