An assistive handwashing system with emotional intelligence

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Agenda

1. Problem Statement
   - Motivation
   - Objectives
2. Basic Concepts
   - Affect Control Theory (ACT)
   - Partially Observable Markov Decision Process (POMDP)
   - The BayesACT Framework
3. Solution: System Design and Implementation
   - Components
   - Coordination between components
4. Experimental Results
5. Discussion
   - Contribution
   - Future Work

Problem Statement - Motivation

The COACH system

- is an assistive system helping with an elder's daily activities
- monitors a user washing his/her hands
- detects when the user has lost track of what he/she is doing
- displays a prerecorded assistive prompt when needed
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Note: The last objective is ill-defined, as the question of how exactly tuning prompts to users will be most effective is not clear at this point.

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The ACT Principal

Actors work to experience transient impressions that are consistent with their fundamental sentiments.

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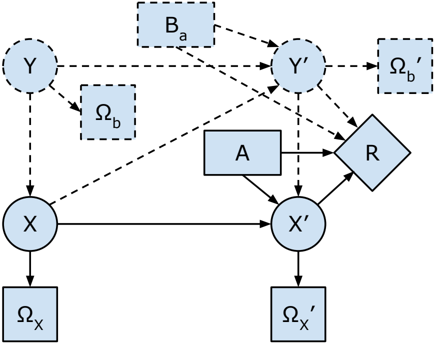

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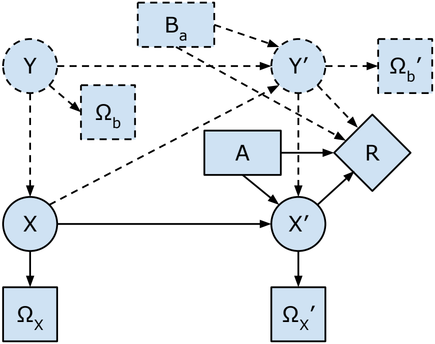

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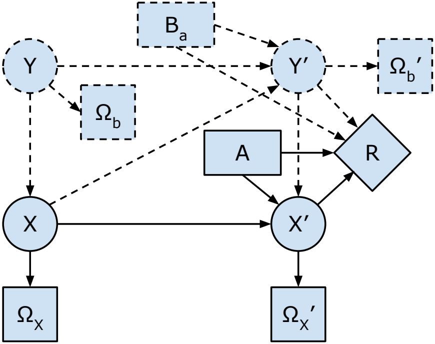

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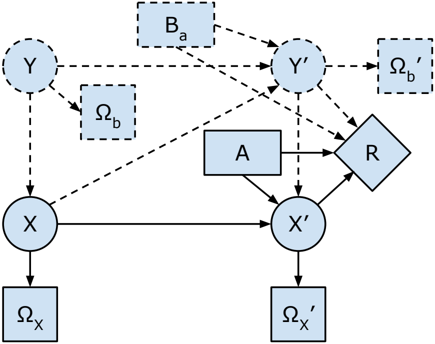

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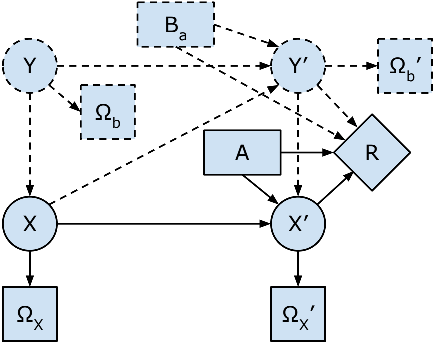

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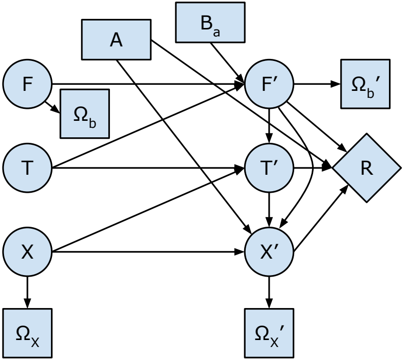

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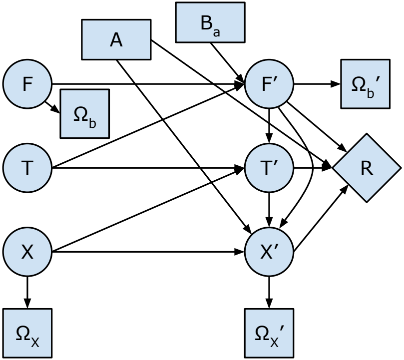

