Federal University of Amazonas
Institute of Computing
Graduate Program in Informatics
Interest Group on Embedded Systems

EMBEDDED MINING CORRELATIONS BETWEEN DISTRIBUTED DEVICES
Prof. Dr. Raimundo Barreto
Márcio André da Costa Alencar

Salvador-BA, November 07th 2018
PRESENTATION SCHEDULE

INTRODUCTION
- Contextualization

PROBLEMATIC
- Definition of main and specifics goals

PROPOSED METHOD
- Components specifications and its interactions

EXPERIMENTS
- Experiments and results

FINAL CONSIDERATIONS
- Important notes
Contextualization

- What is “Internet of Things”? 
Contextualization

- What is “Internet of Things”? There’s no global definition but, a simplistic concept, could be as the scenario where things are connected!

Contextualization

- Until 2020 will be over 50 Bi devices (IDC - 2011)

Contextualization

- Many of them will be in your home;
Contextualization

- Many of them will be in your home;
- Be connected is not enough. **IoT demands intelligence!**
How to provide intelligence to IoT devices?
How to provide intelligence to IoT devices?

The ability to provide intelligence and autonomy in IoT relies primarily on the need to identify activities, patterns and correlations implicit in the activity records of each device that composes it.
How to provide intelligence to IoT devices?

The ability to provide intelligence and autonomy in IoT relies primarily on the need to identify activities, patterns and correlations implicit in the activity records of each device that composes it.

Some points must be considered before that:

- **Architecture**: Centralized / Decentralized
- **Kind of intelligence**: What information extract
- **Devices Limitations**: Much / Few Resources
- **Cost/Benefit**: Expensive or cheap solution
State of art in Machine Learning

- Neural Network (Deep learning)

Source: https://becominghuman.ai/deep-learning-made-easy-with-deep-cognition-403f6b445351?gi=35630fc87e88
State of art in Machine Learning

- Neural Network (Deep learning)
- High computational cost (storage/processing)

(CHEN et al., 2015; MOONS e VERHELST, 2017)

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State of art in Machine Learning

- Neural Network (Deep learning)
- High computational cost (storage/processing)
  (CHEN et al., 2015; MOONS e VERHELST, 2017)
- Centralization / Dependency
- Devices with many resources (expensive / waste of resource)

Source: https://icons8.com/
How to provide intelligence to IoT devices...

Considering:
- Decentralized environment
- Devices autonomy
- Limited processing and storage resources
- Extract knowledge from limited amount of data
Data mining!

A strategy to circumvent such adversities is the use of data mining techniques, but specifically of association rules, which seek to identify frequent patterns in a dataset so that it meets minimum support and confidence criteria.

(CHEN et al., 2015; TAN et al., 2006)
Data mining!

Although each device has a unique usage pattern, some devices have similar characteristics of use, that could be used to correlate them.

(PAL et al., 2017; GONZALES e AMFT, 2015; CHEN et al., 2012; HEIERMAN et al., 2003).
Main Goal

Demonstrate the ability of intelligent integration between devices in the internet of things, through a decentralized mining of implicit correlations between their patterns of state changes.
Preliminary information

It is important to comprehend some components and specifications before a general architecture overview.
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Keep that in mind:

- We want to work with devices that have severe restrictions of processing, storage and memory (Like: ESP8266-01)
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Keep that in mind:

• We want to work with devices that have severe restrictions of processing, storage and memory (Like: ESP8266-01)
• All storage and processing must be performed into each device, there’s no storage server or cloud services.
Preliminary information

It is important to comprehend some components and specifications before a general architecture overview.

Keep that in mind:

• We want to work with devices that have severe restrictions of processing, storage and memory (Like: ESP8266-01)
• All storage and processing must be performed into each device, there’s no storage server or cloud services.
• The devices must talk to each other (http requests) and obtain a global knowledge based on local decisions.
Devices behavior

Each device must be specified as a Finite State Machine, composed by a set of well defined (discrete) states \( S = \{s_1, s_2, ..., s_i\} \) which represents its interactions with environment. It also has a set of actions \( A = \{a_1, a_2, ..., a_i\} \) which allow to transit among the \(|S|\) states;
**Devices behavior**

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Example: Lamp/Light/Binary Device

\[
S = \{“on”, “off”\}
\]
**Devices behavior**

Each device must be specified as a Finite State Machine, composed by a set of well defined (discrete) states \((S = \{s_1, s_2, \ldots, s_i\})\) which represents its interactions with environment. It also has a set of actions \((A = \{a_1, a_2, \ldots, a_i\})\) which allow to transit among the \(|S|\) states;

