IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

Learning Path Recommendation from an Inferred Learning Space

Abstract

Defining a learning space of reference may be a challenging task for the concerned tutor(s). However, once formalized, such a representation of possible learning sequences may serve as a norm to evaluate the current state of a learner and to potentially derive recommendations about the next learning state to target. A pragmatic strategy is introduced in this article to ease the definition of a subjective learning space from a few tutor(s)-provided examples of representative learning paths. A measure is then also inferred from these representative paths that can then be used to evaluate an ongoing learning path. The learning space and the evaluation measure, combined, are then used to suggest the learning activity the learner should address next.

Keywords. Learning space inference | Learner evaluation | Fuzzy measure inference | Recommendation

Auteurs

Madjid SADALLAH

Grégory SMITS

Affiliations

Lab-STICC

IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

Learning Space Inference from a Few Sequences

Learning Space: formal structure (Q, K) that organizes a learner's knowledge states. Two axioms ensure its relevance to model a learning domain:

1. ***learning smoothness***, if $K \subset L \subseteq Q$, there exists a chain of states $K_0 = K \subset K_1 \subset \ldots \subset K_n = L$ where $K_i = K_{i-1} \cup \{q_i\} \subseteq Q$
2. ***learning consistency***, if $K \subset L \subseteq Q$ and $q \in Q/K$, then $K \cup \{q\} \in K$ implies $L \cup \{q\} \in K$

Goal: Leverage an LS inferred from a few positive, non-contrasting and potentially heterogeneous examples

Proposed approach

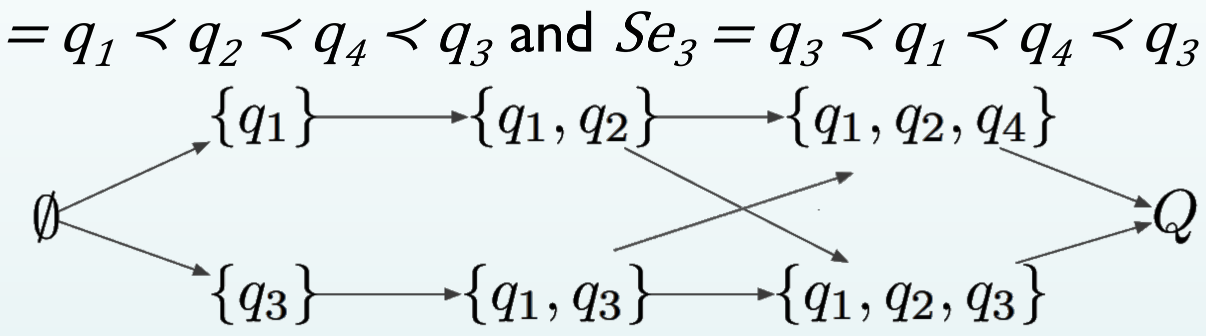
The tutor provides examples of learners who solved a set of problems (Q) as references for the course.

- $\varepsilon = \{e_1, \ldots, e_m\}$ is the set of representative learners.
- Each learner e has a sequence Se, representing step-by-step learning from $\emptyset$ to Q.
- Unions of prefixes of $\{Se_1, \ldots, Se_m\}$ form a LS

Example

Set of problems $Q = \{q_1, q_2, q_3, q_4\}$

Three representative sequences: $Se_1 = q_1 \prec q_2 \prec q_3 \prec q_4$; $Se_2 = q_1 \prec q_2 \prec q_4 \prec q_3$ and $Se_3 = q_3 \prec q_1 \prec q_4 \prec q_3$



Learner's Evaluation wrt. a LS of Reference

- Set ε of representative learners serves as the basis to build the LS and infer an evaluation measure
- Normative evaluations of ongoing learning processes

CHOCOLATE :

- infers the characteristic function of a disjunctive concept from a tiny set ε
- compromise between generalization of shared properties and specialization of singular examples