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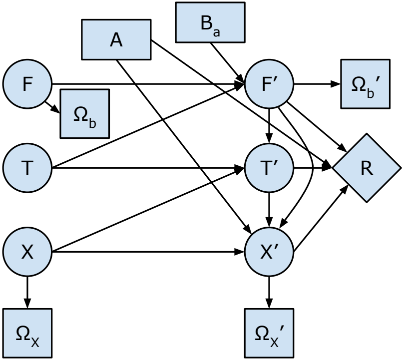

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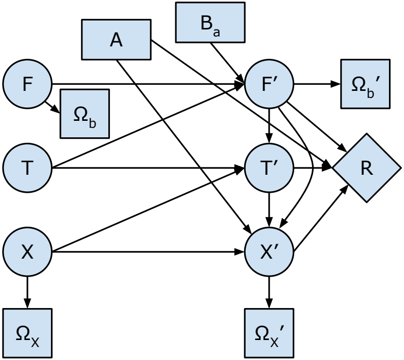

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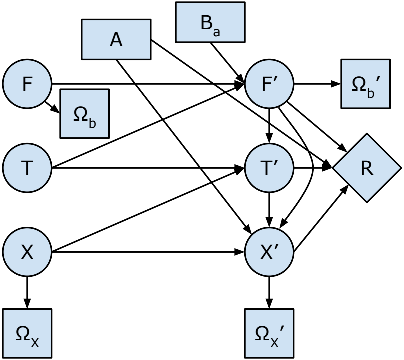

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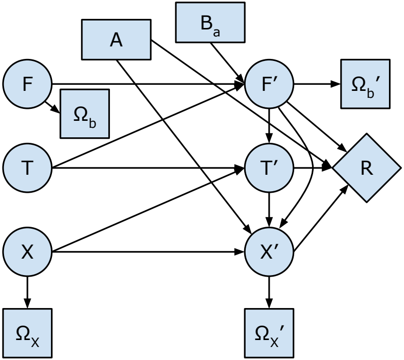

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- Calculate $\{A, B_a\}$ basing on $\{F, T, X\}$

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- $Pr(x'|x, f', t', a)$: how the application progresses
- $Pr(\omega_b|f)$ and $Pr(\omega_x|x)$: observation functions for the client behaviour sentiment and system state

Solution - Overview

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Design an *extensible* system that assists *people with dementia* during a hand-washing process by *assessing their states* and *provide instructions accordingly*.

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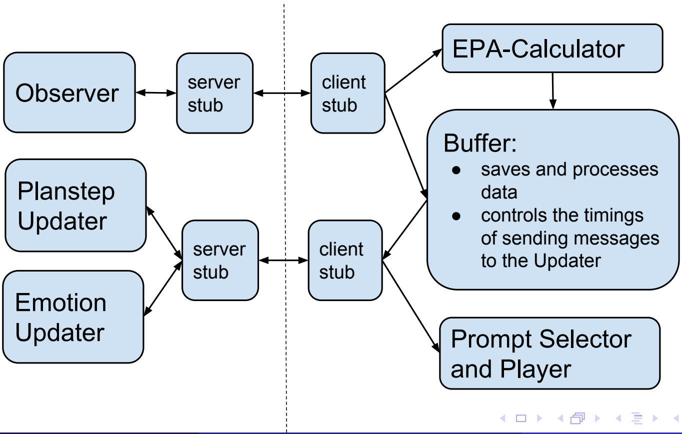
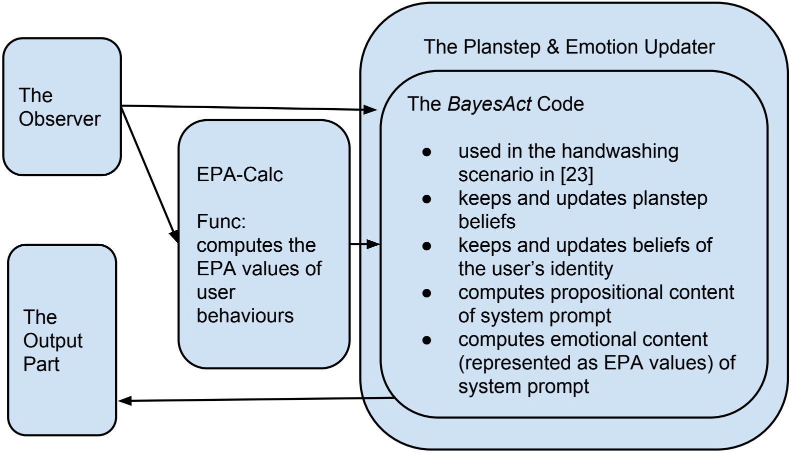


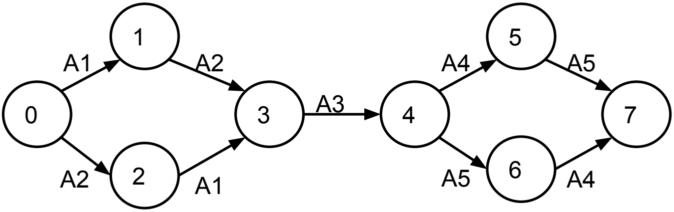
Solution - the Planstep and Emotion Updater

Design the Planstep and Emotion Updaters basing on the BayesAct code



Solution - the Planstep and Emotion Updater cont.

