# Internship M2 Xcale : Report

Camille-Amaury Juge

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**Abstract**

This report aims at highlighting my work during the internship at the Brest University within the Lab-STICC laboratory, MOTEL Team. It took place between the beginning of february 2021 to the end July 2021. There was several tasks to assume during this internship but we can summarize it as : Handle gathering, storage, assessment and prediction of student's Self-Regulated Learning skills using the FRANCE IOI's platform.

## Glossary

**BN** Bayesian Network. 22, 26

**DBN** Dynamic Bayesian Network. 29

**SRL** Self Regulated Learning. 5–15, 18–21, 27, 28, 30, 31, 38

# Contents

# 1 Introduction

In the latest context of Coronavirus and lockdown, students and professors faced new obstacles which forced them to use new ways of teaching and learning through the Internet. The rise of Massive Open Online Courses (MOOC) enabled education to continue through pandemic. However, those environments also raised new constraints. Some of the students have already the required skills to master their study, but others won't and may be heading to failure. Moreover, there is a growing need to understanding and intervening in those environment [1]. That is why, researchers tend to focus on Self-Regulated Learning Theory (SRL) in order to find new ways of targeting students, which are giving up, and suggesting them accurate answers to help them persevere. SRL was firstly introduced as a psychology and educational sciences topic, however nowadays, this theory is also explored by computer scientists. In this master's thesis, we focused on the computer science field, using data science theory and concepts with regards to education. We decided to use Educational Data Mining (EDM) and Learning Analytics approaches (LA) [2], which deal with applying data mining and pattern mining method to educational dataset in order to analyzed how student engage in their learning process and report hidden insights.

Thus this internship is aimed at applying AI algorithm, regarding to SRL in an online environment. Learners should be classified by their behaviours, skills. Then, we want to suggest answers to help them improving in their own learning process and self-regulation skills. For this purpose, we use to work with FRANCE IOI, which is the largest french challenging computer science platform including challenges such as "Concours Castor", "Quick-pi", etc. In the first place, we gathered and stored data by creating web services and modules regarding an activity on the Quick-Pi platform. Then studying data and creating models which are able to correctly classify student's behaviours and SRL skills during the early period of a challenge.

Firstly, we go through SRL Theory and Artificial Intelligence algorithm State of the Art. Secondly, we highlight our work through data gathering and storage. Then, we discuss about indicators and interesting findings in the data. Finally, we conclude with our models and results.

# 2 Self-Regulated Learning

In this section, we present a state of the art summary for the concepts of SRL.

## 2.1 SRL theory models

In order to begin, we have to introduce SRL models, whether they are the most referenced and accepted among researchers or because they show interesting aspects deeper than others do.

### 2.1.1 Zimmerman's approach

Zimmerman was one of the first to put words onto the definition of SRL, his approach was focusing on the psychology part. According to him, the students which possess SRL skills can be defined as "metacognitively, motivationally and behaviorally participants in their own learning." [3]. The metacognitive processes are a group of skills such as planning, setting goals, self-monitoring, self-evaluating. While the motivation aspect takes care of interest in a task, self-efficacy and self-attributions. Finally, the behavior category is grouping : selecting, structuring and creating optimized environment for their own learning. Moreover, the self-regulatory feedback loop is also an important concept [4] : Learners should be able to both negatively and positively judge themselves regarding the outcomes and their goal. Last but not least, studying strategies is also a major concept : Learners may choose strategies over specific conditions and it is important to know why and how they did so, in order to reach their goal.

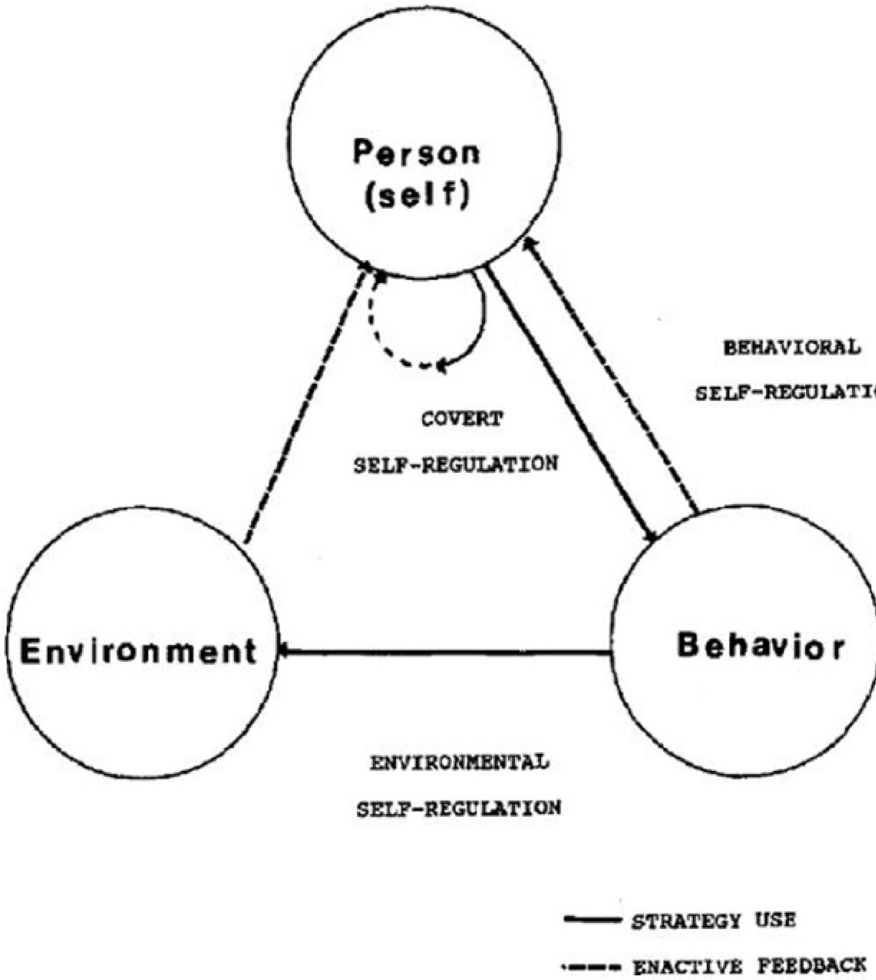


Figure 1: Triadic model of SRL from [4].

Regarding (Figure 1), we can see that nodes which represent important aspect of SRL are represented as a cycle rather than a path. The edges represent the importance of strategy use and feedback in the learning process such that : ones use a strategy which affect his behavior and environment. Then, this environment and behavior will send feedback to the learner regarding his action and the results, enabling him to reconsider his strategy. Then, each aspect can't be only explained by themselves but rather be considered as interdependent. By the time and many other studies, Zimmerman was able to refine is initial loop by adding aspects and specific concepts to it (Figure 2). Firstly, students go over the forethought phase in which they have to be aware of their task, the outcomes they can get and finally the goals and strategies to follow in order to succeed.

Nextly, they have to work actively, by seeking help, being proactively participant in their own learning, creating a suitable studying environment etc. Then, they have to enter the self-reflection phase when it is time to judge whether or not their strategies, goals and satisfaction over the task is optimized or if they can do better. Finally, the cycle repeats even after the knowledge is acquired. Thus, we clearly see that reflection of ones learning is a really important part of the definition.

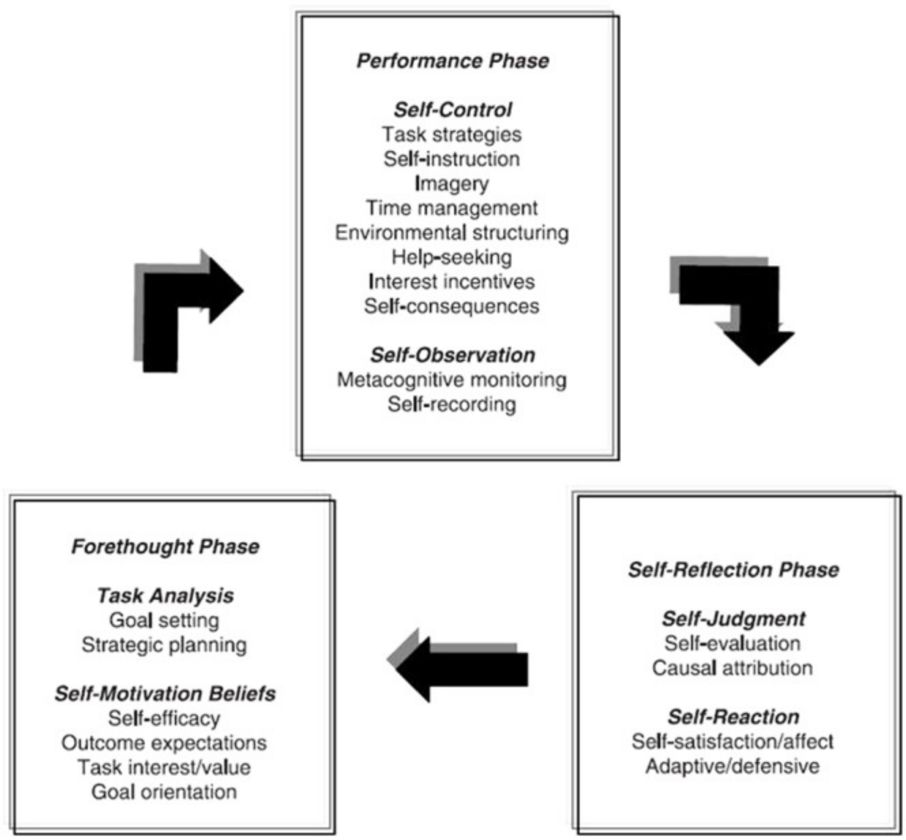


Figure 2: Cyclical phases model of SRL from [5].

### 2.1.2 Boekaerts' approach

As one of the first to conceptualize the concept of SRL, Boekaerts explored the theory in depth with a more clinical and emotional approach. She mainly focused on how feelings, emotion and motivation can drive the SRL pathway in the learning process. Firstly, she created a model which was mainly aimed at helping teachers and educational participants to understand concepts and create new educational tools to assess SRL [6]. As we can see on (Figure 3), there is still this idea of interdependent features such as Zimmerman stated. But this time, more than a loop, it can be considerated as a path which the learners follows during the knowledge acquirement.

