An assistive handwashing system with emotional intelligence

Luyuan Lin

University of Waterloo

Supervisor:
Jesse Hoey

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Overview

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
- works well for some persons, but not as well for others

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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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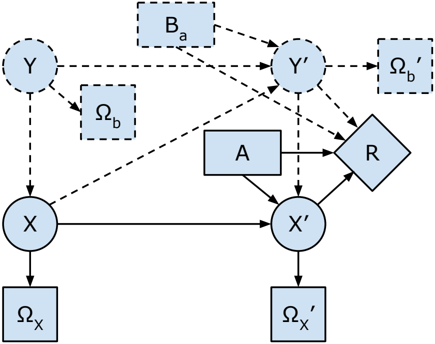
- "fundamentals" of identities and behaviours; shared between people within a same culture
- "transient impressions": emotional feelings of people evoked by a specific event

The ACT Principal

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

Concepts - POMDP

Partially Observable Markov Decision Process (POMDP)



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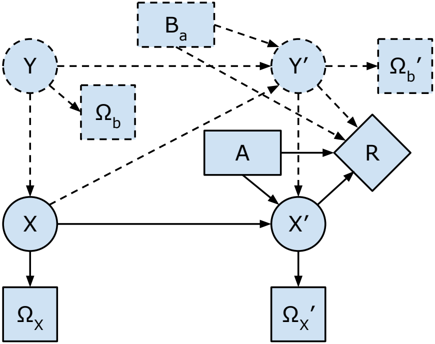

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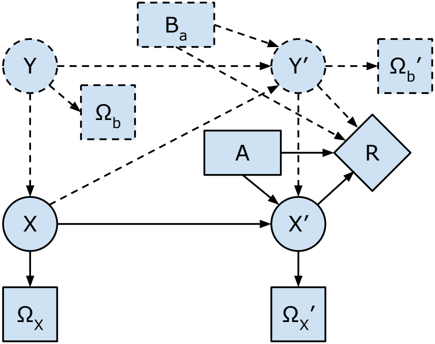

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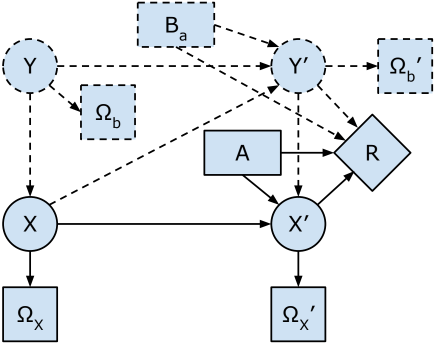

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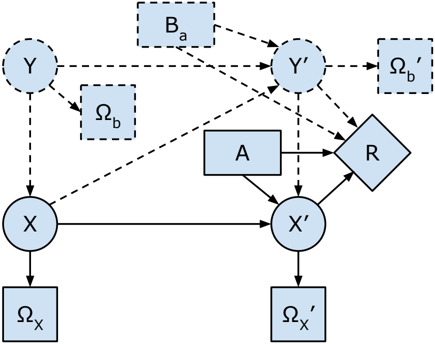

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- Augmented with affective states (dotted lines)

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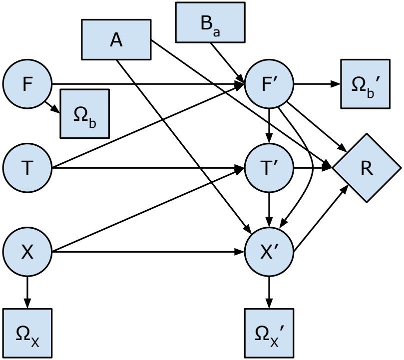

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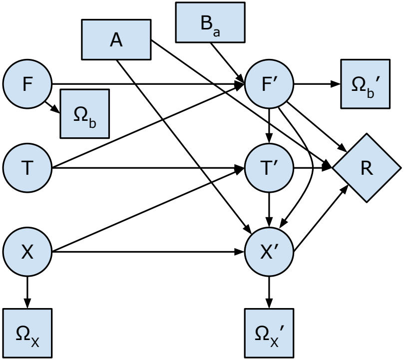

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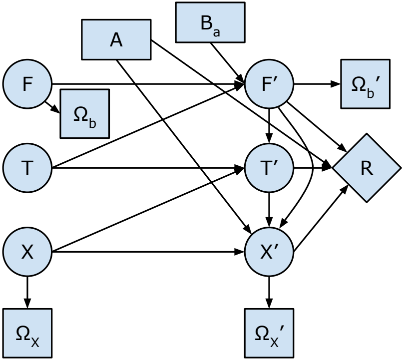