Example: Lamp/Light/Binary Device

\[ S = \{"on","off"\} \]

\[ A = \{"switch on","switch off"\} \]
Embedded data storage

Based on this FSM and assuming a finite set of discretized time interval(slots) as $T = \{t_1, t_2, \ldots, t_j\}$ it is possible to define a embedded database as a counters matrix $M_{ij} = A \times T$ where each element $c_{nm} \in M_{ij}$ is a counter associated to the action $a_n \in A$ at the time $t_m \in T$;

$$M_{ij} = \begin{bmatrix}
  c_{11} & \cdots & c_{1j} \\
  \vdots & \ddots & \vdots \\
  c_{i1} & \cdots & c_{ij}
\end{bmatrix}
$$

$i$: num of items in $A$ ($|A|$);
$j$: num of items in $T$ ($|T|$);
$c_{nm}$: counter for each action $a_n$ at slot $t_m$;
Pattern of changes

The devices’ pattern of changes could be extracted from the embedded dataset by comparing the counters that belongs to the same slots (column in matrix).

<table>
<thead>
<tr>
<th>Switch Off</th>
<th>00:00</th>
<th>01:00</th>
<th>02:00</th>
<th>...</th>
<th>21:00</th>
<th>22:00</th>
<th>23:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>Embedded Database ($M_{ij}$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>switch off</td>
<td>10</td>
<td>2</td>
<td>0</td>
<td></td>
<td>26</td>
<td>14</td>
<td>12</td>
</tr>
<tr>
<td>switch on</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td></td>
<td>34</td>
<td>17</td>
<td>7</td>
</tr>
</tbody>
</table>
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### Pattern of changes

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</tr>
</thead>
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<tr>
<td>switch off</td>
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<td>2</td>
<td>0</td>
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<td>12</td>
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<td>7</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pattern of change (P)</th>
<th>00:00</th>
<th>01:00</th>
<th>02:00</th>
<th>...</th>
<th>21:00</th>
<th>22:00</th>
<th>23:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>SWITCH OFF</td>
<td>-</td>
<td>-</td>
<td>...</td>
<td>SWITCH ON</td>
<td>SWITCH ON</td>
<td>SWITCH OFF</td>
<td></td>
</tr>
</tbody>
</table>
**Mining correlations**

Once that each device satisfies the previously specified conditions, it is possible to identify implicit correlations between its actions by the frequency of a pair of actions that shows together when two patterns are compared slot by slot.
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<table>
<thead>
<tr>
<th>Pattern of change form Device 01</th>
<th>00:00</th>
<th>01:00</th>
<th>02:00</th>
<th>...</th>
<th>21:00</th>
<th>22:00</th>
<th>23:00</th>
</tr>
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<tbody>
<tr>
<td>SWITCH OFF</td>
<td>-</td>
<td>-</td>
<td>...</td>
<td></td>
<td>SWITCH ON</td>
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<td>SWITCH OFF</td>
</tr>
</tbody>
</table>
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**Pattern of change form Device 01**

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<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>SWITCH OFF</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>SWITCH ON</td>
<td>SWITCH ON</td>
<td>SWITCH OFF</td>
</tr>
</tbody>
</table>

**Pattern of change form Device 02**

<table>
<thead>
<tr>
<th></th>
<th>00:00</th>
<th>01:00</th>
<th>02:00</th>
<th>...</th>
<th>21:00</th>
<th>22:00</th>
<th>23:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOOR CLOSE</td>
<td>DOOR CLOSE</td>
<td></td>
<td></td>
<td>...</td>
<td>DOOR OPEN</td>
<td>DOOR CLOSE</td>
<td>DOOR CLOSE</td>
</tr>
</tbody>
</table>
Mining correlations

Once that each device satisfies the previously specifications is possible to identify implicit correlations between its actions by the frequency of a pair of actions that shows together when two patterns are compared slot by slot.

<table>
<thead>
<tr>
<th>Transaction Dataset (D)</th>
<th>00:00</th>
<th>01:00</th>
<th>02:00</th>
<th>...</th>
<th>21:00</th>
<th>22:00</th>
<th>23:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>SWITCH OFF</td>
<td>-</td>
<td>-</td>
<td>...</td>
<td></td>
<td>SWITCH ON</td>
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<td>SWITCH OFF</td>
</tr>
<tr>
<td>DOOR CLOSE</td>
<td>DOOR CLOSE</td>
<td>-</td>
<td>...</td>
<td>DOOR OPEN</td>
<td>DOOR CLOSE</td>
<td>DOOR CLOSE</td>
<td></td>
</tr>
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SWITCH OFF

SWITCH ON

DOOR CLOSE

DOOR OPEN

DOOR CLOSE
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**Transaction Dataset (D)**