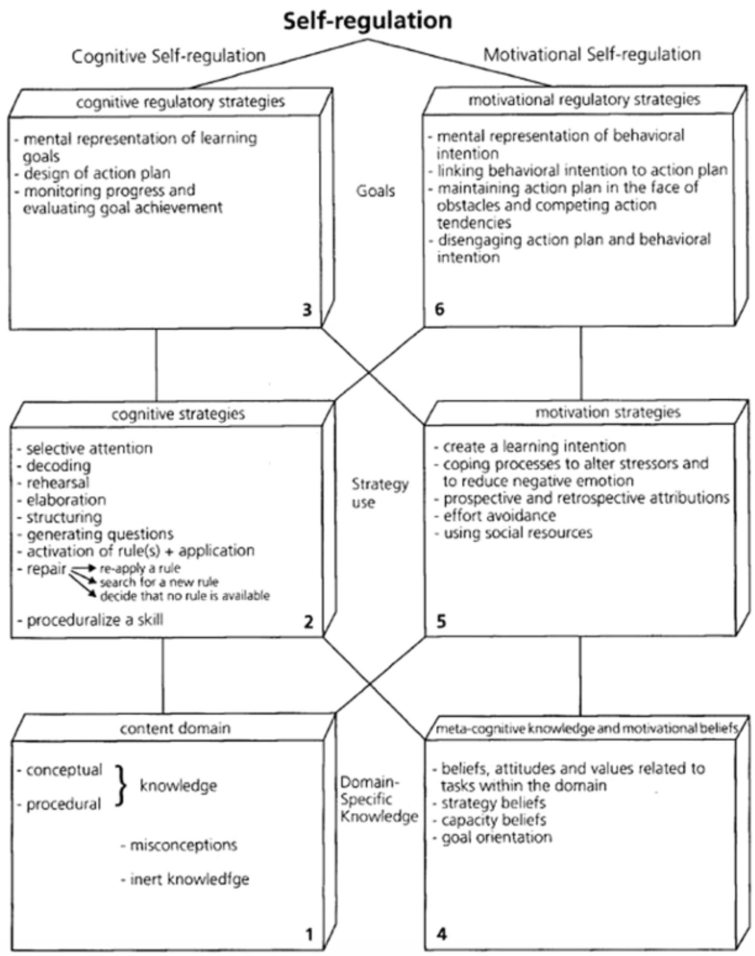


Figure 3: The six component of SRL from [7].

Nextly, she went even further in her research and proposed a new model called the Dual Processing SRL model. She defined two pathway : the mastery or growth pathway which tends to focus on task, goals to reach and needs. Then, the well-being pathway is defined as following emotions, personal motivation goals and protecting the self [6]. These pathways can be used in different approach : the Top-down approach focuses on the mastery/growth path in order to reach the mastery of a skill. The bottom-up approach is the action to move from the mastery path to the well-being path due to some sort of mismatch between the task and the self. The last approach is driven by social pressure, assessment (external) or self-consciousness pressure (internal) and will lead the learners to switch from well being path to the mastery path, (Figure 4). this approach helps to better understand the weight of emotion, motivation in the process of SRL.

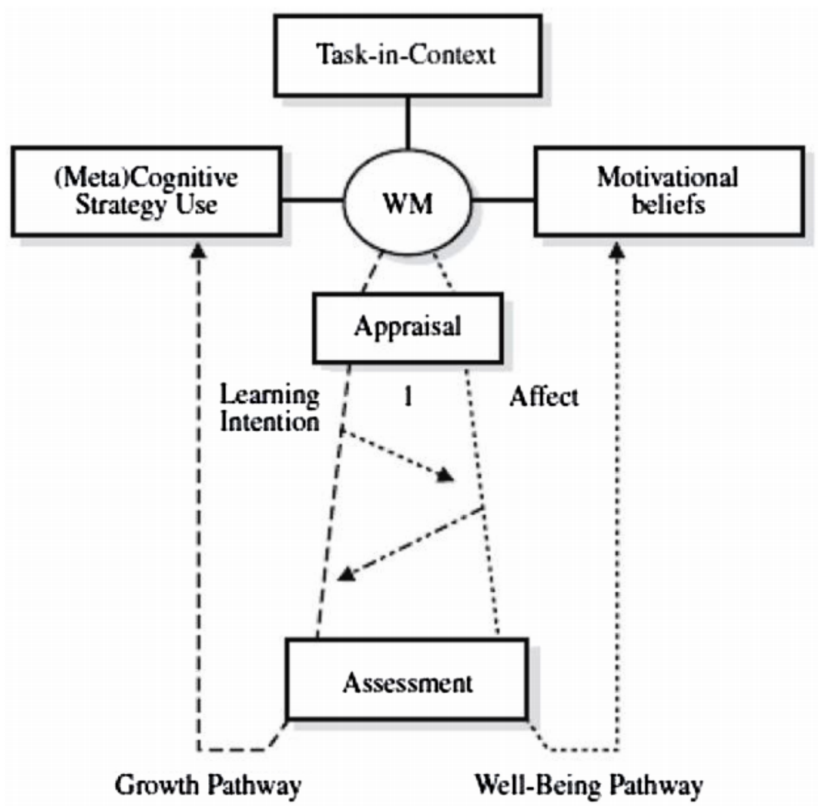


Figure 4: Dual Processing Model from [8].

#### 2.1.3 Winne and Hadwin's approach

Winne and Hadwin developed a model which focus on the meta-cognitive aspects and the use of monitoring in the learning process. Moreover, it is one of the first to introduce the concept of a model which can be used on computers. They clearly explained how the student's cognitive planning, performing and evaluating tasks work. For this purpose, they defined four phases in which the learner goes and monitors himself regarding the task conditions or they cognitive conditions [6]. The definition of task represents the understanding of the objectives. Then, the learner enters in the planning and setting goals phase, where he will have to choose methods to validate objectives. Nextly, learners should conceptualize the action required to follow ones strategy and goals and finally, learners adapt themselves to conditions and will loop again over this process. Regarding (Figure 5), we can see that conditions are a main part of the learning process, they mainly influence how and why the learner take such path and monitoring through the learning process. The authors went in depth into each conditions, providing a really complete understanding of them.

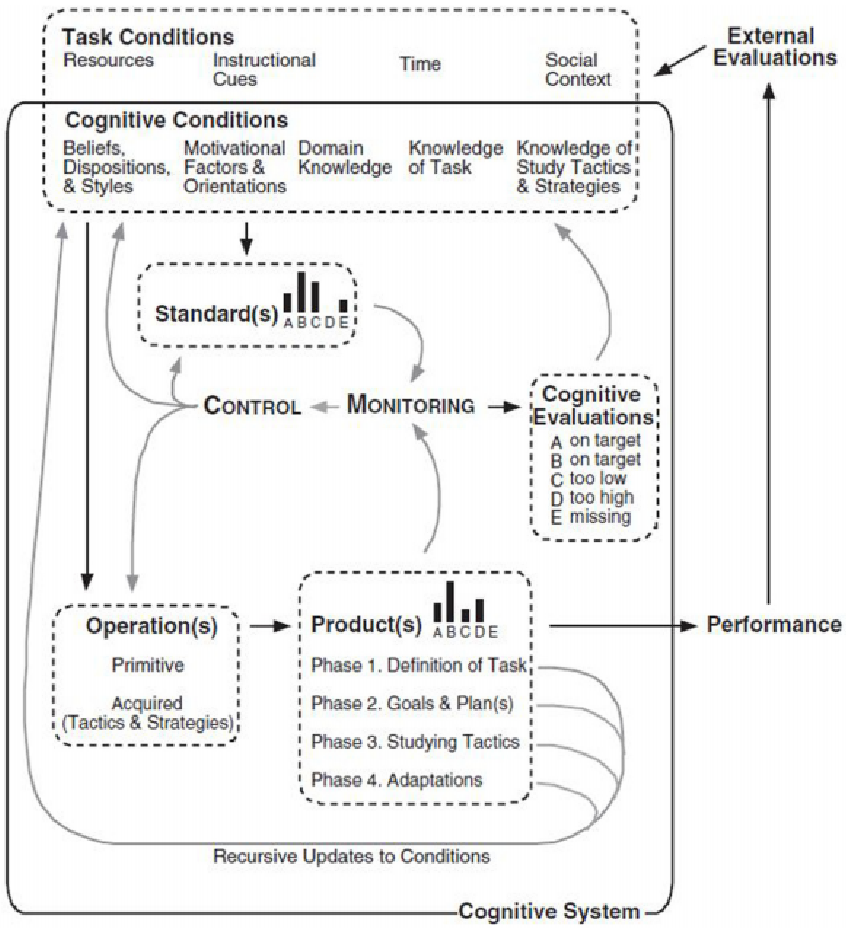


Figure 5: Winne's SRL model from [9].

However, this model barely takes into account emotions and motivations factors, which were proven to be a main part of SRL.

### 2.1.4 Pintrinch's approach

Pintrinch's model is one of the most accepted one towards research community. His work focused on the relation between SRL and motivation, but what makes it so popular is the Motivated Strategies for Learning Questionnaire (MLSQ). In order to better understand this questionnaire, we detail the model and then jump into it. Firstly, the author defined 4 phases which represent all the known aspects of the SRL : the forethought phase which aim at setting goals, strategies, understanding tasks, etc. The monitoring phase which deals about the use of monitoring through motivation, emotions, tasks and context conditions. Then, the control phase which aims at choosing, selecting actions and adaptations in order to reach/abandon ones goals following ones strategies. And finally, the reaction and reflection phase which deals with learners handling of emotions, judgement over their actions and self positioning in the task [6]. As we can see in (Figure 6), these phases use several features such as cognition, motivation and affects, behavior and finally context principles. This follows the fact each feature acts with another and can't be explained alone.

| | Areas for regulation | | | |
|---|---|---|---|---|
| Phases | Cognition | Motivation/affect | Behavior | Context |
| 1. Forethought, planning, and activation | Target goal setting | Goal orientation adoption | [Time and effort planning] | [Perceptions of task] |
| | Prior content knowledge activation | Efficacy judgments | [Planning for self-observations of behavior] | [Perceptions of context] |
| | Metacognitive knowledge activation | Ease of learning judgements (EOLs); perceptions of task difficulty | | |
| | | Task value activation | | |
| | | Interest activation | | |
| 2. Monitoring | Metacognitive awareness and monitoring of cognition (FOKs, JOLs) | Awareness and monitoring of motivation and affect | Awareness and monitoring of effort, time use, need for help | Monitoring changing task and context conditions |
| | | | Self-observation of behavior | |
| 3. Control | Selection and adaptation of cognitive strategies for learning, thinking | Selection and adaptation of strategies for managing motivation and affect | Increase/decrease effort | Change or renegotiate task |
| | | | Persist, give up | Change or leave context |
| | | | Help-seeking behavior | |
| 4. Reaction and reflection | Cognitive judgments | Affective reactions | Choice behavior | Evaluation of task |
| | Attributions | Attributions | | Evaluation of context |

Figure 6: Pintrinch's SRL model from [10].

