

# Web Application Testing

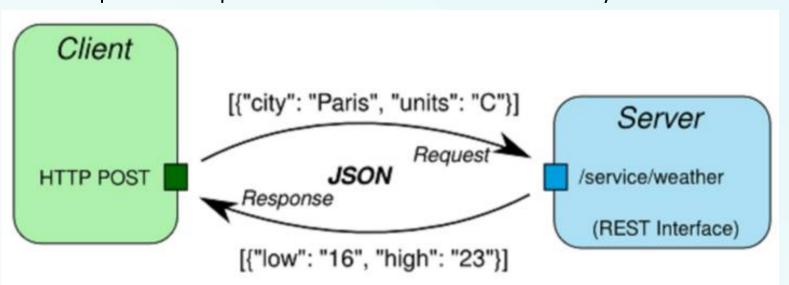
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### Introduction

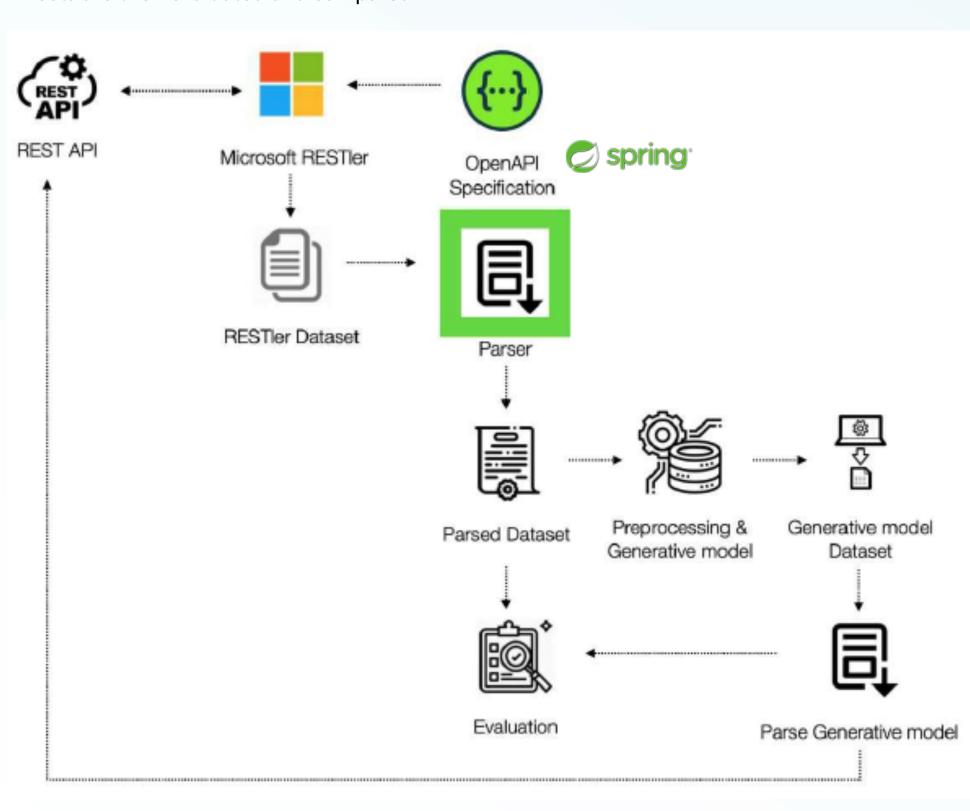
With the ever-increasing demand for web applications, the demand for Rest APIs has gone up exponential, which has led to a huge demand for efficient Rest API testing. This is currently handled with Rest API automation testing, but this has challenges such as requires handling planned failed test scenarios, comparing responses, and sequencing the API calls.

The most common type of API is REST (Representational State Transfer). In REST API when a client sends a request the response is sent back in a standardized way.



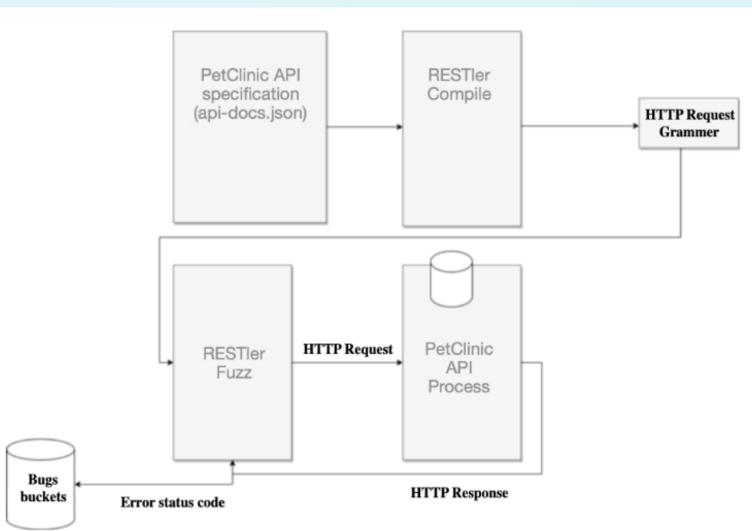
This project aims to look into further automating the Rest API testing and combating the issues highlighted above in the current automation testing by automatically generating the test cases feeding after feeding in the information from the Rest APIs.

This was done by creating test cases using Restler (fuzzy grammer approach) and then feeding the resulting test set into a machine learning generative model. The resulting test sets are then evaluated and compared..