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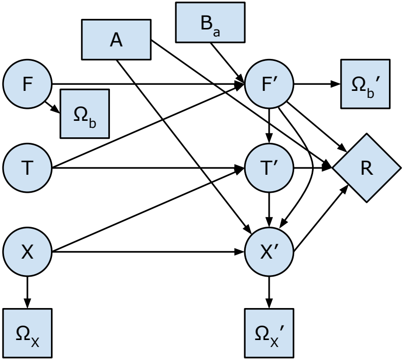

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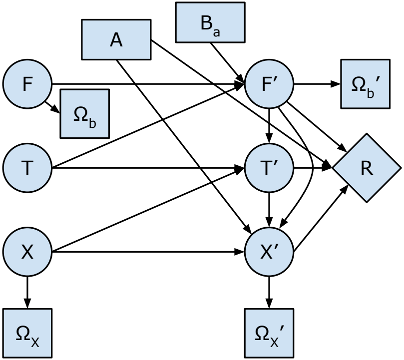

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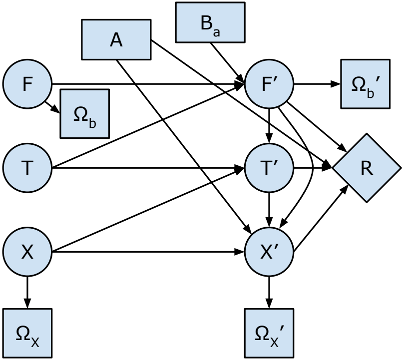

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- By updating F, the probability distribution of the client's identity F_c is learned
- Calculate $\{A, B_a\}$ basing on $\{F, T, X\}$

Concepts - BayesACT cont.

Updates F and Calculates $\{A, B_a\}$ basing on $\{F, T, X\}$

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$$Pr(f'|f, t, x, b_a, \phi) \propto e^{-\phi(f',t')-\xi(f',f,b_a,x)} \tag{2}$$

  where t' can be computed from $\{f', t, x\}$ by empirically derived prediction equations of ACT.

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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

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Goal

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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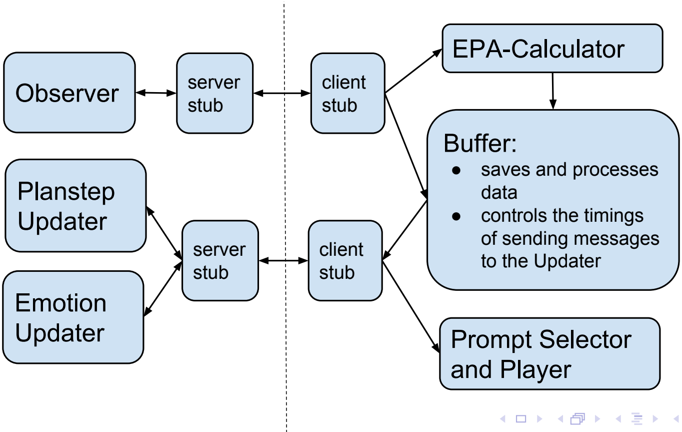
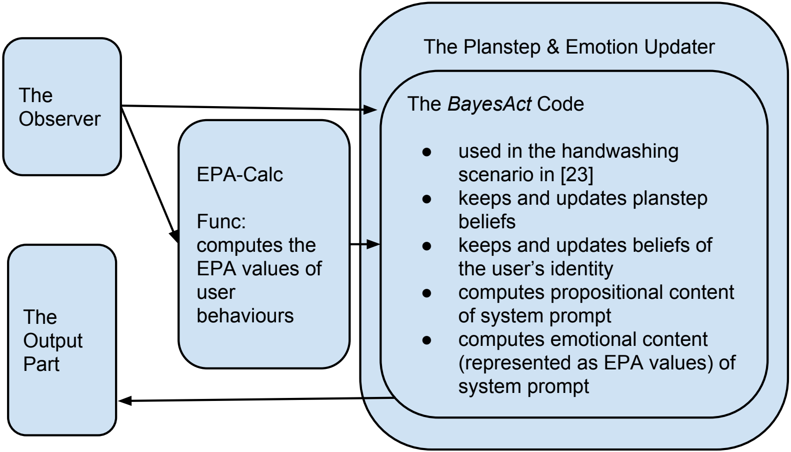


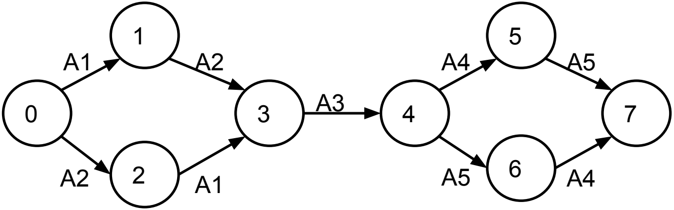
Solution - the Planstep and Emotion Updater