Thus, the MLSQ questionnaire [11] based himself on the previous model. It brings information over strategies, motivation, context and several other features. Every features follows a 5-Likert scales indicating the confidence in the answer. The author provided two version both for high school and college students, but one criticism done to this questionnaire is that it is not proved to work on computer based environments.

### 2.1.5 Synthesis on SRL models

Table 1: SRL models' contribution

| Model | Focus On | Contribution | Lack |
|---|---|---|---|
| Zimmerman | Psychology Self-Reflection | Interdependency of SRL features. SRL Feedback loop. | Not adapted to digital environment |
| Boekaerts | Psychology Clinical and Emotional | Balance between well-being and learning pathways. | Monitoring and feedbacks less taken into account |
| Winne and Hadwin | Psychology Metacognition and Monitoring | Process of Monitoring through strategy, evaluation of self and conditions. Task and Cognitive conditions influencing meta-cognition processes. | Motivation aspect barely taken into account |
| Pintrinch | Psychology Motivation | Impact of Motivation in each SRL phase. Clearly defined area of regulation through phases. | Interactions between each phases and area |

## 2.2 Digital environments supporting SRL

In this section, we discuss the benefits and risks of using SRL in the context of measuring or assessing learners on digital environment.

The major advantage of the SRL is that the student is now the main monitor of his own learning rather than the teacher. Then, it perfectly fits the new web platforms aimed at the education. Nevertheless, Young [12] ran an experience which shows that inequalities between learners increase in a SRL environment. He ran an experiment with the aim to find in which environment the difference between high SRL and low SRL was the higher, and if the difference between the two learning environment made performing high SRL students better. Thus, He conducted a course on an online support where students were randomly affected a CBI environment (Computer-Based Instruction, or also PC : Program Control), and a LC environment (Learners Control). In the first case, student had no choice to follow the given course in the order chosen by the author. In the second case, they could choose which concept to learn at which time they want. They can review or not some course when they wanted to. Thus, he classified each of the student regarding their SRL skills (low or high). He found that, regarding CBI environment, students were quite equal in the results (low : 67.7%, high : 64.7% validation score). However, in the SRL environment, it seems that high SRL students performs better (73.2%) but low SRL students seems to be totally lost (37.0%). Thus, it shows SRL environment can lead to better results but require learners to have specific set of skills that were not really required before. However this experiment was only done on 26 students, meaning that we should be aware of potential statistics inaccuracy.

Moreover, Pressley [13] also found that teaching self-regulation mechanics is harder than the common thinking. Adults are able to experiments by themselves and choose the best strategy regarding their experimentation whether or not a recommendation is done by a third party, whereas children seem to be more confused by the combination of experiences and recommendation. They keep relying on both, even if they clearly had the opportunity to see the effectiveness of one method rather than another. Then, it highlights the fact that children need to have some kind of clear path to follow rather than a total liberty of action.

Surprisingly, Kornell [14] shows that, suggesting action is also a complicated and misleading path. Learners were offered the right to obfuscate words from their learning tasks to focus on the others, expecting them to fully understand those tasks. But the result shows the contrary, learners without any possibilities were doing better on the final evaluation. In addition, advising user to run several experiments in order to learn by themselves can also be counterproductive. In fact, the more a learner struggled by experimenting and if he succeed at the end, the more efficient is the learning process. Contrariwise, if they didn't succeed, it amplifies the waste of time management and ineffectiveness of the learning method.

Therefore, these statements show that we can't consider SRL as a perfect learning environment by itself. In fact, it requires exterior mechanics to help the lowest SRL students, but those mechanics should be also proven not to be counterproductive.

## 2.3 SRL Measurement

Regarding SRL theory, assessing SRL skills is rather a complicated task. In this subsection, we show the motivation of why and how to assess SRL on a computer based environment.

### 2.3.1 Questionnaires

Questionnaires are great tools in scientific literature which help to measure each of the many features of SRL. They are the most approved and used tool. In this context, we focus on one of the most interesting ones for online learning :

the Self-Regulated Online Learning Questionnaire : **SOL-Q**.

Plenty of researchers have already proposed ways to address questionnaires in order to assess SRL skills. Yet, as Jansen [15] stated, it only exists few which are proven for an online environment. Moreover, during the refining of SRL models, questionnaires felt like they miss some aspects of the new models or focus on specific aspect of SRL. In order to show this previous statement, the authors based themselves on the Puustinen's [16] article and model (Figure 7). This model is highly related to previous models that we explained in 2.1, the way we may measure SRL is more or less near to the theoretical models. For example, we find the preparatory phase corresponding to the forethought and planning phase. They proposed three main phases including Preparatory Phase : where the learner understands the task, tries to plan, sets goals and strategies to reach them. Then, the performance phase where the learner manages his environment, time and be proactively part of his own learning by seeking help, being motivated, etc. Finally, the learner arrives at the Appraisal phase where he has to think about his strategies, goals and progress in order to adapt himself.

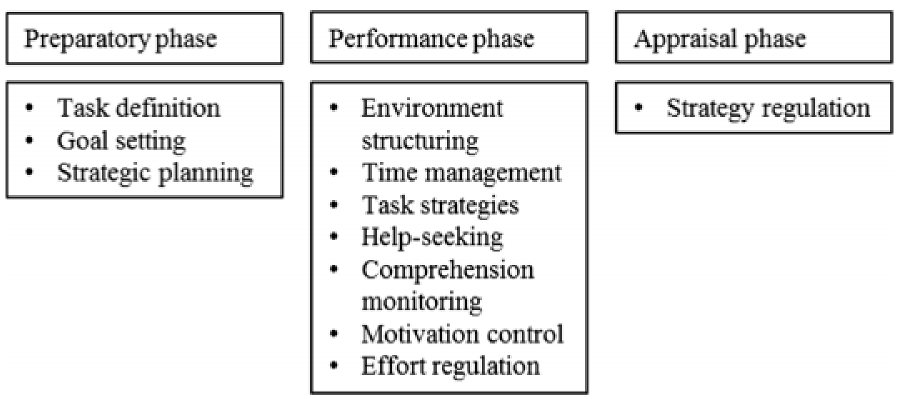


Figure 7: Puustinen's SRL models from [16]

In addition, Jansen proposed to study the four more used questionnaires in the literature including **MSLQ** : Motivated Strategies for Learning Questionnaire [17], **OSLQ** : Online Self-regulated Learning Questionnaire [18], **MAI** : Metacognitive Awareness Inventory [19] and **LS** : Learning Strategies [20] (Figure 8). Then, he proposed a new questionnaire : the **SOL-Q**, validated for the online usage and which takes into account every aspect of the SRL while being the more concise as possible.

| | MSLQ | MAI | OSLQ | LS |
|---|---|---|---|---|
| *Preparatory phase* | | | | |
| Task definition | | X | | |
| Goal setting | | X | X | |
| Strategic planning | | X | | |
| *Performance phase* | | | | |
| Environmental structuring | X | | X | |
| Time management | X | | X | |
| Task strategies | X | X | X | X |
| Help-seeking | X | | X | X |
| Comprehension monitoring | | X | X | X |
| Motivation control | | | | X |
| Effort regulation | X | | | |
| Apprasial phase | | | | |
| Strategy regulation | | X | | |

Figure 8: Scales of each questionnaires from [15]

In this paper, the authors used a two time proof for their questionnaire. Firstly, they regrouped every items of each questionnaires in the previous categories (concatenating overlapping questions, trying to regroup similar ones) and obtained a model with 53 questions. Then, they proposed several new questionnaires based on several methods. We will only focus on the Exploratory Factor Analysis, which aimed at selecting the most important factors from the model. Rather than using Kaiser criterion, they chose to use data matrices which leads them to less controversial results. Finally, they obtained a new model with 36 items and which imposes to refactor the previous categories (Figure 9). For example, the authors showed that metacognitive skills shouldn't be separated in several categories.

