Measuring the Learnability of Interactive Systems

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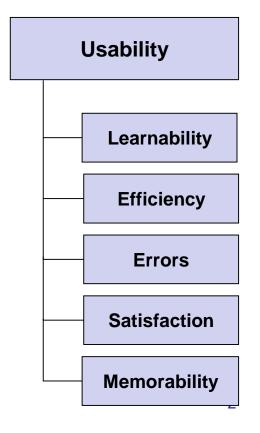
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Definition of Usability

- Usability assesses how easy user interfaces are to use.
- ISO defines usability as "The extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use."
- According to Nielsen [1], usability is defined by 5 quality components:
 - Learnability: How easy is it for users to accomplish correctly basic tasks of a system after having executed it a few times in the past?
 - Efficiency: Once users have learned the design, how quickly can they perform tasks?
 - **Errors**: How many errors do users make, how severe are these errors, and how easily can they recover from the errors?
 - Satisfaction: How pleasant is it to use the design?
 - Memorability: When users return to the design after a period of not using it, how easily can they reestablish proficiency?

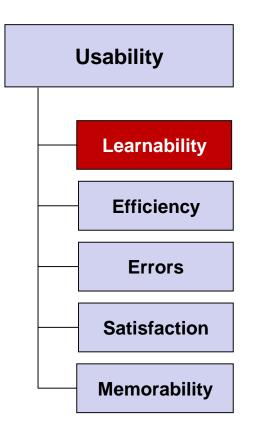




Learnability

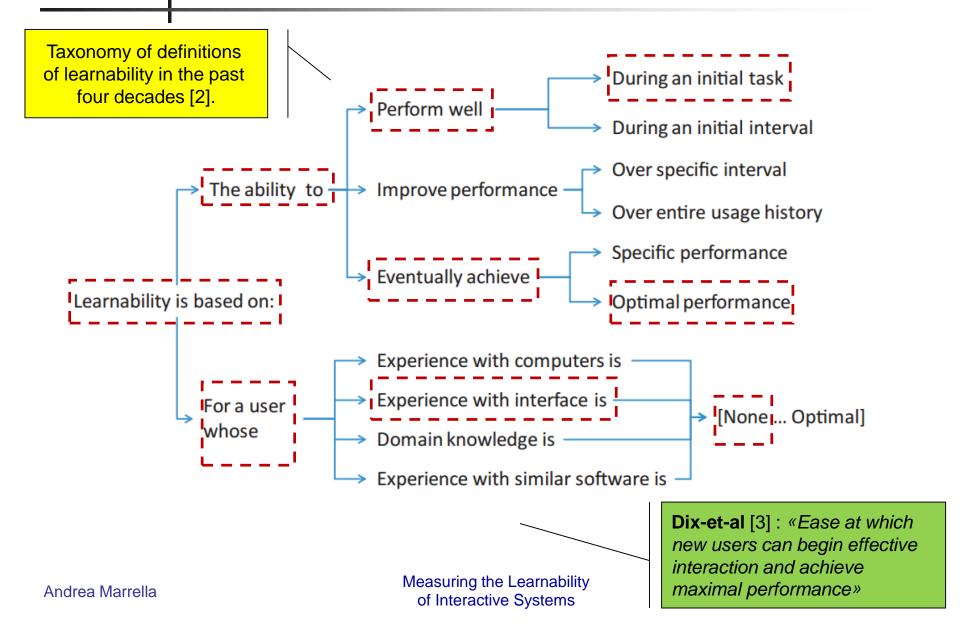
- In the HCI community, learnability is generally recognized as one of the most relevant components of usability [1].
- Learnability in ISO 9126-1
 - "...the capability of the software product to enable the user to learn its application..."
 - Learnability applies to the nature of the performance change of a user when interacting with a system to accomplish a specific task.







How to define learnability?





Some definitions of Learnability

- Nielsen advocates that an interactive system is highly learnable if it "allows users to reach a reasonable level of usage proficiency within a short time" [4].
- Holzinger defines learnability as "allowing users to rapidly begin to work with the system" [5].
- Santos recognizes learnability as "the effort required for a typical user to be able to perform a set of tasks using an interactive system with a predefined level of proficiency" [6].
- Shneiderman defines learnability as "the time it takes members of the user community to learn how to use the commands relevant to a set of tasks" [7].

The above definitions are focused on the initial learning experience of a user that interacts with a system (initial learnability).



Extended Learnability

Extended Learnability: The target is to measure the changes of user performance when interacting with a system.

- In 1980, Michelsen et al. provided one of the first definitions of extended learnability: "a system should be easy to learn over time by the class of users for whom it is intended" [8].
- Butler identifies learnability as "user performance based on self instruction [allowing] experienced users to select an alternate model that involved fewer screens or keystrokes" [9].
- Bevan and Macleod state that learnability is the "quality of use for users over time" [10].



Characteristics of Learnability

- There is no consistent agreement on how the concept of learnability should be defined.
- Some common features that are related to it can be identified:
 - learnability is a function of user's experience; it depends on the type of user for which the learning occurs (experience vs novice users);
 - learnability can be evaluated on a single usage period (initial learnability) or after several usages (extended learnability);
 - learnability measures the performance of a user interaction, in terms of completion times, error and success rates or percentage of functionality understood.
- This lack of consensus has naturally led to a lack of well-accepted metrics for measuring learnability.



How to measure Learnability?

 Several metrics exist, but they are limited to measure specific aspects of the interaction.

Qualitative metrics

They measure the quality of the interaction by analyzing the user feedbacks after the interaction has happened [8,11].

Mental metrics

> They are used to understand **which cognitive processes** drive the user behavior during the interaction with the system [6,12].

