Anomaly Detection in Floodlights for Smart Campus

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Problem Statement: Real-time detection of malfunctioning light groupings from six floodlight circuits in a parking lot for smart campus.

Key takeaways from the example:

- Use Subspace Tracking algorithm to detect anomalies
- Use streaming data for real-time failure detection

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Data Description

- This data set consists of energy consumption captured every five minutes from six floodlight circuits in a parking lot
- Data is captured for over a span of about three months.
- Each of these light circuits has a sensor that measures the energy consumption of the lights.

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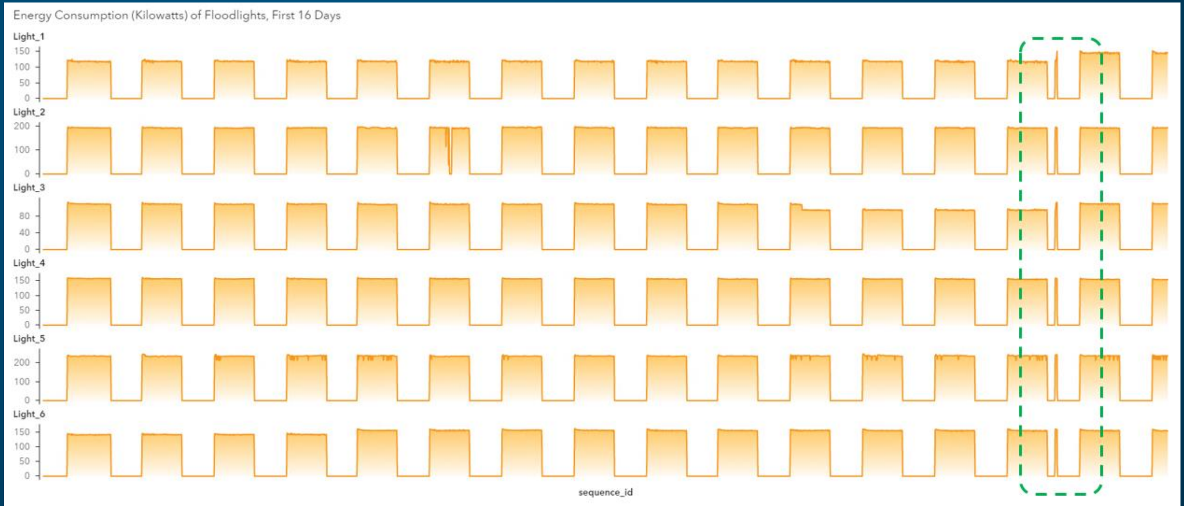
Data Exploration

From analyzing first 16 days of the data we see that the energy consumption throughout the day is zero because the lights are off during the day.

Light_2 has a dip in energy consumption for a couple of hours on the sixth night, indicating that one of the lights controlled by the circuit was not functioning properly.

During day 15, all lights have a spike in energy consumption during the day. A storm occurred on that day, creating enough darkness to trigger the lights to come on briefly. There was no malfunction in the lights.



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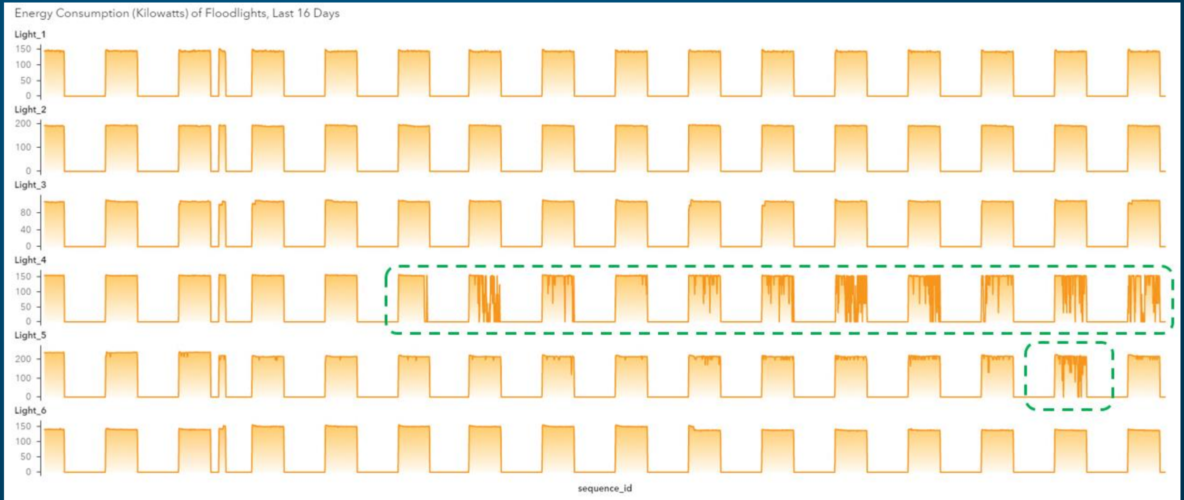
Data Exploration

From analyzing last 16 days of the data we see that Light_4 start to have many dips in energy consumption in the last 11 nights. Several of the lights on this circuit are starting to fail.

Also, Light_5 has dips in energy consumption, especially on the second-last night, indicating that problems are occurring in this circuit as well.



