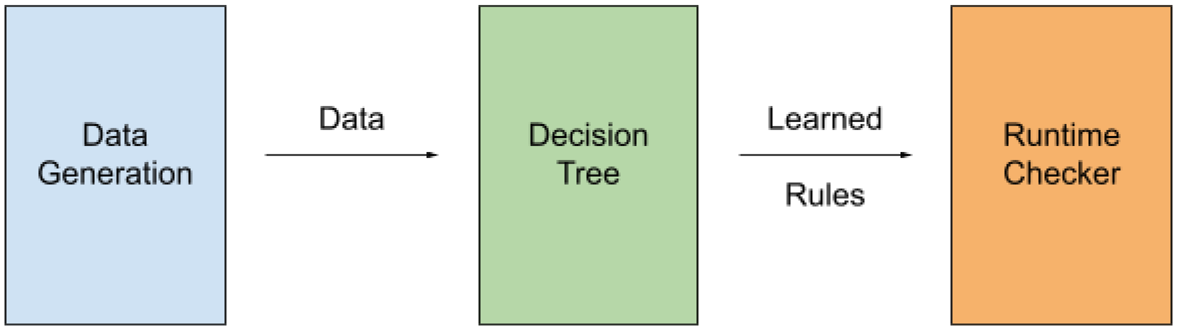
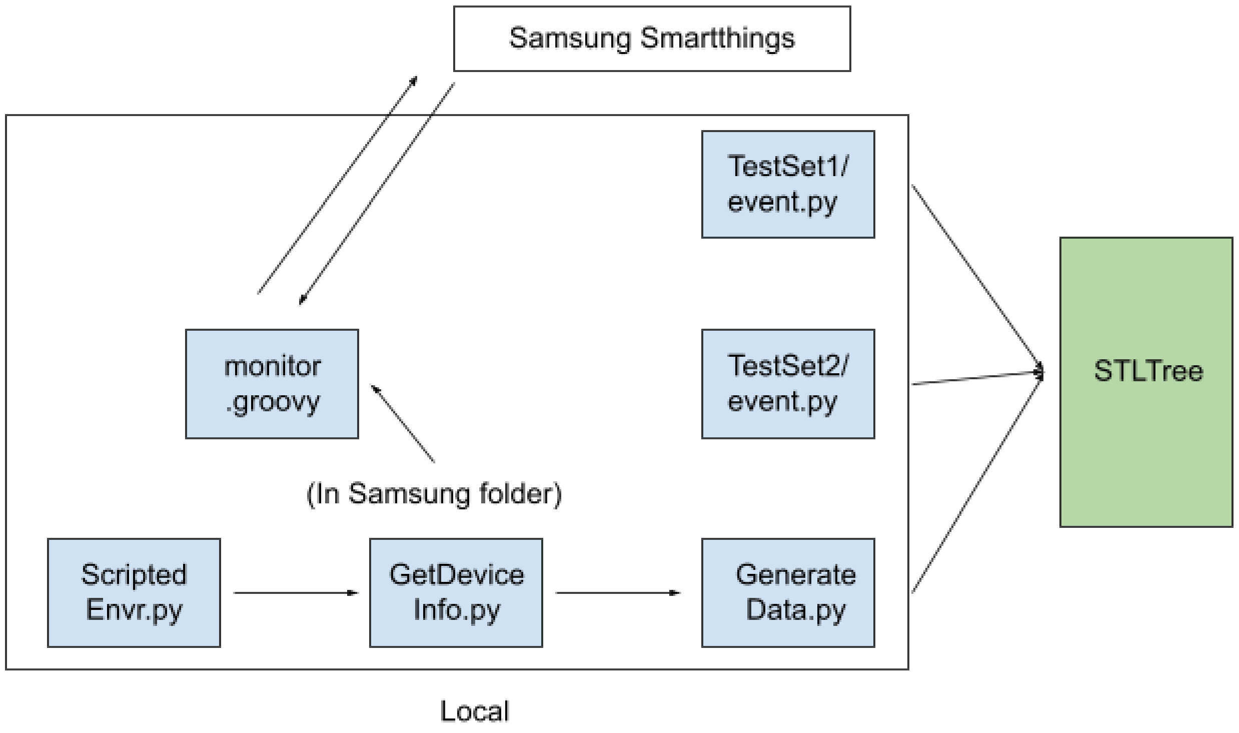
Current Workflow:



Data Generation:



TestSet1 and TestSet2 represented how we initially generated data for our STLTree model. In event.py, we utilized a state machine with hardcoded devices and rules to generate data for an environment with such devices at each timestamp.