Quantitative metrics

- They measure the *performance of a user executing a relevant task through the system* (e.g., completion times, error rates, etc.) [1,13,14].
- All the above measurements are performed in controlled lab environments under the guidance of an external evaluator.



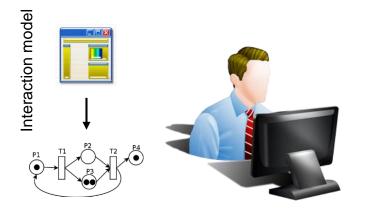
Evaluating Extended Learnability

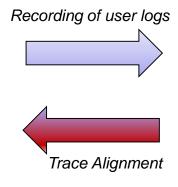
- Issue: Lab measurements have been proven to be particularly suitable for measuring the initial learnability.
 - It represents (at best) a measure of the system's intuitiveness.
 - Measuring intuitiveness is not necessarily an indicator of continued learning [1] over a longer period of use.
- Evaluating extended learnability traditionally requires expensive and time-consuming techniques for observing users over an extended period of time.
- Consequently, due to its prohibitive costs, evaluators have gradually refrained from performing extended learnability evaluation [6].

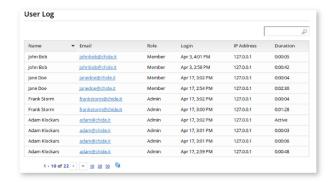


An approach to quantify learnability

- We propose an approach to objectively quantify the extended learnability of interactive systems during their daily use.
 - For any relevant task of the system, we define an interaction model that represents the expected way of performing the task.
 - We use **Petri nets** for modelling human-computer dialogs.
 - We record the user's observed behavior during the interaction with the system in a specific user log.
 - We introduce the concept of alignment to check if the observed behavior as recorded in the user log matches the expected behavior as represented in the interaction model.



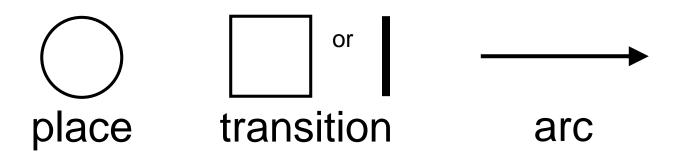






Petri Nets

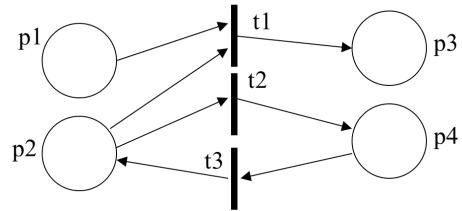
- A Petri Net takes the form of a directed bipartite graph where the nodes are either places or transitions.
- Places represent intermediate states of a system (e.g., a text editor) that may exist during the interaction with it.
- Places can be input/output of transitions.
 - Transitions represent user actions (e.g., windows opened, system commands executed, check boxes clicked, text entered/edited, etc.) to achieve a relevant task (e.g., copy and paste a document).
- Arcs connect places and transitions in a way that <u>places can only be</u> connected to transitions and vice-versa.





Petri Nets: Definitions

- Formally a Petri net N is a triple (P, T, F) where:
 - P is a finite set of places
 - T is a finite set of transitions where $P \cap T = \emptyset$
 - F ⊆ (P x T ∪ T x P) is the set of arcs known as the flow relation



$$P = \{p_1, p_2, p_3, p_4\}$$

$$T = \{t_1, t_2, t_3\}$$

$$F = \{(p_1, t_1), (p_2, t_1), (t_1, p_3), (p_2, t_2), (t_2, p_4), (p_4, t_3), (t_3, p_2)\}\$$



Petri Nets Input/Output places and transitions

A directed arc from a place p to a transition t indicates that p is an input place of t. Formally:

•
$$t = \{p \in P \mid (p, t) \in F\}$$

A directed arc from a transition t to a place p indicates that p is an output place of t. Formally:

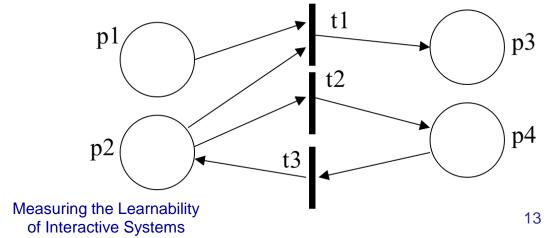
•
$$t \bullet = \{p \in P \mid (t, p) \in F\}$$

With an analogous meaning, we can define input/output transitions of a place. Formally:

•
$$p \bullet = \{t \in T \mid (p, t) \in F\}$$
 and $\bullet p = \{t \in T \mid (t, p) \in F\}$

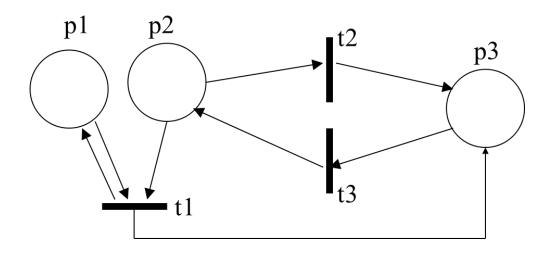
$$t_1 \bullet = \{p_3\}; \bullet t_1 = \{p_1, p_2\};$$

 $\bullet p_2 = \{t_3\}; \bullet p_1 = \emptyset;$
 $p_2 \bullet = \{t_1, t_2\}; p_1 \bullet = \{t_1\}$





Exercise



P =

T =

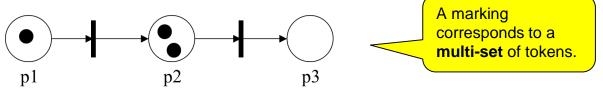
F =

 $t_1 \bullet = \dots ; \bullet t_1 = \dots ;$

• p₂ =; p₂ • =;

Marking

- The operational semantics of a Petri Net N = (P,T,F) is described in terms of particular marks called tokens (represented as black dots).
- Places in Petri Nets can contain <u>any number of tokens</u>.
- Any distribution of tokens across all of the places is called a marking.
 - A marking is a function M: P -> NAT.