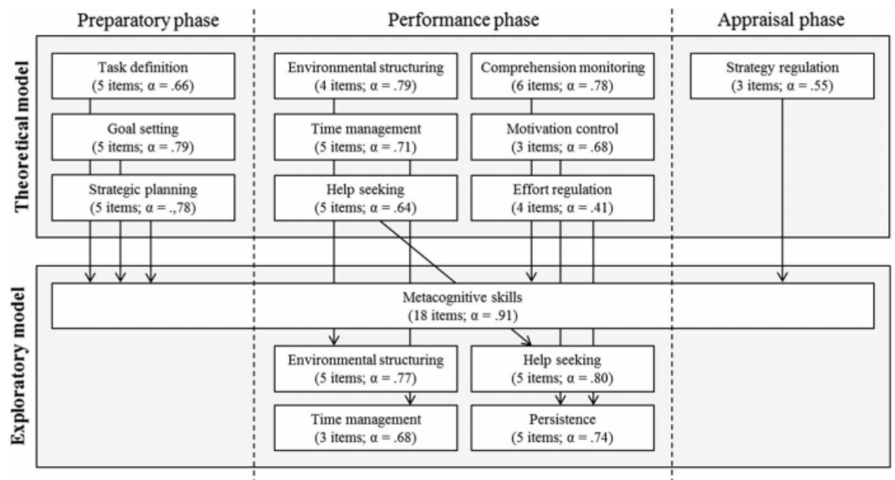


Figure 9: EFA result questionnaire from [15]

Nextly, they ran a second experiment using Confirmatory Factor Analysis. For this purpose, they gathered 159 students' questionnaire over a Dutch and English MOOC using their 4 models (including theoretical model and exploratory model that we already speak about). Each question had to be answered with a 7-Likert scales indicating the confidence or not regarding the question asked. By using several indicators, both relative and absolute fit indices, they were able to obtain relevant results which show that the Exploratory model obtained with the EFA has greater fitting scores (Figure 10). Lastly, following these results, they proposed the SOL-Q questionnaire composed of 36 items dispatched in 5 categories. We won't list them here since the Jansen's paper do it already with great precision in its appendix.

| Statistic | Theoretical model with task strategies | Theoretical model without task strategies | Exploratory model | Exploratory-theoretical model |
|---|---|---|---|---|
| $\chi^2$ | 2530 ($p$ = .000; $df$ = 1270) | 1782 ($p$ = .000; $df$ = 900) | 1066 ($p$ = .000; $df$ = 584) | 1119 ($p$ = .000; $df$ = 573) |
| NC | 1.99 | 1.98 | 1.83 | 1.95 |
| RMSEA | .081 (.076–.085) | .080 (.075–.086) | .074 (.067–.081) | .079 (.072–.086) |
| CFI | .666 | .705 | .777 | .747 |
| AIC | 2852 | 2052 | 1230 | 1305 |

Figure 10: CFA result questionnaire from [15]

While this paper highlights several interesting concepts, such as categories of questions, concise and online adapted questionnaire, it targets older people (the mean age for this questionnaire was near 44 years old). In our context, going from French Elementary school, Middle and High school, the questions can feel a little bit confusing and too hard to be understandable by the children/teenagers. Moreover, authors correctly highlighted the fact that MOOCs are special environments where rules totally change. For example, while in a class context it was assumed that the preparatory phase would be assumed by the teacher, in MOOCs, it is rather the student which will assume this role. Regarding the previous problem of rating SRL skills of children without having any teaching context, it can make our process more complex.

#### 2.3.2 Prompts

Prompts are a main part of SRL assessment when it comes to computer based platform. They are often represented as pop-ups which appear at a specific time during the learning process in order to ask question regarding SRL features to the learner. They allow to gather data before, during and after the exercises. Thus, they enable to add important data for an In-Real Time predictions of SRL and then a response to help the learner which may be detected to be in great difficulties. It also gives crucial information of how the learner is evolving in his environment [21].

In Sabourin's paper [22], the authors built a simulation detective game with the aim of assessing SRL on a computer platform. For this purpose, participants were offered several options to use in context without much information. Their final aim was defined clearly, but they had to conduct by their own an investigation, discover the environment and run experiences. Participant had 55 minutes to end the game. In the first place, they established a pre-profile of the student related to a questionnaire, regarding some aspect of SRL. Then, they gathered data with in-real time prompts during the game about motivations and other evolving factors. Thanks to these prompt, they were able to better predict the category of SRL of each student. As (Figure 11) shows, the authors used the models at several different timers to estimate the best prediction AI models can score. The reports' tags correspond to the SRL in-real time prompts done at 4,11,18 minutes of the game and some trace gathered along the participant actions. These scores show that prompts can make the difference in better predicting the SRL category of students.

| Model | Predictive Accuracy | | | | Low-SRL Recall | | | |
|---|---|---|---|---|---|---|---|---|
| | Initial | $Report_1$ | $Report_2$ | $Report_3$ | Initial | $Report_1$ | $Report_2$ | $Report_3$ |
| Naïve Bayes | 44.2 | 43.5 | 46.1* | 50.5* | 0.47 | 0.28 | 0.54 | 0.52 |
| Neural Network | 42.3 | 43.8 | 46.5* | 45.5 | 0.44 | 0.45 | 0.49 | 0.52 |
| Log. Reg. | 42.7 | 51.2** | 47.7 | 54.5** | 0.45 | 0.65 | 0.66 | 0.73 |
| SVM | 43.5 | 46.9* | 45.7 | 51.4** | 0.51 | 0.55 | 0.56 | 0.62 |
| Decision Tree | 42.7 | 46.2* | 48.1* | 57.2** | 0.45 | 0.55 | 0.71 | 0.71 |

Figure 11: AI model prediction result [22]

Moreover, Wong [23] gathered several studies which show that prompting participants will enable them to overcome some of their difficulties and may lead them to the path of a better self regulation. Firstly, prompting student may increase their planning ability, goal setting [21] and accuracy of seeking information through a free environment [24]. Moreover, learners prompted which were classified as low students SRL can improve themselves due to prompt and become high students SRL, which are able of the same monitoring mechanisms than better students [25]. However, one important aspect that Wong highlights, is that prompting is way more effective on learners who had the opportunity to understand it before using it, or having prior knowledge to it.

### 2.3.3 Interaction Traces

Trace or Log Event are a type of data which contains a timestamp, a link to what it is related and an known event with parameters.

As already mentioned before, stealth methods should be considered as one of the most important part for assessing SRL. Since prompting questionnaires create bias within students behaviors, researchers have though of better ways to gather data and keep student as if they were acting in real conditions. Trace data have been highlighted by several article such as [26] and [27] to better fit the behavior of learners than traditional statistics (mean, median, etc.) [28].

Researchers show that relying on frequency-based statistical analysis doesn't take into account the dimension and time-evolving nature of the SRL features [28]. Moreover, these models consider a group of learners and try to compare their indicators to the individual behavior of a learner. This is not accurate since each individual as his own way of learning and should not refer to the average but to an other category of learner. Whereas, studying data in the perspective of time-series with sequential and temporal pattern mining lead to better understanding of the nature of SRL [26].

Several ways have been explored following this statement, but the most promising ones comes from the Siadaty's article [29] which was one of the first to conceptualize Micro and Macro processing of SRL regarding Trace data. In this article, the authors proposed a model of SRL (Figure 12) where each of the gathered data appears in the form of a Trace/Event Log (Figure 13). Due to their nature, events alone doesn't indicate much to SRL features, but it is rather the combination of series of events which are rather interesting. Then, the aim behind this process is to apply sequential and temporal analysis in order to find recurrent sequences of events which can be then representative of micro-level srl processes (srl features).

**Table 1: Micro-level processes included in the SRL model and their descriptions (Siadaty, Gašević, et al., 2012).**

| Macro-level SRL process | Micro-level SRL process | Description |
|---|---|---|
| Planning | Task Analysis | To get familiar with the learning context and the definition and requirements of a (learning) task at hand |
| | Goal Setting | To explicitly set, define, or update learning goals |
| | Making Personal Plans | To create plans and select strategies for achieving a set learning goal |
| Engagement | Working on the Task | To consistently engage with a learning task, using tactics and strategies |
| | Applying Strategy Changes | To revise learning strategies, or apply a change in tactics |
| Evaluation & Reflection | Evaluation | Evaluating one's learning process and comparing one's work with the goal |
| | Applying Strategy Changes | Reflecting on individual learning and sharing learning experiences |

Figure 12: Siadati's SRL model [29]

| userEvalUserNo | eventTime | eventId | eventType | propKey | propValue | resourceType | resourceURI |
|---|---|---|---|---|---|---|---|
| LA77 | 2012-0... | 17684 | SelectNodeEvent | nodeView | target | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17684 | SelectNodeEvent | nodeid | 1.1.3.1.2... | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17685 | OpenTabEvent | tabName | Asset For... | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17685 | OpenTabEvent | nodeTitle | Referenc... | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17685 | OpenTabEvent | nodeRelName | ASSET | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17685 | OpenTabEvent | nodeView | target | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17685 | OpenTabEvent | serviceName | LPC | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17685 | OpenTabEvent | nodeid | 1.1.3.1.2... | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17686 | TaggingEvent | keywords | website | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17687 | Edit | keywords | website | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17687 | Edit | visibility | Public | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17687 | Edit | assetURL | /reference/ | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17688 | SelectNodeEvent | nodeTitle | The C Pro... | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17688 | SelectNodeEvent | nodeRelName | ASSET | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17688 | SelectNodeEvent | nodeView | target | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17688 | SelectNodeEvent | nodeid | 1.1.3.1.5... | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17689 | OpenTabEvent | tabName | Asset For... | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17689 | OpenTabEvent | nodeTitle | The C Pro... | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17689 | OpenTabEvent | nodeRelName | ASSET | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17689 | OpenTabEvent | nodeView | target | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17689 | OpenTabEvent | serviceName | LPC | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0... | 17689 | OpenTabEvent | nodeid | 1.1.3.1.5... | KnowledgeAsset | http://intelleo.org/triplestore/bc_x#KnowledgeAsse... |
| LA77 | 2012-0 | 17690 | SelectNodeEvent | nodeTitle | [illegible] | Activity | [illegible] |

Figure 13: Trace Event example [29]

Even if this process is still promising and currently a research trend, it should be noticed that there are also limitations due to its newness. One the main criticism is that there are still no framework well accepted and theory is currently evolving in the field. Moreover, considering data as Event doesn't take into account the interdependency of each SRL features with another.

### 2.3.4 A synthesis of SRL measurement

Table 2: SRL Measure Types' contribution

| Measure | Data type | Benefits | drawbacks |
|---|---|---|---|
| Question-naire | Ordinal (Likert) | Complete SRL Features measured. Researcher's approval. Ready to use | Time-consuming. Hardly understandable by under minority learners. Not always adapted to digital usages. Assessment is not stealth. |
| Prompts | Ordinal (Likert) or Categorical (choices) | Adaptive Time and Understanding. Adapted to digital environment | Need to prove efficiency and readability of each question. Assessment is not stealth. |
| Trace | Log (Timestamp, event, information) | Stealth assessment. Report real actions rather than one's thinking. Can display hidden potential SRL features. Adapted to digital environment | Actions alone doesn't mean anything (for example : a click). Data needs to be related to the context of the platform. Hard to aggregate data to find real indicators |

# 3 Bayesian Networks : Theoretical frame and algorithms

In this section, we introduce the main Artificial Intelligence algorithms and theories which help us to understand and categorize learners in online environment.