A planstep update diagram



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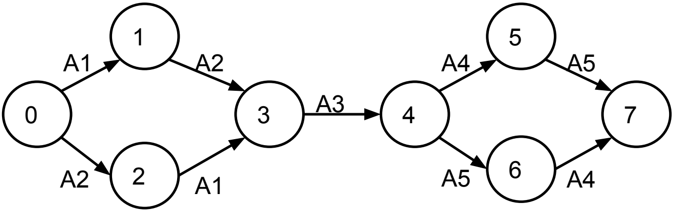

- Eight plansteps: (0) “off/dirty/dry”, (1) “on/dirty/dry”, (2) “off/soapy/dry”, (3) “on/soapy/dry”, (4) “on/clean/wet”, (5) “off/clean/wet”, (6) “on/clean/dry”, (7) “off/clean/dry”

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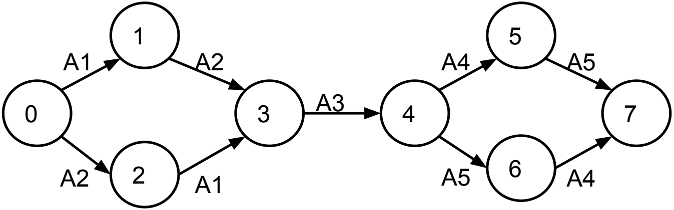

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- Five behaviours: A1 to A5 are "turn on water", "put on soap", "rinse hands", "turn off water", and "use towel", respectively.

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- Temporally smoothing in the Buffer

$$X = \sum_{k=i}^{j} \left(\frac{alpha}{alpha+1}\right)^{j-k} * \frac{1}{alpha+1} * X[k] \tag{3}$$

where $alpha \geq 0$, $X = P$ or $X = A$.

Solution - the Observer

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  - utilize Czarnuch and Mihailidis's body tracker [**?**]
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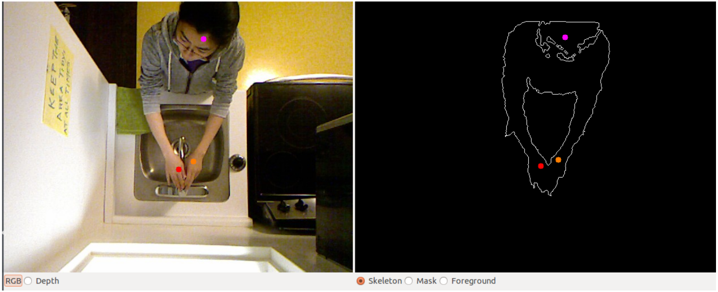

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- Step 2: Map locations to user behaviours
  - compare hands locations with object positions
  - objects: the left-tap, the right-tap, the soap, the water-flow, the towel
  - observation noise handled by the observation function in the Reasoning Engine

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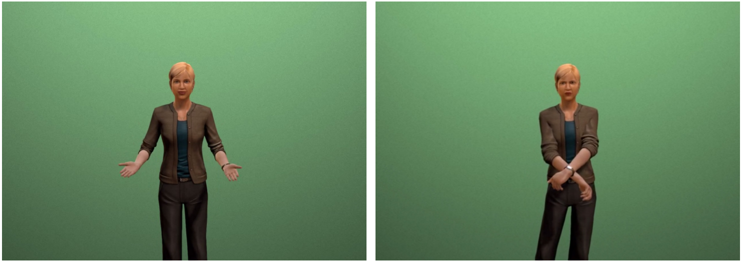
  - the tracker was trained using partially labeled, unbalanced data, and is configurable and re-trainable
- Step 2: Map locations to user behaviours
  - compare hands locations with object positions
  - objects: the left-tap, the right-tap, the soap, the water-flow, the towel
  - observation noise handled by the observation function in the Reasoning Engine
- Serves as an Observer server
  - with the help of the Buffer