- The marking of a Petri net determines its state.
 - > State of the example Petri net: $M = \{(p_1, 1), (p_2, 2), (p_3, 0)\}$ or $M = [p_1, p_2^2]$
- Petri nets must be associated with an initial marking M₀ and with a set of possible final markings.

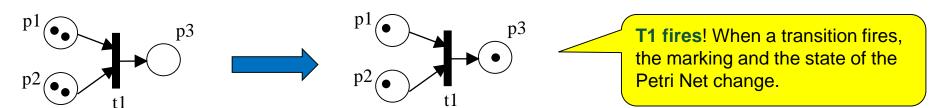


Firing Rules

- The dynamic behavior of Petri nets is characterized by the notion of firing (transition execution). A transition can fire whenever there are one or more tokens in each of its input places.
- A transition t is said to be **enabled** if and only if each input place p of t contains at least one token. Only enabled transitions may fire.
 - A transition t is enabled in a marking M iff for each p, with $p \in {}^{\bullet}t$, M(p) > 0.



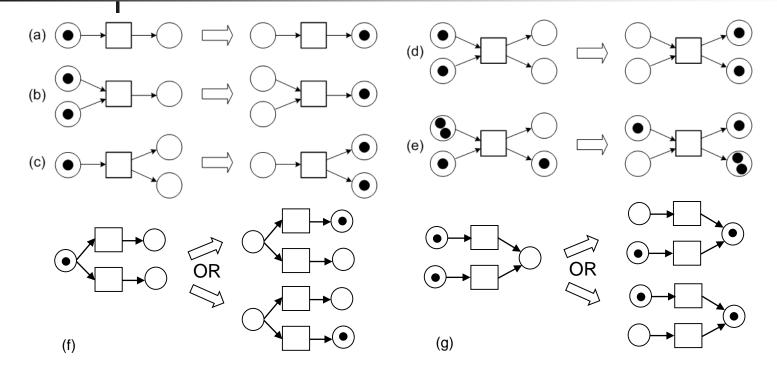
If transition t fires, then t **consumes one token** from each input place p of t and **produces one token** for each output place p of t.





Firing Transitions

Further Examples



- It is assumed that the firing of a transition is an atomic action that occurs instantaneously and can not be interrupted.
- If there are multiple enabled transitions, any one of them may fire; however, for execution purposes, it is assumed that **they can not fire simultaneously**, see example (g).
- An enabled transition is not forced to fire immediately but can do so at a time of its choosing.

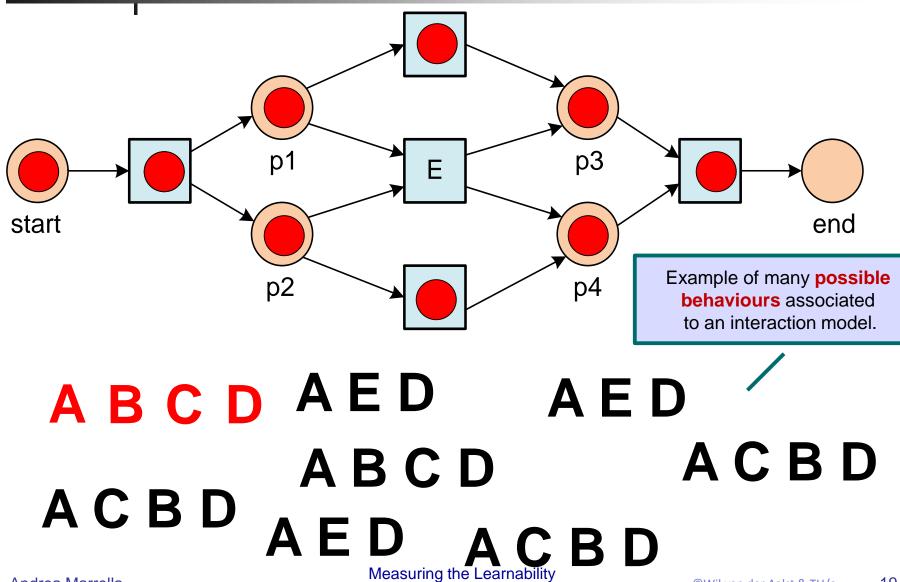


Boundness

- A marking M' is called reachable from marking M (we write M →* M') iff there is a firing sequence σ that leads from M to M'.
- Reachability analysis suffers from the state explosion problem.
- To make reachability analysis possible, a boundness assumption is required.
- A Petri net N with initial marking M_0 is **k-bounded** iff for every reachable marking M, M(p) \leq k (k is the minimal number for which this holds).
 - A 1-bounded net is called safe.
 - The property of boundness ensures that the number of tokens cannot grow arbitrarily.
- In HCI, the focus is on 1-bounded Petri Nets.