## 3.1 An introduction to Bayesian Networks

Bayesian Networks (BN) are part of the probabilistic theory and graphical model. They represent a joint distribution which is aimed to be simplified by the use of independency between variables[30]. They are often represented as a directed acyclic graph (DAG), with nodes representing the variables and the directed edge the dependency between one variable to an other. In (Figure 14), we note Weather as the parent of IsMotivated and IsMotivated as the child of Weather and so on for each node and directed edge.

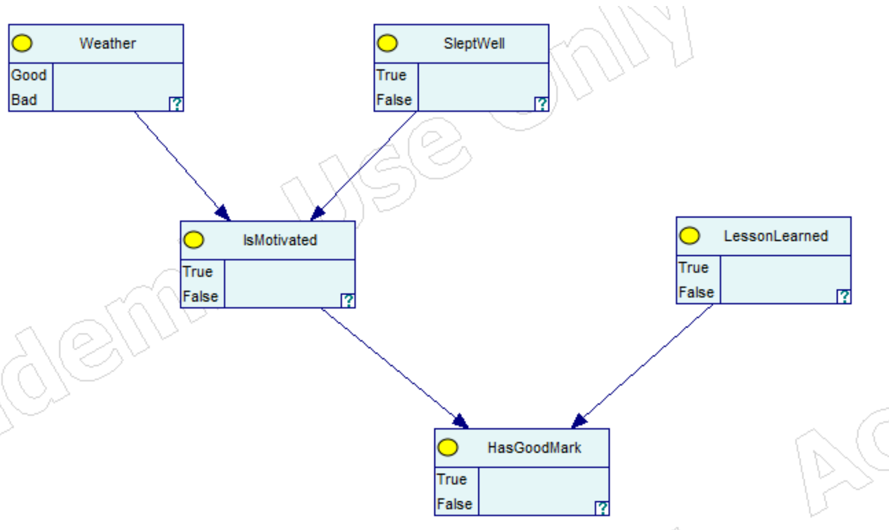


Figure 14: DAG representing a BN using GeNIe Modeler

Bayesian Networks use the Markov assumption which assume that considering a set of variable, each variable will be only dependent with its parents and child. Therefore, it helps to simplify the joint distribution of a set of variables and enables to consider the related node as independent of the past variables and only dependent of their parent variables. Then, each node or variable is expressed as a conditional probability of all its parents. In a set of a binary variables, regarding (Figure 14), the Weather variable would have 2 conditional probabilities to store and the IsMotivated variable $4 * 2 = 8$. This comes from the formula $2^m * n$ with $m$ the number of parent of the node and $n$ the number of state of the variable. Thus, simplifying the network with independencies can be really a gain over the complexity problem, but it assumes that every variables can be totally independent with another which is rarely the case in real problems. The way to handle this problem is to only consider a sufficient amount of the best dependent variables. The more we add variables and edges, the more it is supposed to be near from reality. Last but not least, BNs are really useful model to understand the relation between variables, as they provide easily readable graphical representation and interaction. So they can be built from data or/and expert in the field.

## 3.2 Belief Propagation

When the networks is complete with all Conditional Probability Dependencies (CPDs), we can make several observations regarding only some of the variables. Regarding (Figure 15), the variable IsMotivated is observed to True. This totally changes each probability for each nodes since we are sure that IsMotivated is set to true. Thus, the belief propagation is aimed at updating all the network regarding every observed nodes. One of the main algorithm for this task is the Message Passing Algorithm [31].

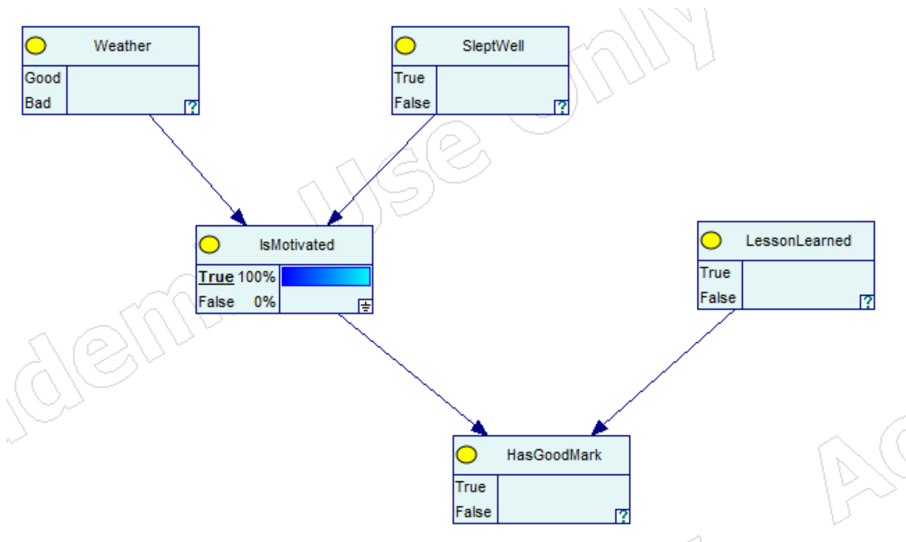


Figure 15: Bayesian Network with observed node

In order to update each variables, we will create two messages, one from the parents of the node and ascendant of parents to the node. Another from the children of the node and descendent of children of the node. Each message coming to the node will be used with CPDs to compute the marginal probabilities of the node [30]. In (Figure 16), after applying the message passing algorithm, each state of each node obtain a new marginal probability regarding observed nodes. This is helpful to understand relations between variables in our network, it makes the Bayesian Networks a powerful tool to understand interactions with variables in a dataset.

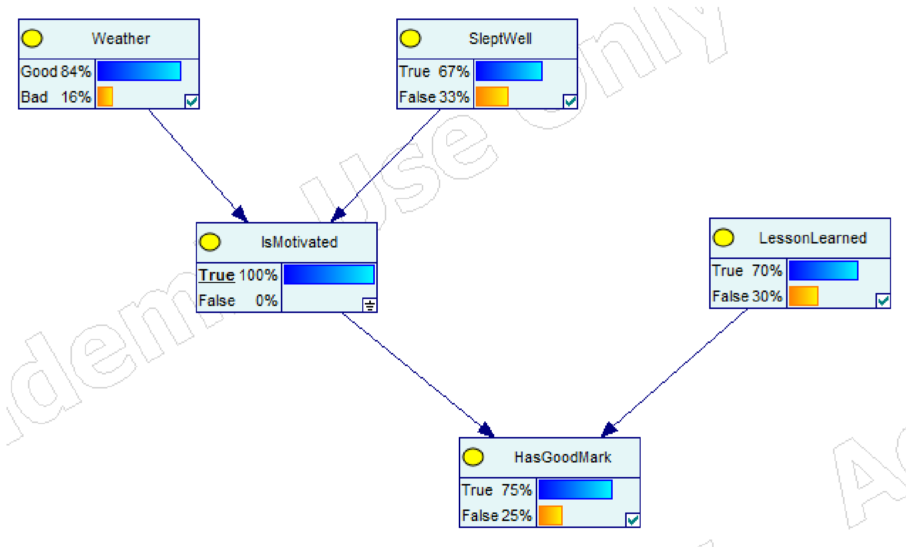


Figure 16: Bayesian Network with observed node and belief propagated

### 3.3 Parameter Learning

As we already mentioned it before, the CPDs can be built with both expert knowledge but also datasets. When an expert is not available or that we have some confidence in our dataset, we can try to estimate our CPDs using the parameter learning's algorithm. It is obvious that, the more data we have in our dataset, the more the estimation will be robust. There are two cases : when the dataset has complete data and incomplete data.

#### 3.3.1 Complete Data

In the case of complete Data, it exists several algorithm but we will focus only on Maximum Likelihood Estimation (MLE) and Expection A Posteriori (EAP). Regarding MLE[32], the aim is to estimate each state of parameter $\theta$ (conditional probabilities) :

$$\hat{P}(X_i = x_k | Pa(X_i) = x_j) = \theta^{MLE}_{i,j,k} = \frac{N_{i,j,k}}{\sum_k N_{i,j,k}} \tag{1}$$

with $N_{i,j,k}$ the number of occurrences of $X_i = x_k$ and $Pa(X_i) = x_k$. And $Pa(X_i)$ the parent CPD state regarding $X_i$.
Regarding **Table 1**, we obtain :

- $P(V1 = a) = \frac{4}{4+3} = \frac{4}{7}$
- $P(V1 = b) = \frac{3}{7}$

- $P(V2 = a|V1 = a) = \frac{3}{4}$
- $P(V2 = b|V1 = a) = \frac{1}{4}$

One of the major problem of MLE is that it requires a certain amount of data to be statistically confident. If our data are not sufficient and biased regarding the reality, there will be not adjustment or regulation over the likelihood computation and thus it can lead to really biased CPDs.

Therefore, we consider using the EAP algorithm which use Dirichlet coefficient to regulate the likelihood [33]. we compute :

$$\hat{P}(X_i = x_k|Pa(X_i) = x_j) = \theta^{EAP}_{i,j,k} = \frac{N_{i,j,k} + \alpha_{i,j,k}}{\sum_k (N_{i,j,k} + \alpha_{i,j,k})} \tag{2}$$

with $\alpha_{i,j,k}$ a Dirichlet coefficient. We define the Dirichlet coefficient :

- $\alpha$ of $P(V1) = [50, 50]$
- $\alpha$ of $P(V2|V1 = a) = [90, 10]$

with index corresponding to letters in the alphabetic order. Regarding **Table 1**, we obtain :

- $P(V1 = a) = \frac{4+50}{4+3+100} = \frac{54}{107}$
- $P(V1 = b) = \frac{53}{107}$
- $P(V2 = a|V1 = a) = \frac{93}{104}$
- $P(V2 = b|V1 = a) = \frac{11}{104}$

Here, the fraction are more balanced regarding the Dirichlet coefficient. But the more data with have in our dataset, the less those coefficients will have some weight in the computation.

Table 3: Small example Dataset for complete Parameter Learning

| V1 | V2 |
|---|---|
| a | a |
| a | b |
| b | b |
| a | a |
| a | a |
| b | b |
| b | a |

### 3.3.2 Incomplete Data

In some cases, our dataset can lack some values in observed or gathered variables. It may be a problem since, regarding complete data analysis, we would have to eliminate each of the row which contains at least 1 missing value. Then, it will bias our model and result. But in those rows, there are still interesting values, which can be used to improve some of the conditional probabilities.