Solution - the Output Part

- The prompt dataset: the audio-visual prompts generated and evaluated in Malhotra's study [?]
  - created 30 video clips using the USC Virtual Human Toolkit
  - EPA values of videos evaluated by human raters
  - the participants' answers are consistent with each other



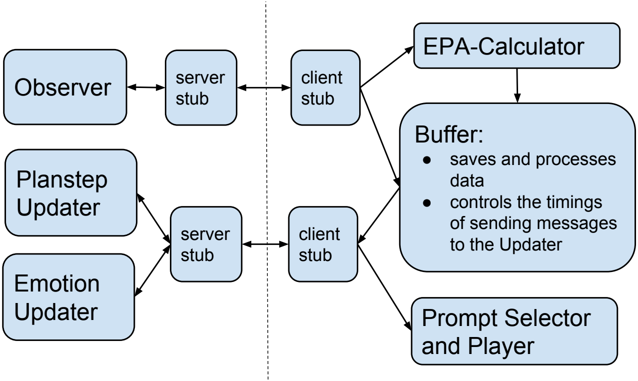
Solution - the Output Part

- The prompt dataset: the audio-visual prompts generated and evaluated in Malhotra's study [?]
  - created 30 video clips using the USC Virtual Human Toolkit
  - EPA values of videos evaluated by human raters
  - the participants' answers are consistent with each other

- A proper prompt is selected as the final prompt if it:
  - has the same propositional labels as the desired prompt
  - has the closest emotional (EPA) values as the desired prompt

Solution - Coordination between components

- The system is designed with independent components.



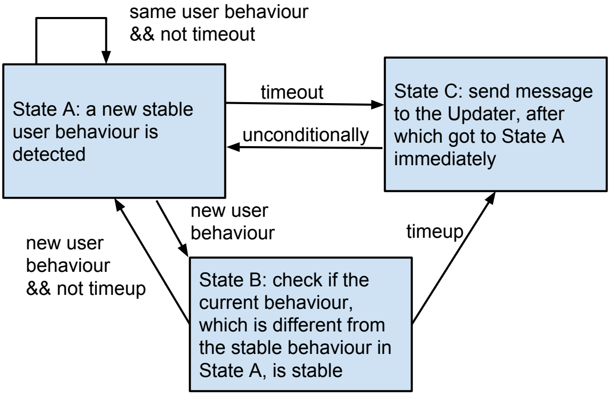
- How to coordinate between the components?
  - timings of sending request and response messages?

Solution - The Buffer

- Between the Observer, the EPA-Calc, and the Reasoning Engine

Solution - The Buffer

- Between the Observer, the EPA-Calc, and the Reasoning Engine
- Controls timings of sending messages



Solution - The Buffer

- Between the Observer, the EPA-Calc, and the Reasoning Engine
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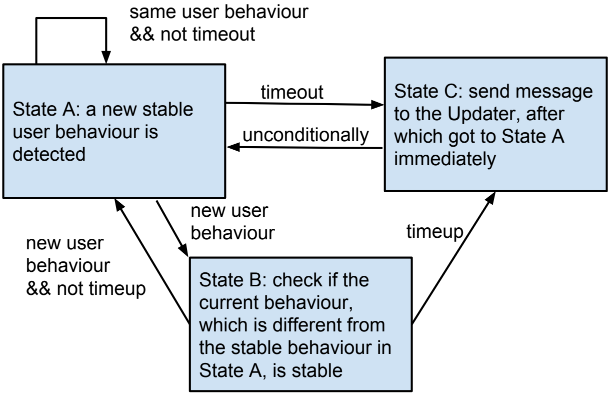

- Smoothes EPA values calucated by the Calculator

Experiments - Parameter values used in laboratory experiments

Param.	Value	Defined in which component
n	10	EPA-Calc
distance	$\{-\infty, 0, 8, 40, 128, 160, +\infty\}$	EPA-Calc
potency	$\{-4.3, -4.3, 0, 1, 2, 4.3, 4.3\}$	EPA-Calc
difference	$\{-\infty, 0, 3.5, 17.5, 35, 70, +\infty\}$	EPA-Calc
activity	$\{-4.3, -4.3, -2, -1, 0, 4.3, 4.3\}$	EPA-Calc
alpha	0	Buffer
timeout	300	Buffer
timeup	1	Buffer
β_a^0	0.001	Updater
β_c^0	2.0	Updater
γ	$(100000, 1.0, 0.5)$	Updater
N	2000	Updater
f_a^0	$[1.5, 0.51, 0.45]$	Updater
f_c^0	Different in each test	Updater

Experiments - Latency of the system

Experiments conducted on the system show that an average latency of

- 46.79ms is caused by the Observer component of the system
- 0.009ms caused by the Buffer
- 1.65s caused by the Updater

The overall average latency of the system is around 1.70s:
the system runs in real-time from the perspective of its user group

Experiments - Two laboratory tests

Two laboratory tests

- link to test #1
- link to test #2

Another 15 tests were also run. Results are in the Appendix.