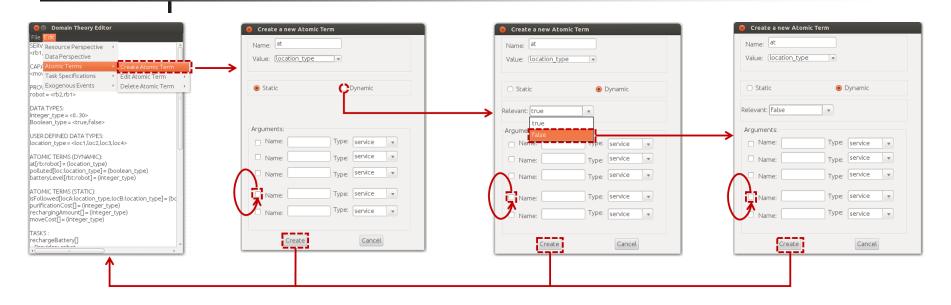
Behaviors associated to a Petri Net

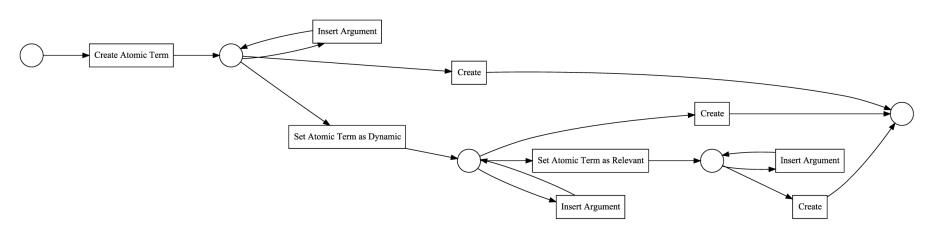


of Interactive Systems



Petri Nets as Interaction Models

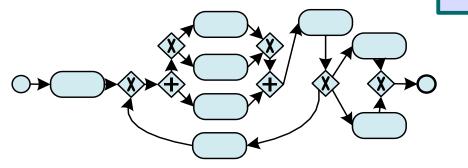






Generation of User Logs

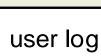
Interaction models are not enforced by software systems.
Traces can be dirty, with redundant or missing actions



interaction model

Execution of relevant tasks

Any execution of a relevant task produces a new execution trace recorded in a user log.





Example of a User Log

case id	event id	properties			
		timestamp	activity	resource	case
	35654423	30-12-2010:11.02	register request	Pete	
1	35654424	31-12-2010:10.06	examine thoroughly	Sue	_
	35654425	05-01-2011:15.12	check ticket	Mike	1
	35654426	06-01-2011:11.18	decide	Sara	1
	35654427	07-01-2011:14.24	reject request	Pete	1 2
	35654483	30-12-2010:11.32	register request	Mike	2
2	35654485	30-12-2010:12.12	check ticket	Mike	_
	35654487	30-12-2010:14.16	examine casually	Pete	3
	35654488	05-01-2011:11.22	decide	Sara	
	35654489	08-01-2011:12.05	pay compensation	Ellen	4
	35654521	30-12-2010:14.32	register request	Pete	7
3	35654522	30-12-2010:15.06	examine casually	Mike	5
	35654524	30-12-2010:16.34	check ticket	Ellen	5
	35654525	06-01-2011:09.18	decide	Sara	
	35654526	06-01-2011:12.18	reinitiate request	Sara	6
	35654527	06-01-2011:13.06	examine thoroughly	Sean	_
	35654530	08-01-2011:11.43	check ticket	Pete	
	35654531	09-01-2011:09.55	decide	Sara	
	35654533	15-01-2011:10.45	pay compensation	Ellen	
	35654641	06-01-2011:15.02	register request	Pete	50
4	35654643	07-01-2011:12.06	check ticket	Mike	100
	35654644	08-01-2011:14.43	examine thoroughly	Sean	400
	35654645	09-01-2011:12.02	decide	Sara	200
	35654647	12-01-2011:15.44	reject request	Ellen	200
	35654711	06-01-2011:09.02	register request	Ellen	50
5	35654712	07-01-2011:10.16	examine casually	Mike	400
	35654714	08-01-2011:11.22	check ticket	Pete	100
	35654715	10-01-2011:13.28	decide	Sara	200
	35654716	11-01-2011:16.18	reinitiate request	Sara	200
	35654718	14-01-2011:14.33	check ticket	Ellen	100
	35654719	16-01-2011:15.50	examine casually	Mike	400
	35654720	19-01-2011:11.18	decide	Sara	200
	35654721	20-01-2011:12.48	reinitiate request	Sara	200
	35654722	21-01-2011:09.06	examine casually	Sue	400
	35654724	21-01-2011:11.34	check ticket	Pete	100
	35654725	23-01-2011:13.12	decide	Sara	200
	35654726	24-01-2011:14.56	reject request	Mike	200
	35654871	06-01-2011:15.02	register request	Mike	50
6	35654873	06-01-2011:16.06	examine casually	Ellen	400
	35654874	07-01-2011:16.22	check ticket	Mike	100
	35654875	07-01-2011:16.52	decide	Sara	200

case id	trace
1	$\langle a,b,d,e,h \rangle$
2	$\langle a,d,c,e,g \rangle$
3	$\langle a, c, d, e, f, b, d, e, g \rangle$
4	$\langle a,d,b,e,h \rangle$
5	$\langle a, c, d, e, f, d, c, e, f, c, d, e, h \rangle$
6	$\langle a, c, d, e, g \rangle$

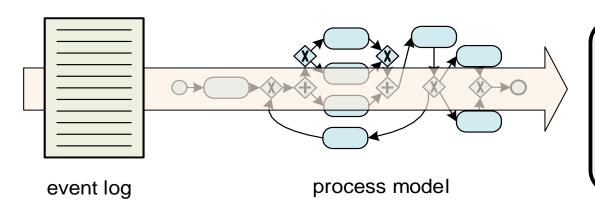
The user actions belonging to a relevant task are ordered and form a **trace**, which can be seen as one complete execution of a task.

a = register request,
b = examine thoroughly,
c = examine casually,
d = check ticket,
e = decide,
f = reinitiate request,
g = pay compensation,
and h = reject request



Replay

- Replay approaches use a user log and an interaction model (that may have been constructed by hand or discovered) as input. The user log is replayed on top of the interaction model.
- In this way, discrepancies between the log (observed behavior) and the model (expected behavior) can be detected and quantified.