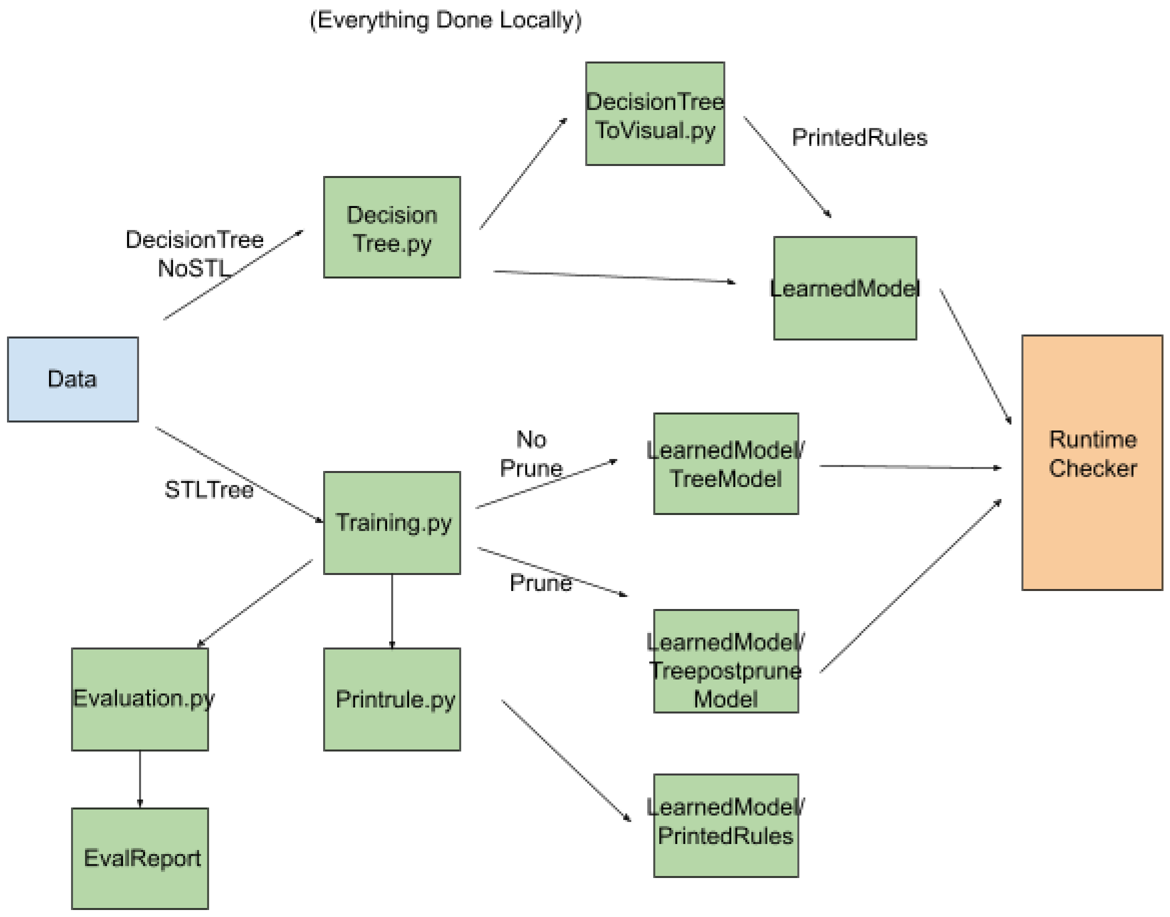
Running **python3 event.py** will generate the data, and the amount of timestamps generated is done through changing the number of iterations in the **genEvent()** function.

The Samsung folder generates data on Samsung Smartthings development platform directly through simulations. We hardcoded some interactions with devices and Smartapps, and generated data through automation with Selenium. For new test environments, we would need to make a new **ScriptedEnvr.py** for Selenium to run.

Samsung/GetDeviceInfo.py calls a monitor smartapp (**Smartapp/monitor.groovy**) to access state changes for each device in the environment, with which we use to generate the test data through generateData.py. In actual use of our runtime checker, we would access Samsung device state changes with the same workflow.

Note: The APIkey and endpoint in **Samsung/GetDeviceInfo.py** should match the token and endpoint in **Smartapp/monitor.groovy** when installing the monitor to the environment on Samsung hub.