Revised to input sequences, not just sets

Weighting Strategy

- Function $\delta: Q \rightarrow [0, 1]$ gives problem importance
- δ measures problem frequency in states within K
- Higher occurrence in K = higher problem importance

$$\delta(q) = \frac{|\{k \in \mathcal{K} \text{ st. } q \in k\}|}{|Q|}$$

Example (Fig.):
$\delta(q_1) = 6/7$, $\delta(q_2) = \delta(q_3) = 4/7$ and $\delta(q_4) = 2/7$

Relevance of a sequence of problems

- Function μ: a fuzzy measure that quantifies the relevance of a (sub)sequence
- Relevant seq = a possible learning seq in LS

$$\mu(S) = \max_{e \in \mathcal{E}} \max_{i=1}^{|S_e|} \frac{|S_e^i| \times (S_e^i \blacktriangleleft S)}{|S_e|}$$

S^i_e prefix of size i of S_e ; $|S|$ is the length of seq S, and $(S_e{}^i \blacktriangleleft S)$ is a predicate returning 1 if $S_e{}^i$ is a subsequence of S 0 otherwise

Example (LS of Fig.): let $S = q1 \prec q3 \prec q2 \prec q4$ then $\mu(S) = ¾$ as $S^3{}_{e2} = q1 \prec q2 \prec q4$ is the longest subseq of S in ε

Combining μ with the δ function using a *Choquet integral* allows evaluating an ongoing learning seq.

$$\mathcal{C}(S) = \sum_{j=1}^{|S|} [\mu(H_j(S)) - \mu(H_{j-1}(S))] \times \kappa_j(S)$$

- $\kappa_j(S)$ returns the j^{st} most important learning activity (in terms of prerequisite) in S and
- $H_j(S)$ returns the sequence composed of the j most important learning activities

Example (LS of Fig.): let $S = q1 \prec q4 \prec q2$. Its score:
C(S) = ¼ × 6/7 + (¼ – ¼) × 2/7 + (2/4 – ¼) × 4/7 = 5/14

Recommending the next Learning Activity

C(S) feedback informs learners about the adequacy between their current learning process and reference paths while LS and C(S) combined provide personalized recommendations for the next learning activity.

- $N(S) = \{q \in Q \mid S\}$ represents the remaining problems for the learner.
- Outer fringe: Subset of knowledge states reachable from the current state.
- $\gamma(q, S)$ measures the gain for the learner by addressing problem q :

$$\gamma(q, S) = \mathcal{C}(S \prec q) - \mathcal{C}(S)$$

- Proposed strategy suggests addressing q with maximum $\gamma(q, S)$ among $N(S)$.
- Next Problem: Find q where

$$\gamma(q, S) = \max_{q' \in N(S)} \gamma(q', S)$$

Example (LS of Fig.): If learner has completed only one activity $S = q1$, the next reachable problems are $\{q2, q3\}$. As $C(q1 \prec q2) = 5$ and $C(q1 \prec q3) = 3/14$, q2 is suggested

Outlook

Ongoing experiments. Assessing proposed evaluation strategy and recommendations in using data from IMT MOOCs.
Future research goals. Personalized feedback and recommendations using an inferred LS and assessment metrics to enhance learning outcomes in MOOCs.

References

Doignon, J.P., Falmagne, J.C.: Knowledge spaces. Springer Science & Business Media (2012)

Smith, E.E., Medin, D.L.: The exemplar view. Foundations of cognitive psychology:Core readings pp. 277–292 (2002)

Smits, G., Yager, R., Lesot, M., Pivert, O.: Concept membership modeling using a choquet integral. In: International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems. pp. 359–372. Springer (2020)

Wang, Y., Yao, Q., Kwok, J.T., Ni, L.M.: Generalizing from a few examples: A survey on few-shot learning. ACM computing surveys (CSUR) 53(3), 1–34 (2020)

ECTEL
EUROPEAN CONFERENCE ON TECHNOLOGY ENHANCED LEARNING

EC-TEL 2023
Aveiro, Portugal
4-8 September 2023