- extended model showing times, frequencies, etc.
- diagnostics
- predictions
- recommendations

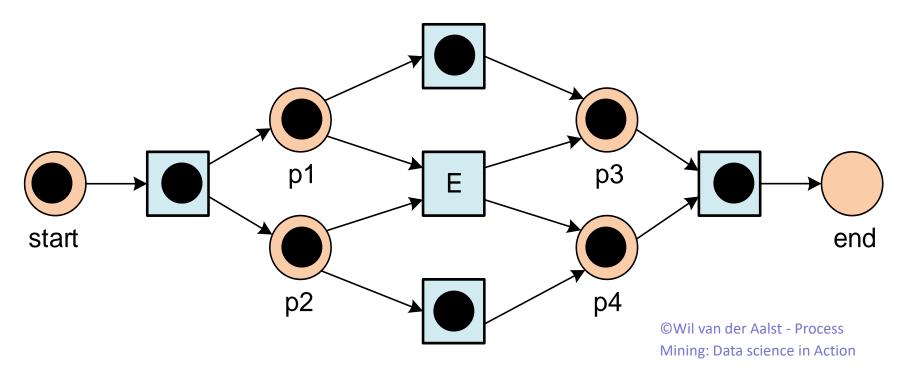
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Replay

A B C D

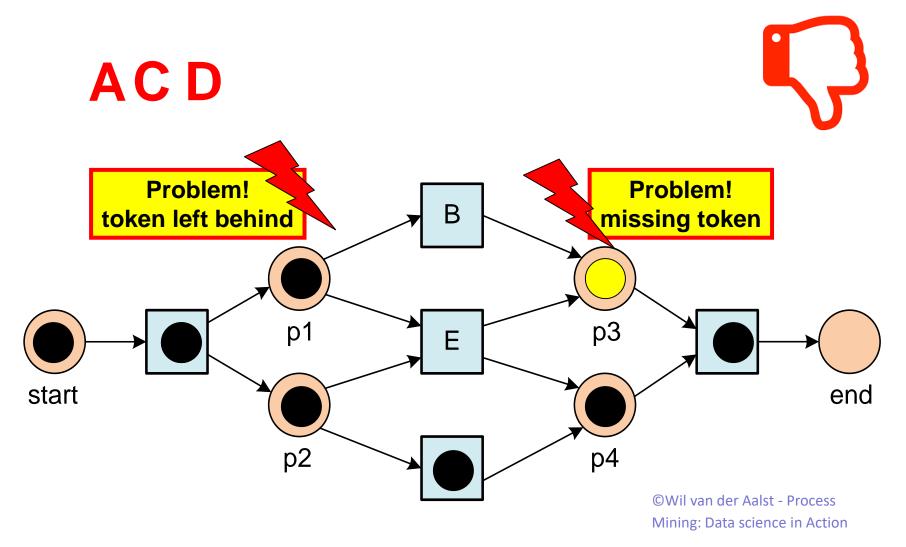




Measuring the Learnability of Interactive Systems



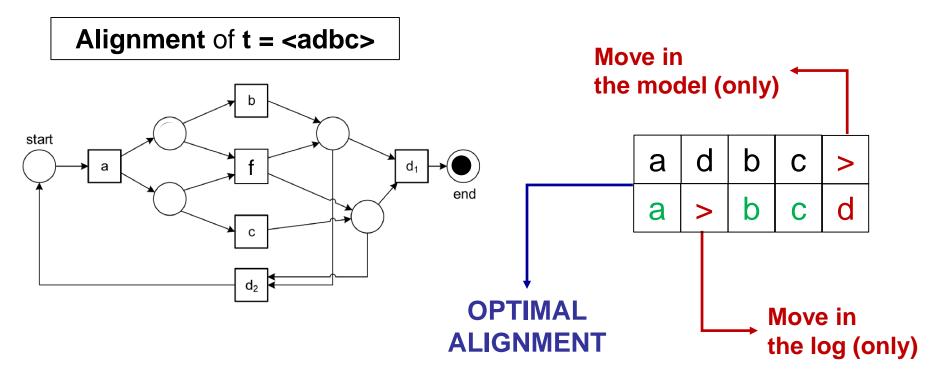
Replay





Trace alignment

- Investigate relations between moves in the log and moves in the model to establish an alignment between the model and a trace.
- Replay: If a move in the log cannot be mimicked by the model and viceversa, such "no moves" are denoted by > (and may have a cost).

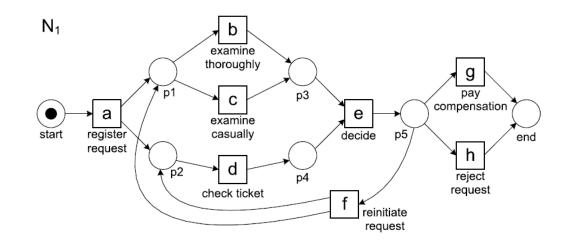




Several possible alignments

<abdes

a	b	d	е	g
a	b	d	е	g



а	b	»	d	е	g
а	»	С	d	е	g

а	b	d	е	g	»	»	»	»	»
»	»	»	>>	»	а	С	d	е	g



Moves have costs

Standard cost function:

•
$$c(x, *) = 1$$

•
$$c(*,y) = 1$$



•
$$c(x,y) = 0$$
, if $x=y$

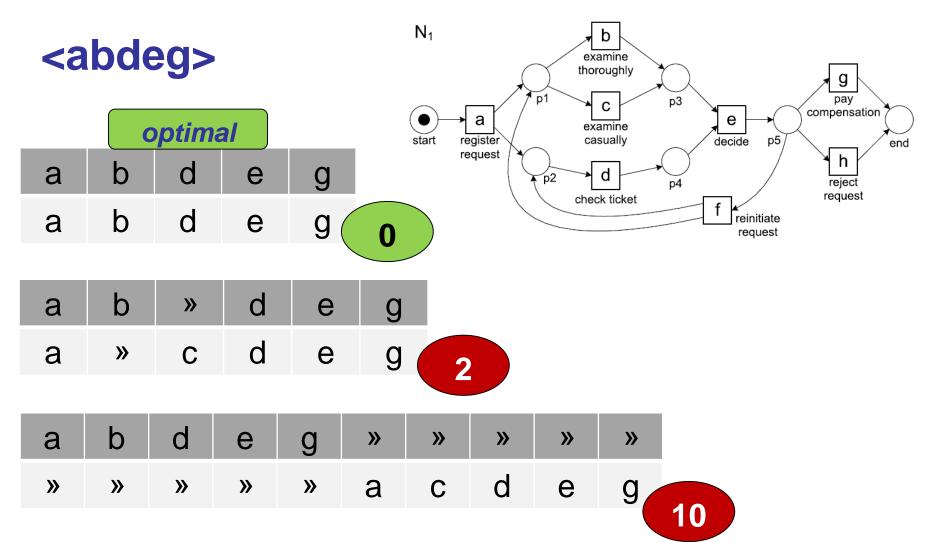
•
$$c(x,y) = \infty$$
, if $x \neq y$

OPTIMAL ALIGNMENT alignment with minimum deviation cost

Any cost structure is possible!



Optimal alignments





Learnability via fitness values

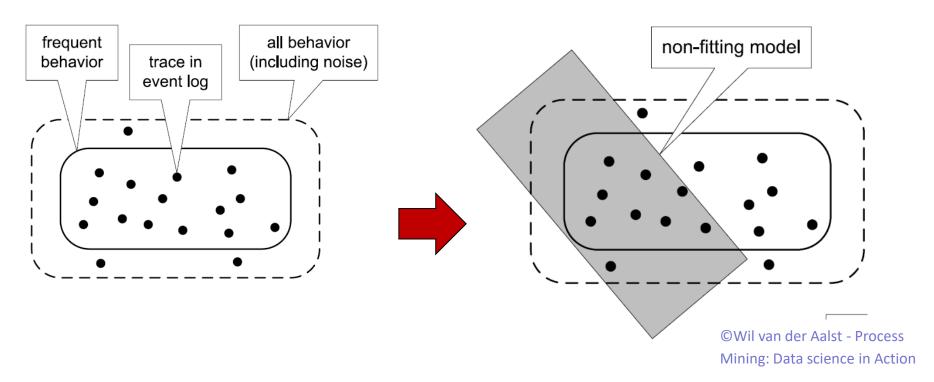
- Trace alignment allows to:
 - verify if a trace is compliant with an interaction model;
 - identify the root and the severity of each deviation;
- The result of the alignment task is the fitness value, i.e., how much the log adheres to a model of the interaction.
 - The fitness value can vary from 0 to 1.
- To measure the learnability of a system we can analyze the rate of the fitness values corresponding to subsequent executions of the system over time.
 - An increasing rate will correspond to a system that is easy to be learnt with respect to its relevant tasks.
 - Given an initial low fitness, a not-increasing or stable rate may indicate the presence of some learning issues that need to be fixed.



Fitness

Fitness: the interaction model should allow for the behavior seen in the user log.

 A model has a perfect fitness if all traces in the log can be replayed from the beginning to the end.





Fitness based on alignments

Cost of the **optimal** alignment of the trace σ

$$fitness(\sigma, N) = 1 - \frac{\delta(\lambda_{opt}^{N}(\sigma))}{\delta(\lambda_{worst}^{N}(\sigma))}$$

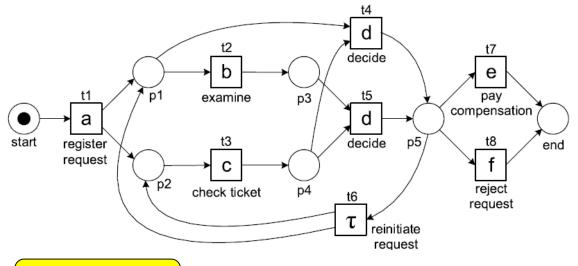
In a worst-case alignment:

(i) all events in trace σ are converted to log moves and (ii) a shortest path from an initial state to a final state of the model is added as a sequence of model moves

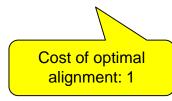
Cost of the **worst-case alignment** where there are no sinchronous moves and moves in model and log only.



Example



$$\gamma_{5,2a} = \begin{vmatrix} a & b \gg d & f \\ a & b & c & d & f \end{vmatrix}$$



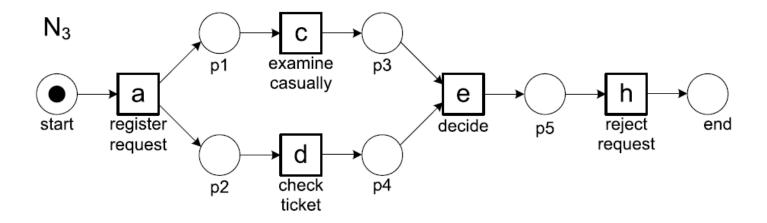
$$\gamma_{5,2w} = \begin{vmatrix} a & b & d & f \gg \gg \gg \gg \\ \gg \gg \gg \gg a & c & d & f \end{vmatrix}$$

$$fitness(\sigma_2, N_5) = 1 - \frac{1}{8} = 0.875$$



Exercise

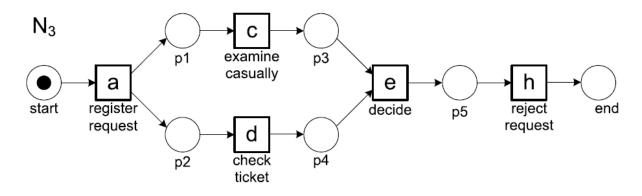
 Calculate the fitness of the trace <a,d,b,e,h> with respect to the model N₃