Experiments - Conclusion

- Functionality performance
  - sometimes false positively recognizes an user behaviour
  - is able to produce propositionally useful system prompts in general

Experiments - Conclusion

- Functionality performance
  - sometimes false positively recognizes an user behaviour
  - is able to produce propositionally useful system prompts in general
- Emotionality performance

No.	mean of behav.	init of f_c	mean of f_c	mean of prompt
#1	$[0, 1.32, -1.3]$	$[1.61, 0.84, -0.87]$	$[2.8, 1.03, -0.73]$	$[1.62, 0.32, 0.75]$
#2	$[0, 0.77, -1.74]$	$[-0.64, -0.43, -1.81]$	$[1.13, -0.43, -1.47]$	$[1.53, 0.66, 0.08]$

Experiments - Conclusion

- Functionality performance
  - sometimes false positively recognizes an user behaviour
  - is able to produce propositionally useful system prompts in general
- Emotionality performance

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#2	$[0, 0.77, -1.74]$	$[-0.64, -0.43, -1.81]$	$[1.13, -0.43, -1.47]$	$[1.53, 0.66, 0.08]$

Generally, for tests the actor acted more powerfully and more actively:

- larger P and larger A values were computed for user behaviours
- larger P and larger A values were achieved for f_c's
- smaller P and larger A values were produced for prompts, among which the differences between A values are more obvious

Discussion - Contribution

Recall - Objective of this thesis

- is designed in a portable and extensible way
- runs in real-time from the perspective of the user group
- provides at least a level of functional assistance of as high quality as the COACH
- is able to tune the prompts in some way according to the emotional state of a user

Contribution

Discussion - Contribution cont.

Contribution

- Reviewed previous work in all the four aspects of emotional intelligence

Discussion - Contribution cont.

Contribution

- Reviewed previous work in all the four aspects of emotional intelligence
- Designed and implemented a prototypical hand-washing system that
  - is extensible and portable
  - runs in real-time from the perspective of the user group
  - provides a level of functional assistance
  - produces system prompts that have encoded to some extent the emotional state of the user

Discussion - Contribution cont.

Contribution

- Reviewed previous work in all the four aspects of emotional intelligence
- Designed and implemented a prototypical hand-washing system that
  - is extensible and portable
  - runs in real-time from the perspective of the user group
  - provides a level of functional assistance
  - produces system prompts that have encoded to some extent the emotional state of the user
- Tests also indicated that user behaviours with higher P and higher A values may lead to f_c 's with higher P and higher A values and system prompts with lower P and higher A values

Discussion - Future Work

Future Work

- Improve the EPA-Calculator
- Improve the prompt generation process
- Improve the Planstep- and Emotion- Updater
- Conduct clinical trials for the system

Acknowledgement

This work is based on previous works of:

1. The bayesact paper
2. The tracker paper.
3. The survey paper.

I'd like to take this opportunity to thank:

- Jesse Hoey
- James Tung and Peter van Beek
- Xiao Yang, Chengbo Li and Enxun Wei
- My family and friends

The end

Thank you!

- Questions?
- Comments?

Update X'_{ps} based on Ω_x and $\{X_{ps}, X_{behav}, X_{aw}, F, T\}$

- $SampleXVar()$ and $evalSampleXVar()$
- Pseudocode of $SampleXVar()$ (on next page)
- $Pr : X_{behav} \rightarrow \Delta(\Omega_x)$ used in $evalSampleXVar()$

Update X'_{ps} based on Ω_x and $\{X_{ps}, X_{behav}, X_{aw}, F, T\}$ cont.

```
if Deflection(F, T) is high then
    threshold = high
else
    threshold = low
end if
if aw high then
    if prompted then
        if random_prob() < threshold then
            aw = low and not moving forward
        else if prompt wrong then
            aw = low and not moving forward
        else if likely then
            moving forward
        else if random_prob() < threshold then
            aw = low and not moving forward
        end if
    else
        if random_prob() < threshold then
            aw = low and not moving forward
        else
            aw stays high and moving forward
        end if
    end if
else
    if prompted then
        if random_prob() > threshold and prompt correct then
            move on and aw high
        else
            unlikely: aw high and not moving forward
        end if
    else
        unlikely: aw high and moving forward
    end if
end if
```