In this part, we will mainly focus on the Expectation Maximization algorithm (EM), which one of the most known and accepted through researchers. But we can use several other methods such as Gibbs Sampling, RBE Algorithm or data perturbation [34]. This algorithm proceeds with several steps : In the initialisation process, we estimate the conditional probabilities of the network based on several methods (Random, Complete Data analysis, Constrained EM, ...). Then, we can enter in the Expectation phase were we will loop for the first time over the dataset, taking each row one by one, considering only the one with missing values. By using inference with each row, we are able to obtain new count values for missing values and then, each missing values will have as many probability than the number of categories it has, such that each category has a probability regarding inference of the row. Therefore, we can use those probabilities on each row to increase our contingency table and thus update the parameters (conditional probabilities), this is the Maximization phase. Since our model is more reliable by the end of the previous process, researchers have shown that repeating the process until the parameters converges will lead to better estimations [35].

However, the EM algorithm is still subject to criticism. In the context of important missing values, it may performs poorer than expected and lead to biased results [34], researchers proposed the CEM algorithm with tends to improve this process. Moreover, EM found itself easily stuck in local minimum rather than global minimum without the possibility to get out, researchers [36] also found a way to improve such results.

## 3.4 Dynamic Bayesian Network

Dynamic Bayesian Network concept lies between probabilistic graphical model and the Markov Theory. They are often used to represent complex BNs with a discrete time parameter. It means that a set of variable X exists at several fixed time intervals and repeats itself such that $X = \{X_1, ..., X_t\}$ with $t$ the discrete time. Such set of variables has inner-dependencies, meaning that all the variables in $X_1$ are dependent or not to other variables in $X_1$, and external dependencies such that, $X_1$ variables are dependent or not to $X_2$ variables and so on [37]. An example is shown in (Figure 17), where we represented the simplified human process of eating. In DBNs, the current time set of variable is said to be only dependent of its past nodes. Each past variable can interact with a future variable which is may not be in the next set but in the n-th set, these relations are said to be order n. In (Figure 17), there are only first-order relation between past and current variables.

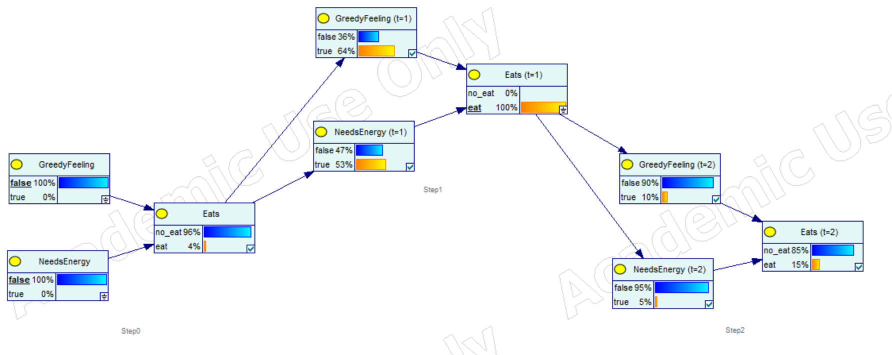


Figure 17: Dynamic Bayesian Network using GeNIe Modeler

In the purpose of easily understanding, we do not present in details the mathematics behind inference and parameter learning since they are quite the same than Bayesian Networks. At least, there are some adaptations to do in order to have EM algorithm and Forward-Backward inference propagation working [30]. We discuss in further section the implementation and interest of Dynamic Bayesian Networks in online learning assessing.

# 4 SRL supports using BN and DBN

In this section, we show previous research which apply Bayesian Networks and Dynamic Bayesian Networks on concrete digital game environment. In this purpose, we will mainly focus on the Sabourin's studies [22, 38] since they are the nearer and best representing researches for our context. Moreover, the process is well explained and reliable.

## 4.1 Introduction of the research

In the first paper [22], researchers decided to run experiments which aimed at predicting the SRL class of someone. They stated that, since low SRL people are the ones who suffer the most from SRL features, they need to be detected early on and helped in their journey through a game, a platform or a course.

Nevertheless, they firstly had to run an experiment to show the difference between 3 categories : low SRL, medium SRL and high SRL students. So, they could examine the result and try to predict their category through series of collected data.

For this purpose, they used and managed a simulated game environment called Crystal Island. People had 55 minutes to solve a mystery without knowing anything else than the features proposed (taking notes ...). Thus, they were prompted to do a pre-test in order to collect 26 features which represent the candidates (emotion, goal set, personality ...). Then, at 4, 11 and 18 minutes, they received a small self-report about their feeling, their progress and whether or not they felt lost. Finally, at the end of the game, all the candidates went in a separate room to answer questions regarding the game (post-test).

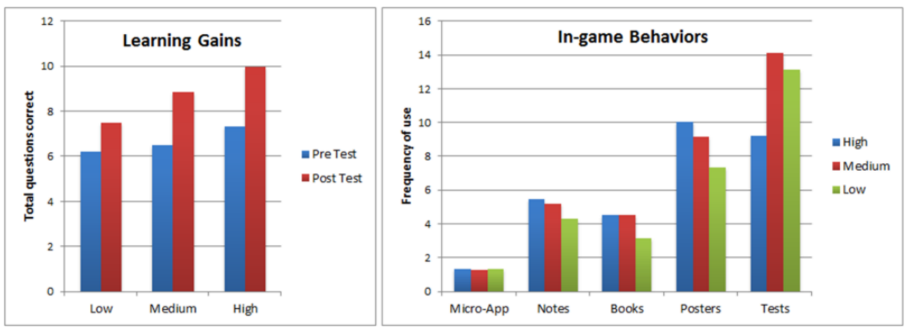


Figure 18: Learning gains and In-Game Behavior SRL groups from [22]

In the first place, they show that during the pre-test, candidates from low to high SRL had quite the same results (medium and high being just a little better than the low ones). But regarding the post-test, the results totally changed : low SRL progressed a little, medium ones did really well and high SRL were the best (Figure 18). Thus, they confirmed the fact that, beginning from the same point the inequalities through a SRL environment were aggravated between the different classes. Moreover, they also compared the actions done by the students during the game and showed that some of the behaviors were part of the success of some of the students, **Fig. 2**.

In the second and last experiment, they try to predict the category of SRL of students during the pre-test, 4,11 and 18 minutes reports. They use several Machine Learning models such as Naïves Bayes, Neural Network, Logistic Regression, SVM, Decision Tree. As we can see, the results were quite balanced for the pre-test and first report. They reach at most 51.2% accuracy (which is better than 1/3). Without any surprise, the accuracy increases with the more data gathered (second and third reports) and reaches at most 57.2% with the decision Tree. Regarding the experiments, it means that at 18 out of 55 minutes, we can detect with an accuracy of 57.2% a candidate's SRL class (Figure 11). This seems to be a better score but it also represents 1/3 of the total time to detect a SRL class (which can be a little bit late regarding real-life examples).

## 4.2 Using BN and DBN to improve results

Following their previous work, Sabourin et al. [38] reused the same experiments in order to try a new model : Dynamic Bayesian Networks (DBN). The intuition is totally justified since DBN are a subpart of Bayesian Network using variables and conditional relations to represent a problem, but which follows Markov Theory. It means that, instead of having only one system, we have the same system over and over regarding a periodic event which in our case can be represented as pre-test, 4, 11 and 18 minutes self-reports.

Therefore, it totally fits the experiments since there are some dynamic data given by the game player's actions and choices and fixed ones which totally depend on the player. Moreover, the authors decided to create three variables which are an aggregation of all the variables :

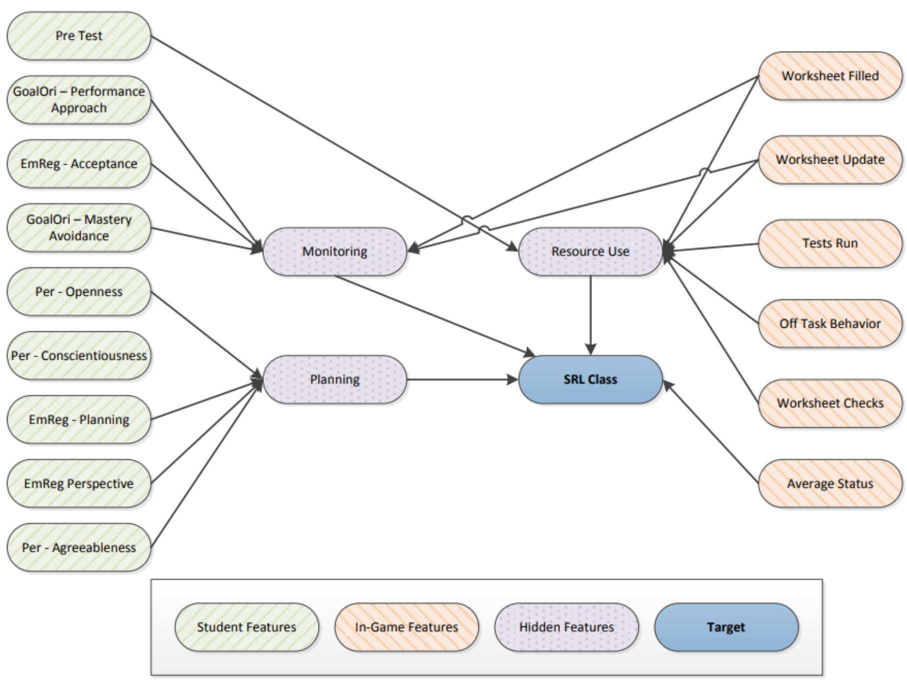


Figure 19: BN structure [38]

- **Resource Use** : In-Game behavior and actions
- **Planning** : How the students plan in new situations, handle cognitive emotions ...
- **Monitoring** : goal set, learning consciousness, use of worksheet ...