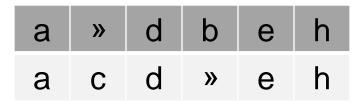




Solution

 Calculate the fitness of the trace <a,d,b,e,h> with respect to the model N₃





Cost of optimal alignment: 2



• Fitness: $1 - \frac{2}{10} = 0.8$

Cost of worst-case alignment: 10



Fitness for the entire log

This is the sum of all costs when replaying the entire event log using optimal alignments

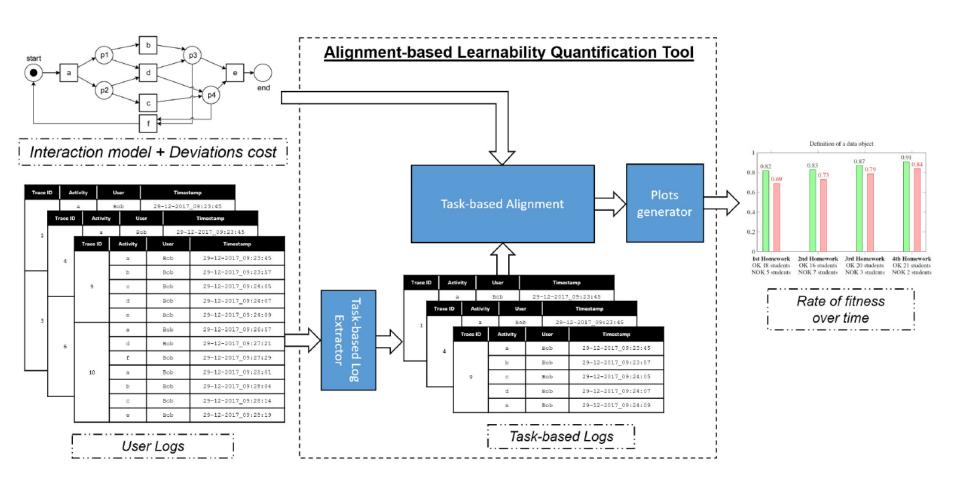
Number of occurrences of a specific trace in the log (e.g., if a trace σ appears 200 times in the log, L(σ) will be equal to 200)

$$fitness(L, N) = 1 - \frac{\sum_{\sigma \in L} L(\sigma) \times \delta(\lambda_{opt}^{N}(\sigma))}{\sum_{\sigma \in L} L(\sigma) \times \delta(\lambda_{worst}^{N}(\sigma))}$$

It is divided by the sum of the cost of all worst-case scenarios to obtain a normalized fitness value



The tool for quantifying learnability [15]





Extraction of task-based log

Trace ID	Activity	User	Timestamp
	ā	Bob	29-12-2017_09:23:45
	b	Bob	29-12-2017_09:23:57
1	С	Bob	29-12-2017_09:24:05
	d	Bob	29-12-2017_09:24:07
	е	Bob	29-12-2017_09:24:09
	h	Bob	29-12-2017_09:25:19
2	j	Bob	29-12-2017_09:25:54
	P	Bob	29-12-2017_09:26:17
	a	Bob	29-12-2017_09:26:57
	d	Bob	29-12-2017_09:27:21
	f	Bob	29-12-2017_09:27:29
3	a	Bob	29-12-2017_09:28:01
	b	Bob	29-12-2017_09:28:04
	c	Bob	29-12-2017_09:28:14
	e	Bob	29-12-2017_09:28:19

Trace ID	Activity	User	Timestamp
	a	Bob	30-12-2017_17:13:45
1	d	Bob	30-12-2017_17:13:57
	е	Bob	30-12-2017_17:14:09
	h	Tom	30-12-2017_17:15:19
2	j	Tom	30-12-2017_17:15:54
	р	Tom	30-12-2017_17:16:17
	a	Tom	30-12-2017_19:56:57
3	d	Tom	30-12-2017_19:57:21
	е	Tom	30-12-2017 19:57:29

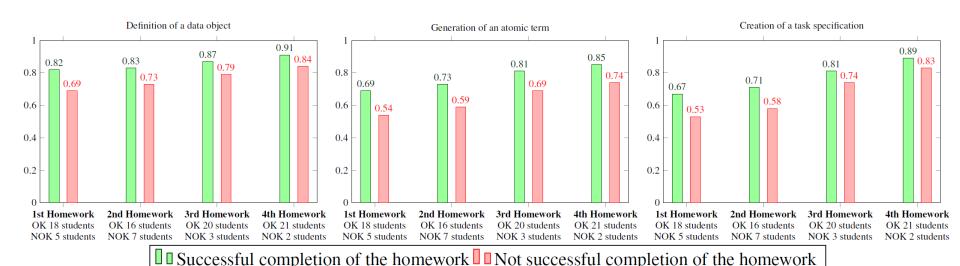
	Trace ID	Activity	User	Timestamp
Γ		a	Bob	29-12-2017_09:23:45
		b	Bob	29-12-2017_09:23:57
	1	С	Bob	29-12-2017_09:24:05
		d	Bob	29-12-2017_09:24:07
		е	Bob	29-12-2017_09:24:09
1		a	Bob	29-12-2017_09:26:57
		d	Bob	29-12-2017_09:27:21
		f	Bob	29-12-2017_09:27:29
	3	a	Bob	29-12-2017_09:28:01
		b	Bob	29-12-2017_09:28:04
		С	Bob	29-12-2017_09:28:14
		е	Bob	29-12-2017_09:28:19
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Trace ID	Activity	User	Timestamp
	a	Bob	30-12-2017_17:13:45
1	d	Bob	30-12-2017_17:13:57
	e	Bob	30-12-2017_17:14:09