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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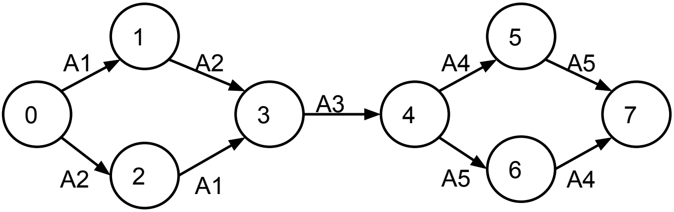

- Eight plansteps: (0) "off/dirty/dry", (1) "on/dirty/dry", (2) "off/soapy/dry", (3) "on/soapy/dry", (4) "on/clean/wet", (5) "off/clean/wet", (6) "on/clean/dry", (7) "off/clean/dry"

Solution - the Planstep and Emotion Updater cont.

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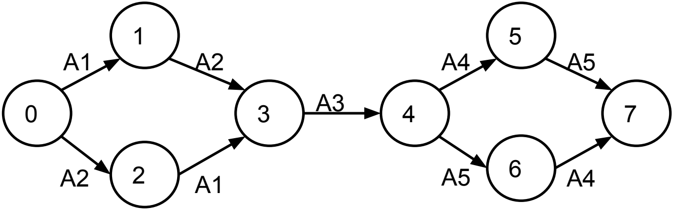

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- Five behaviours: A1 to A5 are “turn on water”, “put on soap”, “rinse hands”, “turn off water”, and “use towel”, respectively.

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Use the BayesACT framework in the handwashing scenario

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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

- Step 1: Get the locations of the user's hands
  - utilize Czarnuch and Mihailidis's body tracker [**?**]
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  - the tracker was trained using partially labeled, unbalanced data, and is configurable and re-trainable

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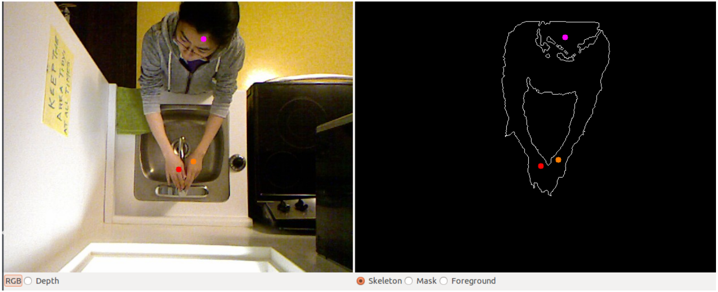

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  - observation noise handled by the observation function in the Reasoning Engine

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- 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

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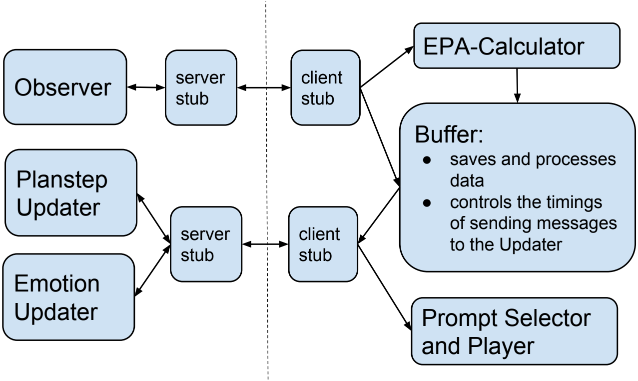
  - the participants' answers are consistent with each other

- 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

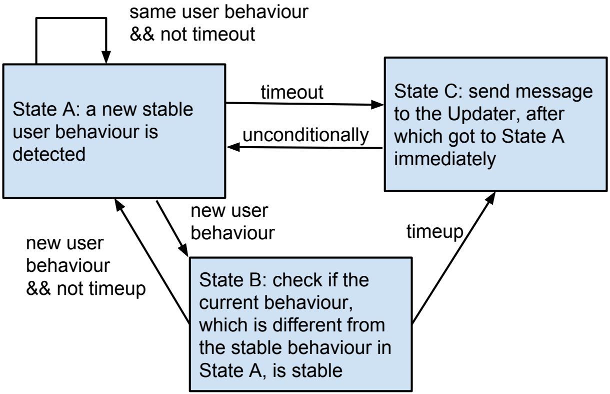
- The system is designed with independent components.



- 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
- Controls timings of sending messages



- Smoothes EPA values calucated by the Calculator

Experiments - Variables and Parameters

Experiments - Variables and Parameters cont.

Experiments - Test #1

Experiments - Test #1 cont.

Experiments - Test #2

Experiments - Test #2 cont.

Experiments - Conclusion

Discussion - Contribution

Discussion - Future Work

References

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

Acknowledgement

Jesse Hoey
James Tung and Peter van Beek
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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*()

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
```

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

- $SampleXVar()$ and $evalSampleXVar()$
- Pseudocode of $SampleXVar()$

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

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