As we can see in (Figure 19), the authors chose to represent the aggregated variables as a dependency of in-game and students' features. Then, the SRL class is a variable dependent on the aggregated variables and the self-reports. Moreover, they selected only 15 of all the initial variables with a statistical test (to be significant). Finally, they decided to run the EM algorithm to approximate the Conditional Probability Tables. Notice that everything was produced with the help of the software GENIe, Thus, we obtain the following DBN :

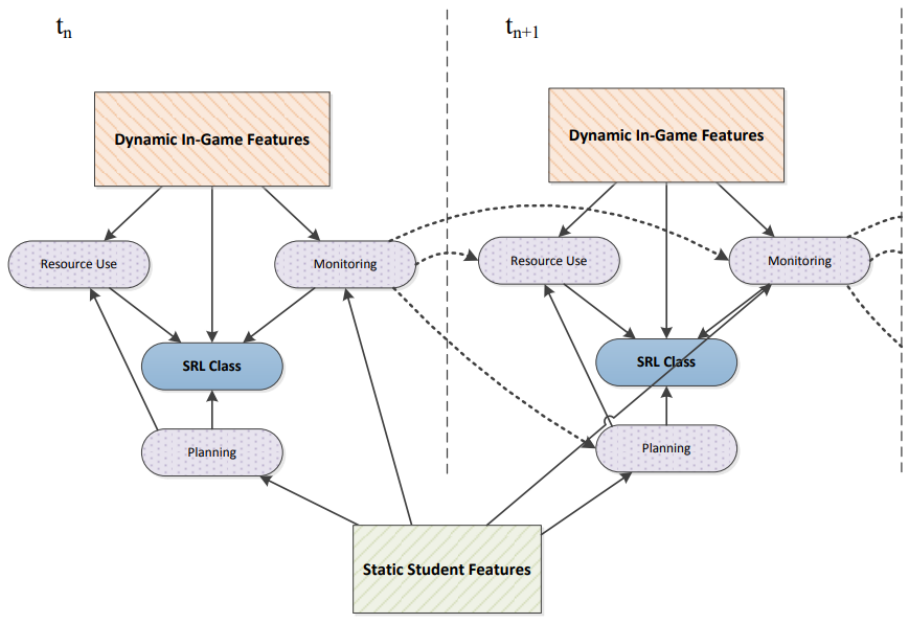


Figure 20: DBN structure [38]

(Figure 20) shows us the periodic structure of the DBN, that it is needed to be repeated 4 times in order to have every events of the experiment. We can see that, they chose to only select the Monitoring variable to represent the periodic dependency between events (Monitoring$_n$ $\perp$ Ressource Use$_{n+1}$, Monitoring$_n$ $\perp$ Planning$_{n+1}$, Monitoring$_n$ $\perp$ Monitoring$_{n+1}$).

| Model | Predictive Accuracy: Initial | $Report_1$ | $Report_2$ | $Report_3$ |
|---|---|---|---|---|
| Top Prior Model | 42.7 | 46.2 | 48.1 | 57.2 |
| Bayesian Network | 64.8 | 67.0 | 67.5 | 68.5 |
| Dynamic Bayes Net | 64.5 | 80.5 | 81.3 | 83.1 |

Figure 21: Predictive model accuracy [38]

| Class | Bayesian Network | | | | Dynamic Bayesian Network | | | |
|---|---|---|---|---|---|---|---|---|
| | Initial | $Report_1$ | $Report_2$ | $Report_3$ | Initial | $Report_1$ | $Report_2$ | $Report_3$ |
| Low | 0.67 | 0.67 | 0.70 | 0.58 | 0.73 | 0.71 | 0.73 | 0.75 |
| Medium | 0.61 | 0.57 | 0.59 | 0.68 | 0.49 | 0.78 | 0.80 | 0.84 |
| High | 0.66 | 0.77 | 0.73 | 0.79 | 0.71 | 0.92 | 0.91 | 0.91 |

Figure 22: Predictive accuracy regarding SRL classes and prompts [38]

This architecture leads researchers to obtain promising results as we can see in (Figure 21). Compared to previous model results, the Bayesian network increases its accuracy of 20% in early stage and 10% at the last self report. This leads to, at least, more than 2/3 chance to predict the SRL class. But even better, the DBN obtain a score of 80.5% at the first self report regarding other results and the time spent in game. At the end, the model gains 3%.

Last but not least, In (Figure 22), we also observe that the DBN and BN struggle the most to predict low SRL class compared to medium and high classes. It ensures us to have a good classification for the ones who need less to be detected and a rather worse one for the other.

## 4.3 A synthesis of BN and DBN usage

As we may already have mentioned before, the results are quite promising since they offer a good accuracy early on in the process. Therefore, within 4 minutes, the DBN is able to isolate correctly the low class SRL with a 75% success. Classifying such students in these categories could help the worst ones to progress and maybe reach the medium or high classes in the next report, to correct the middle ones to reach the high class and finally, to try to raise even more the high class.

Nevertheless, we may discuss some aspect of the previous research :

- **Reproductibility** : In this paper, the major part of the data, the statistic methods and processes have been explained. However, we tried to obtain their data but we are still waiting for the answer. In addition, those types of data are hard to simulate since there is no information about their nature (range, distribution, type).

- **Conditional Probability Tables** : CPDs are really important if we want a model that fits the reality. In this paper, the EM algorithm was used to approximate them since they had no clue or reason to do it manually (with expert knowledge) [39]. This may lead to worse results and maybe some contradictions even if the EM algorithm is proven to be a good solution.

- **DBN dependencies** : Regarding the directed edges in the DBN, we may criticize the choices. Can we really say that the variables are dependent of Monitoring or that Monitoring is dependent of the variables ? They chose the second option and then this could be discussed. In another study [40], Gherasim et al. show a "top-down" approach which considers the indicators "state of the component" as a central variable on which other variables are dependent ("state of wind farm" and "failing indicators"). This could be reproduced in this DBN by inverting some arrows between aggregated variables (Monitoring, Planning, Ressource Use) and candidates/in-game features.

# 5 France's IOI platform : quick-pi

In this section, we focus on the platform we choose to implement our modules and models.

Quick-pi is a web platform, built by France IOI, which is aimed at providing learning activities and challenges to high school french students. The main theme is connected objects and IoT. Learners enroll themselves in 3 learning paths : Discovering sensors and electronic equipment, Discovering memory and programming language specificity and finally advanced language structure and communication between devices. At least, Quick-pi receive a large traffic per year near 80.000 participants, and can be used by independent learners or classrooms. Thus, even if the targeted audience is still the same, learners do not have the same environmental structure and help seeking possibilities. However, on the platform, they will have to answer the same problems and exercises.

Each activity follows the same process : Before anything begins, the learner is prompted the programming language he wants to use between Scratch, Python and Blockly. Then, he enters the exercise panel where he can select one. Focusing on an exercise also call subject, the learner is facing an well-designed interface where he can program and solve the challenge. Regarding (Figure 23), the interface is segmented between several areas. Firstly, at the top of the web page, there is the basic information of the subject but also the activity as the number of cumulated points obtained when succeeding an exercise. Stars represents the difficulty also call version of the subject from two to four. Nextly, we have the subject's information and execution display on the left middle and upper side. This provides context and goal of the exercise, with in addition, help link for the learner. On the bottom left corner, there is the code execution control. It helps the students debugging, testing and be their own manager of the code's execution. they can control speed, step to step, go to end and validation of their answer. Lastly, on the right side, there is the programming prompt where learners write code. Moreover, they have floating icons which enables them to seek help if they struggle.

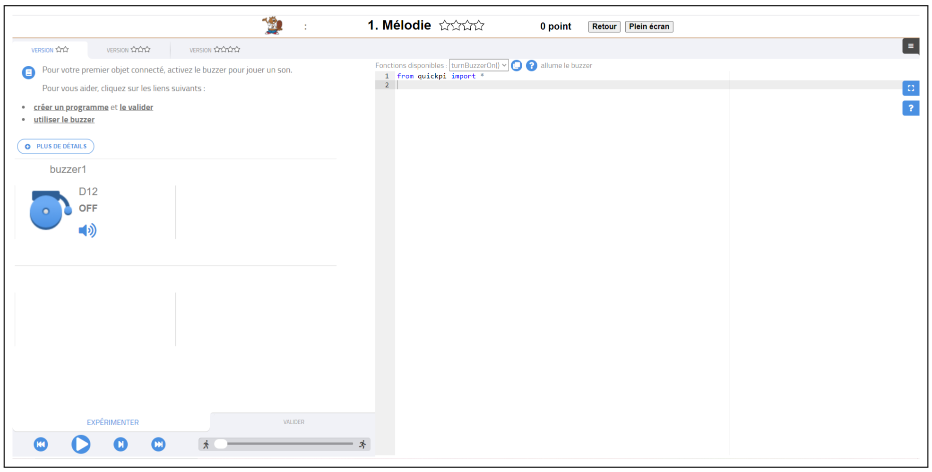


Figure 23: Quick-pi subject interface

In the first time, we decided to only work with this platform. The learning process will not be followed during several activities, then we focused on a unique session to gather data, interpret them and propose solution to the learner.

# 6 Our contribution

In this section, we highlight our contribution to the research field and the learning process on quick-pi. In the first place, we show how we decided to gather data, then in a second point, we focus on our experiments and data exploration. Finally, we present the different strategies and models we use to predict SRL.

## 6.1 Gathered Data

One of the most time-consuming aspect of this internship was to build a new module from scratch which will handle the gathering of data on quick-pi. This module works on its own and is just called by the platform. It had to handle both, prompts drawing and interaction trace gathering.