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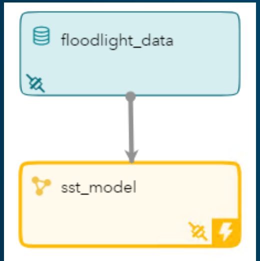

Subspace tracking (SST) can be used for anomaly detection. It is frequently used in the IoT world where data is gathered from many sensors that are connected to each other and have high correlation.

This approach converts a set of correlated variables to a set of linearly uncorrelated variables known as principal components.

Because the first few principal components usually capture most of the variability in the data, they can be tracked over time to assess whether any changes have taken place in the subspace that is spanned by the data.

We can use SST to detect outliers by tracking angle changes between principal components or by using principal component distances away from the mean.

It can be run using forget factors or using sliding window. See *Details* for more information.

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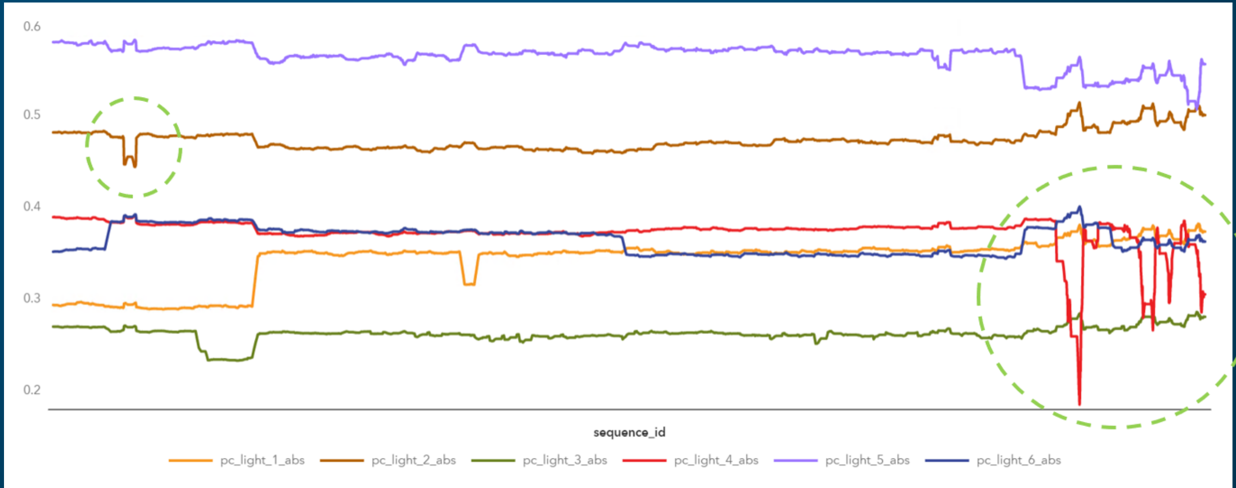
1. **Light 2** starts deviating from the first principal components that are associated with the other lights around the same time that the dips were observed on the sixth night for these lights.
2. **Light 4** starts deviating from the first principal components that are associated with the other lights again around the same time that the dips for this light were observed towards the end.

Result Interpretation



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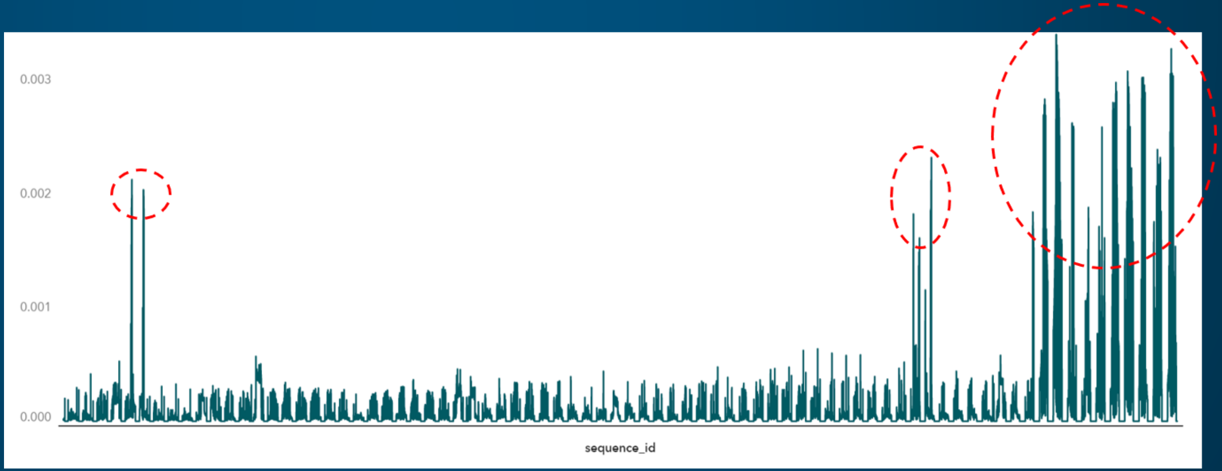
Result Interpretation

- Plot angle changes of the first principal component between consecutive windows
- Value of angle change is relatively higher when an outlier enters the window
- Checking value of angle change can detect when a light circuit is not functioning properly



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Summary:

Decisions can be put into place to trigger maintenance activities when the angle change value is above an acceptable level or abnormal behavior is observed.

We can build online models using Subspace tracking algorithm packaged in SAS Event Stream Processing Analytics to detect outliers in real time on streaming data. It is a method to detect anomalies and system degradation in systems that generate high-frequency, high-dimensional data.