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<th>…</th>
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<th>22:00</th>
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</tr>
</thead>
<tbody>
<tr>
<td>DEVICE OFF</td>
<td>-</td>
<td>-</td>
<td>…</td>
<td>SWITCH ON</td>
<td>SWITCH ON</td>
<td>SWITCH OFF</td>
<td></td>
</tr>
<tr>
<td>DOOR CLOSE</td>
<td>DOOR CLOSE</td>
<td>-</td>
<td>…</td>
<td>DOOR OPEN</td>
<td>DOOR CLOSE</td>
<td>DOOR CLOSE</td>
<td></td>
</tr>
</tbody>
</table>

**Possible Rules**

- SWITCH OFF ⇒ DOOR CLOSE
- SWITCH OFF ⇒ DOOR OPEN
- SWITCH ON ⇒ DOOR CLOSE
- SWITCH ON ⇒ DOOR OPEN
Mining correlations

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<tbody>
<tr>
<td>SWITCH OFF</td>
<td>-</td>
<td>-</td>
<td>...</td>
<td></td>
<td>SWITCH ON</td>
<td>SWITCH ON</td>
<td>SWITCH OFF</td>
</tr>
<tr>
<td>DOOR CLOSE</td>
<td>DOOR CLOSE</td>
<td>-</td>
<td>...</td>
<td></td>
<td>DOOR OPEN</td>
<td>DOOR CLOSE</td>
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</tr>
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</table>

Possible Rules

- SWITCH OFF ⇒ DOOR CLOSE
- SWITCH OFF ⇒ DOOR OPEN
- SWITCH ON ⇒ DOOR CLOSE
- SWITCH ON ⇒ DOOR OPEN

Which rule(s) is(are) more frequent?
**Mining correlations**

Association Rules correlate an “Action X” from “Device 01” with an “Action Y” from “Device 02” and give an importance to that rule based on:

Device 01(Action X) ⇒ Device 02(Action Y)
**Mining correlations**

Association Rules correlate an “Action X” from “Device 01” with an “Action Y” from “Device 02” and give an importance to that rule based on:

- **Support**: How frequent is this rule in transactions dataset (D);
- **Confidence**: How reliable is this rule.
- **Lift**: How dependent are antecedent and consequent;

\[
\text{Device 01(} \text{Action X} \text{) } \Rightarrow \text{ Device 02(} \text{Action Y} \text{)}
\]

\[
\text{[ supp: 80\%, lift: 4.3, conf: 96\%]}
\]
Mining correlations

Put in other words, those metrics are:

Rule: \( X \Rightarrow Y \)

**Support** = \( \frac{\text{freq}(X,Y)}{N} \)

**Confidence** = \( \frac{\text{freq}(X,Y)}{\text{freq}(X)} \)

**Lift** = \( \frac{\text{Support}}{\text{Supp}(X) \times \text{Supp}(Y)} \)

\*N = Size of dataset transaction
**Mining correlations**

Minimum Thresholds must be defined to avoid unnecessary processing of non-frequent itemsets:
Mining correlations

Minimum Thresholds must be defined to avoid unnecessary processing of non-frequent itemsets:

```
null
```

```
a  b  c  d
```

1-itemset
Mining correlations

Minimum Thresholds must be defined to avoid unnecessary processing of non-frequent itemsets.

[Diagram with nodes labeled a, b, c, d, ab, ac, ad, bc, bd, cd]
Mining correlations

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Mining correlations

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**Mining correlations**

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Minimum Thresholds must be defined to avoid unnecessary processing of non-frequent itemsets:

- 1-itemset
  - a
  - b
  - c
  - d
- 2-itemset
  - ab
  - ac
  - ad
  - bc
  - bd
  - cd
- 3-itemset
  - abc
  - abd
  - acd
  - bcd
- 4-itemset
  - abcd

**non-frequent itemset**
Mining correlations

This approach does not combine actions from the same device. Also, it is not necessary to create itemsets greater than 2;
Mining correlations

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Mining correlations

This process repeats to each device in network updating the most relevant rules in correlation dataset.
What should I do now!?

Based on those rules it is possible to Device 01 perform a request to Device 02 change its states to satisfy the rule;
What should I do now!? 

Based on those rules it is possible to Device 01 perform a request to Device 02 change its states to satisfy the rule;

RULES IN DEVICE 01

SWITCH ON ⇒ CLOSE DOOR
SWITCH OFF ⇒ OPEN DOOR
What should I do now!?