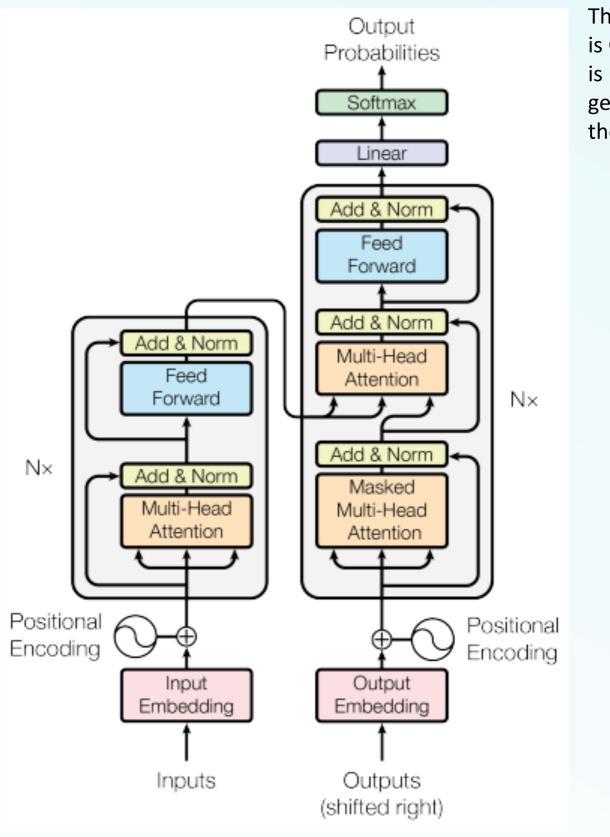


# Methodology

### Dataset generation with RESTler



Model architecture



Transformer Model Architecture

The deep neural network that is used in this work is Generative Pre-trained Transformer 2 (GPT2). It is a generative unsupervised model, which can generate new data similar to existing data during the pre-training step

RESTler has two main

components, a compiler and

an engine. The compiler

takes an API specification

and produces the fuzzing

grammar, which has all the

schema information about

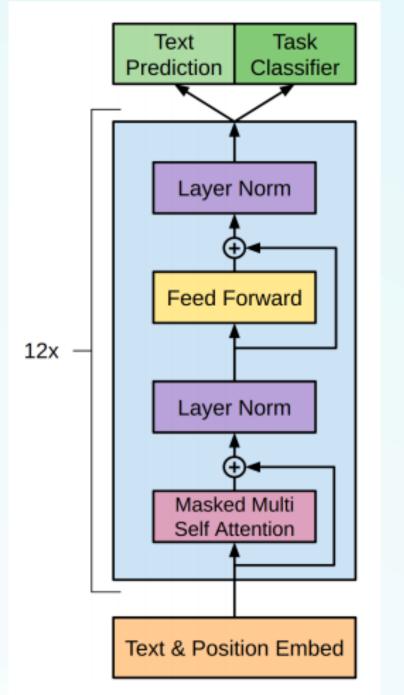
the requests. The RESTler

test engine takes the fuzzing

grammar and some other

settings in order to run tests

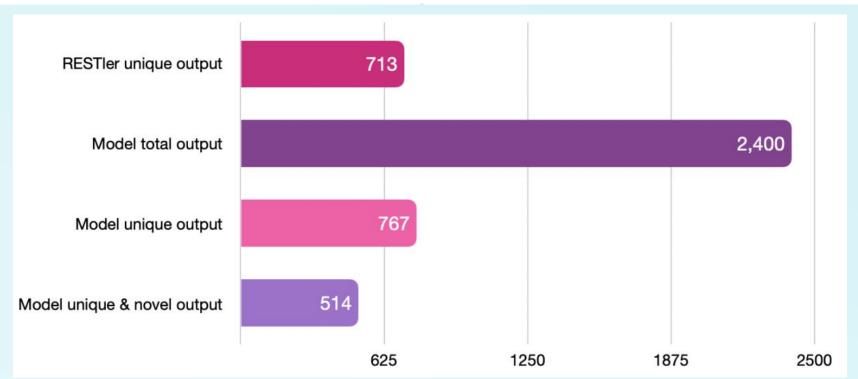
and find bugs.



Decoder-Only Architecture used by GPT-2

# Results

| Evaluation Metric   | Restler         | Generative<br>Model |
|---|-----------------|---------------------|
| Total Number of test cases  | 45,099          | 2,365               |
| Unique Test Cases   | 713             | 787                 |
| Number of test cases passed (Response code 200-299)                             | 43,245          | 216                 |
| Number of test cases failed (Response code 400-599)                             | 1,854           | 2149                |
| Average Response Time   | 0.01347 seconds | 0.00442 seconds     |
| Uniqueness = Number of unique tests / Total tests generated                     | 1.58%           | 33.28%              |
| Valid Test Cases Percentage = Number of valid tests / Total number of tests     | 96%             | 9.13%               |
| Invalid Test Cases Percentage = Number of invalid tests / Total number of tests | 4%              | 90.86%              |



**Evaluation of RESTtler and GPT Model** 

# **Anomaly Detection**

Anomaly detection algorithms can be categorized into these groups :

- **1. Supervised:** Used when the data set has labels identifying which transactions are an anomaly and which are normal. (this is similar to a supervised classification problem).
- **2. Unsupervised:** Unsupervised means no labels, and a model is trained on the complete data and assumes that the majority of the instances are normal.
- **3. Semi-Supervised:** A model is trained on normal data only *(without any anomalies)*. When the trained model is used on the new data points, it can predict whether the new data point is normal or not (based on the distribution of the data in the trained model).

## Conclusion

Overall, the generative model successfully created an expanded dataset where there is a higher percentage of uniqueness and endpoints called. However, this test set could be further improved upon by expanding the range of error codes and producing more test cases. Moreover, in the future anomaly detection model also will be improved with provided evaluation metrics.