Preliminary Experiments

- We performed a preliminary longitudinal study with 23 Master students against a GUI-based tool developed to support the design activity of business processes. We recorded all the user actions in specific user logs.
 - We assigned 4 different homeworks of growing complexity in 4 consecutive weeks.
 - The students were requested to complete the homework assigned to them in a specific week within the end of the week itself.
 - Before the assignment of a new homework, we shown to the students the minimal optimal solution to perform correctly the previous homework.
- We replayed user logs over three interaction models of the system describing the expected ways to achieve three relevant tasks.





From Petri Nets to Declare

1. What is DECLARE?

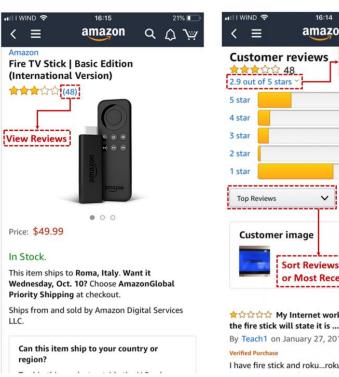
Formal semantics grounded in Linear Temporal Logic (LTL) that has been proven to be adequate for designing interaction model

- 2. The use of declare models enables an HCI designer to define just the behavior of interest, making it easier to define the models
- Models expressed as set of constraints, such that everything that does not violate the model is accepted

Constraint	Explanation	Examples
Existence constraints		
EXISTENCE(a)	a occurs at least once a	√ bcac × bcc
ABSENCE(a)	never occur	√ bcc × cac
Relation constraints		
$Response(\mathbf{a},\mathbf{b})$	If a occurs, then b occurs after a	√ caacb × caac
$PRECEDENCE(\mathtt{a},\mathtt{b})$	b occurs only if preceded by a	\checkmark cacbb \times ccbb
Mutual relation constraints		
COEXISTENCE(a, b)	If b occurs, then a occurs, and vice-versa	√ cacbb × cac
$SUCCESSION(\mathtt{a},\mathtt{b})$	a occurs if and only if it is followed by b	\checkmark cacbb \times bac
CHAINSUCCESSION(a,b)	a and b occur if the latter immediately follows the former	√ cabab × cacb
Negative relation constraints		
NOTCOEXISTENCE(a, b)	a and b never occur together	√ cccbbb × accbb
$NotSuccession(\mathtt{a},\mathtt{b})$	a can never occur before b	✓ bbcaa × aacbb
$Not Chain Succession(\mathtt{a},\mathtt{b})$	a and b occur if a does not immediately follows b	√ acbacb × abcab



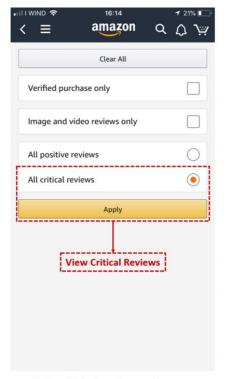
Capturing user actions with Declare



(a) Reading reviews.



(b) Filtering reviews.



(c) Critical reviews.



(d) Adding to cart.

Some screenshots of the UI of Amazon shopping mobile app. In this example, we focus only on a subset of possible user actions such as the user reading only the critical reviews associated to a Fire TV stick, and then purchasing it.



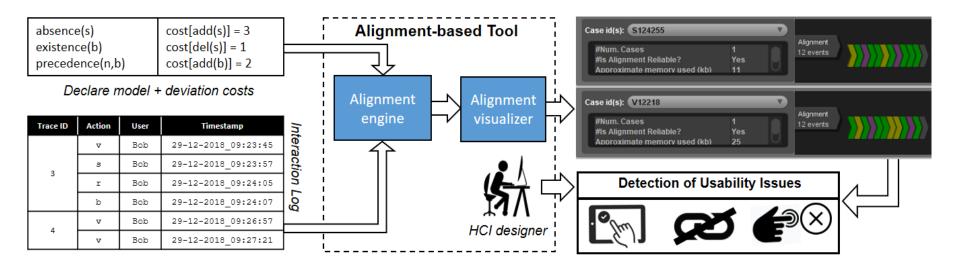
Interaction models via Declare

If we consider our running example, we can specify the interaction model that describes the expected behavior underlying the relevant task, such as the user only reading the critical reviews associated to a Fire TV stick, and then proceeding to buy it, as the set consisting of the following declare constraints:

- absence(s) means that action s = Sort Reviews by Quality or Most Recent cannot ever be performed.
- existence(b) means that action b = Buy Product must be executed at a certain point of the interaction.
- precedence(n; b) forces n = View Critical Reviews to precede b = Buy Product.



The declarative approach [16]





Conclusion and Future Works

 Our approach couples interaction models represented as Petri nets with the notion of alignment wrt. user logs to obtain a more precise measurement of the learnability of interactive systems.

STRENGTHS

- The approach can be enacted while the system is used in real user contexts.
- The ability of associating **different weights** to the deviations identified during an alignment.
- For a specific system's task, different interaction models can be developed to represent the different interaction strategies of novice and experienced users

LIMITATIONS

- Only few interactive systems provide a structured recording of user logs.
- There should be one or more identifiable entry/exit points in the user log for extracting the specific traces associated to the task.

FUTURE WORKS

- Further robust longitudinal studies to be performed in longer time frames.
- Identification of threshold values for the fitness.



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