Learning Rules with Decision Trees:



After data is generated, we learn rules on the environment with our decision tree models:

STLTree: Learns rules based on temporal logic, where we assign a number for each state a device can have, and have the following rules:

- **F[a, b](x < c):** In interval [a, b], device x becomes a state w/ number less than c
- **G[a, b](x < c):** In interval [a, b], device x is always a state w/ number less than c

- **F[a, b]G[0, d](x < c):** In interval [a, b], device x is in a state w/ number less than c for d seconds

Running **python3 training.py** will learn two trees of STL rules for each (Device, state) tuple in the environment, pruned and unpruned version. The learned tree can be found in a file in the format “{deviceName}_{stateName}.pkl" in **LearnedModel/Treemodel** and **LearnedModel/Treepostprintmodel** . There is also a readable version under directory **LearnedModel/Treeprint** and **LearnedModel/Treepostpruneprint** with name format “{deviceName}_{stateName}.txt”.

To have a readable format of the learned rules, run **python3 printrule.py** after training the model.

To evaluate our model’s accuracy, run **python3 evaluation.py** on the evaluation set.

The data used for training and validation for pruning in the STLTree model can be modified in **training.py.** The data used for evaluation is modified in **evaluation.py.** There are multiple parameters can be modified in the STLTree through command line argument, listed below:

For **python3 training.py:**

- **Data Handling:** Our data is currently separated into 10 second intervals for our tree to learn with an offset of 2. That is, we start at timestamp 1 to 10 as first data, then 3 to 12 as second, etc. The state for the last timestamp in the interval determines the label for the device of our interest. The interval amount and offset for data handling can be changed to n and m correspondingly with flag **--interval=n, --offset=m** (default n = 10, m =2)

- **Training Iterations:** Our model utilizes the simulated annealing method, which the process is determined by **Temperature** and **Steps**. Temperature determines how likely we would choose to random walk rather than staying idle while steps determine the number of iterations of random walk. To set maximum Temperature to t and steps to s, we can run with flag **--Tmax=t --Steps=s** (both has default 20000)

- **Tree stop conditions:** We choose to stop splitting on a tree either we reached maximum depth d, or the accuracy for the current node exceeds fraction f, or there are less than n objects in the node. The three parameters can be changed with flags **--maxDepth=d --fracSame=f, minObj=n** (Default: d = 4, f = 0.95, n = 30)

For **python3 evaluation.py**

- **Error Threshold:** Since there is randomized behavior in our data generation, there are some rules learned by our model that are fairly inaccurate. We would only print out the rules that we are confident with low error. The error threshold t is set with flag **--offset=t** (default = 0.10)

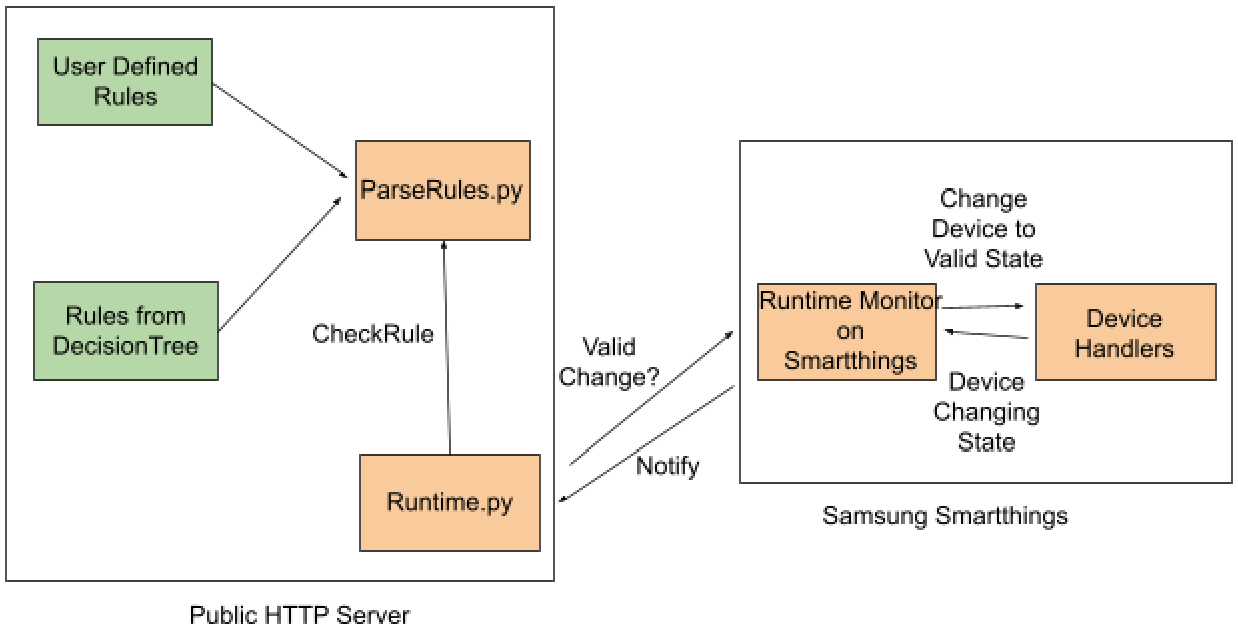
- **Data Handling:** The test data should be handled the same way as training data, with same flags **--interval=n, --offset=m**