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SWITCH ON ⇒ CLOSE DOOR  
SWITCH OFF ⇒ OPEN DOOR
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RULES IN DEVICE 01

SWITCH ON ⇒ CLOSE DOOR
SWITCH OFF ⇒ OPEN DOOR

DEVICE 01

DEVICE 02

ALWAYS!? THAT’S SOUND STUPID DANGEROUS
Slot restrictions

To avoid unusual integrations the trigger is fire only if the input action were the most probable to occur at the current slot.
Slot restrictions
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RULES IN DEVICE 01
SWITCH ON ⇒ CLOSE DOOR
SWITCH OFF ⇒ OPEN DOOR

<table>
<thead>
<tr>
<th>Time</th>
<th>Action</th>
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<tbody>
<tr>
<td>00:00</td>
<td>SWITCH OFF</td>
</tr>
<tr>
<td>01:00</td>
<td>-</td>
</tr>
<tr>
<td>02:00</td>
<td>-</td>
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<tr>
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<td>...</td>
</tr>
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<tbody>
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<td>00:00</td>
<td>CLOSE DOOR</td>
</tr>
<tr>
<td>01:00</td>
<td>CLOSE DOOR</td>
</tr>
<tr>
<td>02:00</td>
<td>-</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>21:00</td>
<td>OPEN DOOR</td>
</tr>
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RULES IN DEVICE 01

SWITCH ON ⇒ CLOSE DOOR
SWITCH OFF ⇒ OPEN DOOR
Slot restrictions

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RULES IN DEVICE 01
SWITCH ON ⇒ CLOSE DOOR
SWITCH OFF ⇒ OPEN DOOR

SWITCH ON
DEVICE 01

00:00 SWITCH OFF
01:00 -
02:00 -
... ...
21:00 SWITCH ON
22:00 SWITCH ON
23:00 SWITCH OFF

00:00 CLOSE DOOR
01:00 CLOSE DOOR
02:00 -
... ...
21:00 OPEN DOOR
22:00 CLOSE DOOR
23:00 CLOSE DOOR

DEVICE 02
Slot restrictions
To avoid unusual integrations the trigger is fire only if the input action were the most probable to occur at the current slot.

RULES IN DEVICE 01
SWITCH ON ⇒ CLOSE DOOR
SWITCH OFF ⇒ OPEN DOOR
Slot restrictions

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RULES IN DEVICE 01

SWITCH ON ⇒ CLOSE DOOR
SWITCH OFF ⇒ OPEN DOOR

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Process Overview

Once that each devices satisfies the previously specifications is possible to identify implicit correlations between its actions.
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Once that each devices satisfies the previously specifications is possible to identify implicit correlations between its actions.

- **Step I:** Identify the local pattern
Process Overview

Once that each device satisfies the previously specified conditions is possible to identify implicit correlations between its actions.

- **Step I:** Identify the local pattern
- **Step II:** Obtain the (next) remote pattern (http request/response)
Process Overview

Once that each device satisfies the previously specifications is possible to identify implicit correlations between its actions.

- **Step I**: Identify the local pattern
- **Step II**: Obtain the (next)remote pattern (http request/response)
- **Step III**: Fusion the patterns (create a transaction dataset)
PROPOSED METHOD

Process Overview

Once that each device satisfies the previously specifications is possible to identify implicit correlations between its actions..

- **Step I**: Identify the local pattern
- **Step II**: Obtain the (next)remote pattern (http request/response)
- **Step III**: Fusion the patterns (create a transaction dataset)
- **Step IV**: Extract the correlations (Associative rule mining)(*Back to II)
Experiment

Identify correlations between two devices.

Teste the integration between their actions (if exists).

Implemented in Lua (https://nodemcu-build.com/)
Important Notes

Dataset dimensionality (|A|x|T|): The database dimensionality grows proportionally to the number of actions and the number of slots. (The higher is the number of states/slots, the higher will be the memory consumption)
Important Notes

Dataset dimensionality ($|A| \times |T|$): The database dimensionality grows proportionally to the number of actions and the number of slots. (The higher is the number of states/slots, the higher will be the memory consumption)

Pattern sharing: All devices must be able to handle its own patterns and dataset AND a remote device’s pattern. (patterns fusion and associative analysis)
**Important Notes**

**Dataset dimensionality** \((|A| \times |T|)\): The database dimensionality grows proportionally to the number of actions and the number of slots. (The higher is the number of states/slots, the higher will be the memory consumption)

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Device discovery: Multicast uses UDP!
QUESTIONS?

Manaus, July 13th 2018
Federal University of Amazonas
Institute of Computing
Graduate Program in Informatics
Interest Group on Embedded Systems

THANK YOU

Manaus, July 13th 2018
## Associative Analysis Metrics

- **Support:** Number of elements in a set

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### TRIGGERS CORRELATIONS

#### Associative Analysis Metrics
- **Support:** Number of elements in a set
- Define Max Transaction Value ( \(|T| = 7\) )

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