For **python3 printrule.py**
- **Error Threshold: --offset=t**

TreeNoSTL: Learn rules in the environment that are not time related. I.e. when some device changes to a state, the other device must immediately change to the state also.
The model utilizes the sklearn.tree package by python. The output for learned rule is directly shown under **LearnedModel** folder with format "{deviceName}_{stateName}.pkl" and can be visualized under **LearnedModel** folder with format "{deviceName}_{stateName}.txt"

To learn the rules, run **python3 ModelsNoSTL/DecisionTree.py**
To visualize the rules, run **python3 ModelsNoSTL/DecisionTreeVisualization.py**

Runtime Checker (Still in Implementation)



Our current runtime checker first parses the rules learned from the decision tree and possible user defined rules. Due to the limitation of DONT rules only, we are only supporting user input rules in the format of

THE {Device}_{State} STAYS {State Value} AFTER {number} {SECONDS/MINUTES/HOURS} WHEN {State} OF {Device} IS {State Value} FOR {number} {SECONDS/MINUTES/HOURS}
-- Translates to a G rule for PTSL

THE {Device}_{State} STAYS {State Value} AFTER {number} {SECONDS/MINUTES/HOURS} WHEN {State} OF {Device} BECOME {State Value} IN LAST {number} {SECONDS/MINUTES/HOURS}
-- Translates to a F rule for PTSL

THE {Device}_{State} STAYS {State Value} AFTER {number} {SECONDS/MINUTES/HOURS} WHEN {State} OF {Device} BECOME {State Value} IN LAST {number} {SECONDS/MINUTES/HOURS} FOR {number} {SECONDS/MINUTES/HOURS}
-- Translates to a FG rule for PTSL

Example:
THE Door_lock STAYS unlocked AFTER 3 SECONDS WHEN alarm OF Smoke Alarm IS siren FOR 5 SECONDS (=> G[3, 7](Smoke Alarm = Siren) if at 10 second interval)

Workflow of Monitor:
We would first start a public http server using **python3 runtime.py** to communicate with a Samsung Smartapp that is created to subscribe to all the device changes in the environment, **Smartapp/runtimeChecker.groovy**. Whenever a device's state gets changed, the RuntimeChecker sends the event to the http server.

The http server then keeps an internal state of devices in the environment, and when a device change is received, it then checks for if the change violates any learned rules. If it does, it will send back to the RuntimeChecker to the actual state of the device it should be in, and the RuntimeChecker automatically changes the device back to its state.

Parameters that can be changed in the workflow:

- HTTP server port. In my implementation, I have used my server at home, which I would need to run Runtime.py when SSH'ed into the server. The general code should work for any server hostname with a working port. This is changed on top of **runtime.py** also in **RuntimeChecker.groovy** for it to connect to the server.

- User Defined rule: The user defined rule file is specified at the very beginning of **runtime.py**

Command Line options for running **python runtime.py**

- Only checking important devices. We can also only check for important device changes in the environment, and ignore other device changes. This is done by whenever an important device change gets sent to the monitor, the monitor requests each device state in the environment and analyzes the change based on stored data. However, the Samsung Hub has a ~10 second delay on storing device changes, so such runtime checking may not be accurate. To activate the feature, run with flag **--important=True**.

- To check for DO rules, that is if a device has not changed to a desired state for 2 seconds after all rules for the state change have been satisfied, the monitor automatically changes the device to the desired state. The feature is included by default, run with flag **--do=False** to deactivate the feature.

- Determining the maximum past state changes the monitor stores for each device. The number of state changes to store can be configured to **n** by running with flag **--maxStates=n** (default: 5)

- Error Threshold when converting rules. Similar to the tree model before, only accurate rules would be converted. The error threshold is changed with **--threshold=t** (default 0.10)

- “Cap” when converting rules. To make our learned PTSL rules in the model easy to check, we converted the interval **[a, b]** into **[a’, b’]**, where **a’, b’** represents the interval from a’ seconds ago to b’ seconds ago from now. This conversion needs the time interval size we use to train our model, which is specified with arg **--interval=i** (default: 10)

Note: The APIkey and endpoint in **runtime.py** should match the token and endpoint in **Samsung/monitor.groovy** when installing the monitor to the environment on Samsung hub. These are specified at the top of **runtime.py**