### 6.1.1 Timestamped Prompts

As one of the most important aspect of assessing SRL as we described in 2.3.4 and 4.2, we choose to use prompts as a manner to gather data on the learner thinking of one-self and self-regulated processes. We define three prompts which appear before, during and after the activity. But in order to have as accurate question as possible, we based ourselves on the SOL-Questionnaire. Since our audience is high school student, we greatly reduce the number of questions from the original questionnaire in order to take into account the time constraint of the activity but also the capacity of comprehension of learners. We only keep the most important aspect of this questionnaire, simplifying the most part while keeping the original SRL feature measured. Moreover, some of the questions were not accurate regarding the different process of learning in a MOOC and on a unique challenging session. We detailed the categorical and ordinal possible answers in the appendix 7.2.2.

| **Num** | **Question** | **Response** | **Category** | **SOL-Q questions** |
|---|---|---|---|---|
| 1 | Have you already used quick-pi ? | Ordinal | Metacognitive Skills | 1,2 |
| 2 | Have you ever programmed ? | Ordinal | Metacognitive Skills | 1,2 |
| 3 | Where do you practice this activity ? | Categorical | Environmental Structuring and Help Seeking | 22,23,24,25; 33,35,36 |
| 4 | Is there someone to help you ? | Ordinal 5-Likert Scale | Help Seeking | 32,34 |
| 5 | What is the reason for you doing this activity ? | Categorical | Environmental Structuring | 26 |
| 6 | What is your goal ? | Categorical | Metacognitive Skills | 3,4,5 |

Table 4: Initial Prompt

Firstly, we define the Initial Prompt (Table 4). It will appear to the user before the beginning of the activity in order to have several data regarding the context and the learner. You can refer to the Appendix 7.2.1 to see how it is displayed to the user.

| Num | Question | Response | Category | SOL-Q questions |
|---|---|---|---|---|
| 7 | Are you motivated and interested in this activity ? | Ordinal 5-Likert Scale | Persistence | 27,28,29,30, 31 |
| 8 | How do you handle your time ? | Ordinal 5-Likert Scale | Time Management | 19 |
| 9 | Do you think you can reach your goal ? | Ordinal 5-Likert Scale | Metacognitive Skills | 13 |

Table 5: Mid-term Prompt

Then, we define the Mid-term Prompt (Table 5). It will appear to the user at the middle of the activity in order to gather data regarding the feelings, the behaviors and self-consciousness of the learner.

| Num | Question | Response | Category | SOL-Q questions |
|---|---|---|---|---|
| 10 | How have you handled your time ? | Ordinal 5-Likert Scale | Time Management | 19 |
| 11 | What do you think about your strategy in order to reach your goal ? | Ordinal 5-Likert Scale | Metacognitive Skills | 9,18 |
| 12 | Have you reach your goal ? | Ordinal 5-Likert Scale | Metacognitive Skills | 9,14,18 |
| 13 | Something else you want to tell us | Commentary | Out of SRL | - |

Table 6: Final Prompt

Lastly, we define the Final Prompt (Table 6). It will appear to the user at the end of the activity in order to collect data regarding the result obtained, the thinking regarding goals and management of ones learning.

We are aware that considering SOL-Q, this prompt lacks some aspects or regroup many questions in one. We don't pretend to have the perfect prompts but we choose simplicity and understanding over accuracy on each concept. Moreover, we also are conscious of the fact that, Traces will help to gather data which will answer some of the questions of SOL-Q that prompts didn't.

### 6.1.2 Interaction Traces

In order to enhance our data through SRL perspective, we implement the gathering of many interactions between the participant and the platform. This enables to keep track of true actions unlike reported thinking of learners. In addition, it helps us simplifying the questionnaires / prompts asked to student in order to keep them concentrated in their task. The gathering is stealth and done during while the participant is taking actions. We define several interactions :

| Name | Description | Utility |
|---|---|---|
| Focus | If the user leave or get back to the web page | the user is doing something else, is looking for outside content |
| Navigation | If the user navigate on a platform's module (exercise, help ...) | keep tracking of exercise investment, organization of ones solving. |
| Modification | If the user change something in his solution | keep tracking of exercise solving evolution. |
| Mouse | The user movement and actions with the mouse input | keep tracking reading, playing behavior with the mouse. |
| Keyboard | The user actions with the keyboard input | keep tracking typing. |
| Step to step | If the user execute his code, with which speed and step to step or not | See if the participant try to understand, if he manages correctly his environment. |
| Validation | If the user validate his code, the score associated and the potential error | what kind of error learners make, test strategy or not. |

Table 7: Interaction Trace synthesis

As already mentioned before, those events doesn't mean anything alone. Their associated timestamp give better information to deduce behaviors, but the most interesting aspect is to be able to aggregate a set of continuing traces and give them accurate signification. Our aim is to be able to take into account aspect like strategy, environment usage and behavior. We detail with more accuracy our database model in the appendix 7.1.2.

## 6.2 Experiment

Coming soon ...

### 6.2.1 Prompt Validation

Coming soon ...

### 6.2.2 Data exploration

Coming soon ...

### 6.2.3 First Dynamic Bayesian Network

Coming soon ...

## 6.3 Approach and models

Coming soon ...

# 7 Appendix

In this section, we will discuss of the architecture we built in details.

## 7.1 The architecture

We were offered two main possibilities : the first one was to create module which is integrated into the main targeted platform of France IOI. The advantage is that everything works on the same website and it doesn't require new web servers. However, we rather choose the second option which is to create a separate module from front-end to back end and database, which will only be called by the platform when needed. Even if it represents more hardware components or containers, this process helps us to generalize for every France IOI's platform and then easily maintain and propagate the module.

### 7.1.1 Architecture

In order to gather and transmit data to our back-end and database, we developed a front-end module using the framework React.js (Javascript based). This module will also use the JSChannel framework or HTML IFRAMEs, which helps to import a web page into another one and use all the inner javascript functions. Then, it enables us to create a separate front-end with his own function, which handle JSON formatting of the gathered data and then push them into a back-end API. As stated before, we choose to have a single array to transmit specific object in JSON, enabling us to send data with handling congestion and timers avoiding us to lose some important data due to unwanted disconnection or a bad manipulation of the users.

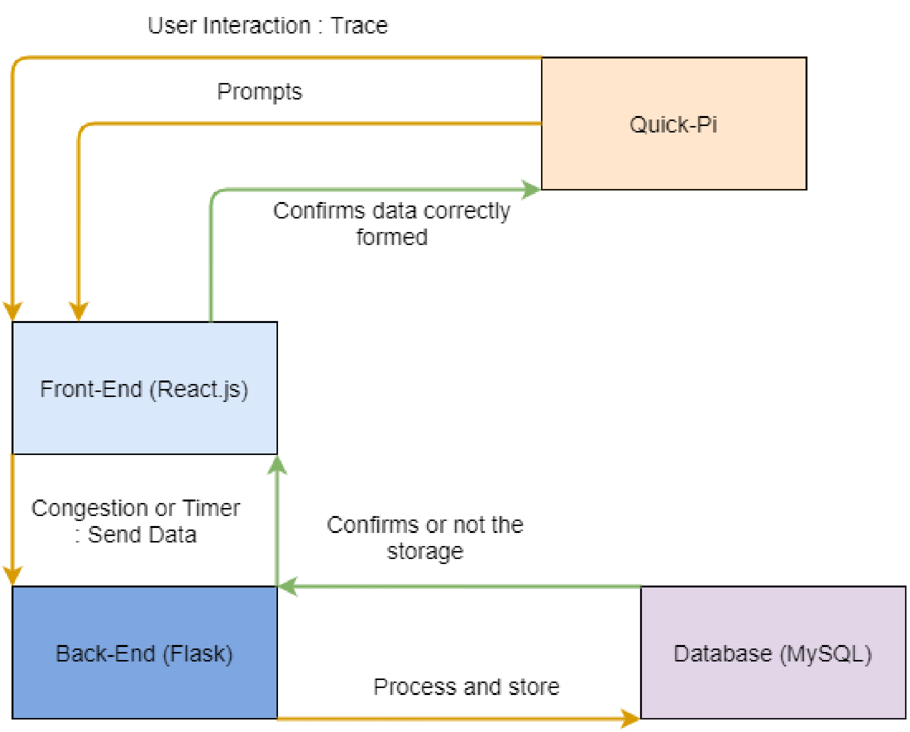


Figure 24: Interactions between modules

Moreover, the module also contains the SRL prompt : Initial, In-Real Time and Final. They just need to be called through a function or will be shown at various regular intervals (In-Real Time). Then, every prompt is handled in our side and helps us to easily modify the code without focusing on the France IOI's platform. Finally, all the design needed to be minimal as France IOI's design chart wants to adapt on the most web navigators possible (even really older version) with the less complicated design possible. Thus, we used the Bootstrap's framework with its easy responsive and simple designed component.

In the second place, we developed a back-end API in Python 3 using the Flask framework. We choose this language because it is one of the most known and complete for AI generally speaking. Considering Flask which is a really great tool to simplify REST API due to its swaggers, we mainly choose it since it is one of the most accepted web framework for python. This server handles and receives JSON data and process them (check, refactoring, add information), they are formatted respecting a JSON Schema validator, enabling security and reducing errors. Then, it sends every piece of information to the MySQL database. It uses the REST technology to handle asynchronous call from various front-end member called on several computers. In the first time, this server is only dedicated to brute storage of information coming from the

France's IOI platform, but after, we also decided to deploy our models and response to our model's results.

### 7.1.2 MySQL database

We decided to use MySQL conceptor to show the relation between our tables. Moreover, Participant are identified by a unique URI which doesn't give any personal information.

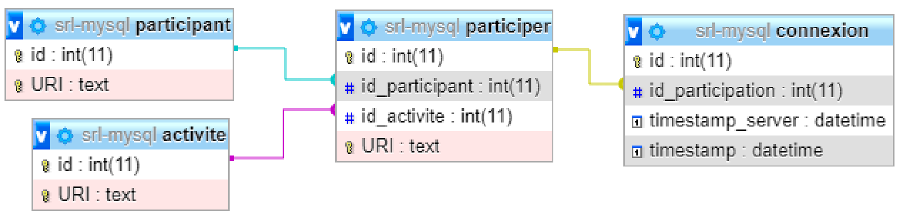


Figure 25: Basic Relations

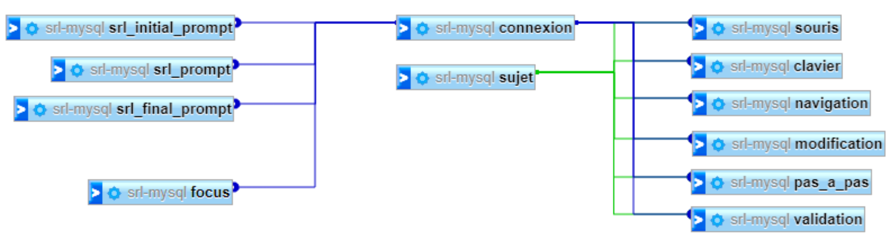


Figure 26: Traces and Prompts Relations

One participant should involve in an activity thanks to the participate table. Then, he can have disconnection or several-days course for one activity, the connection table handle those behaviors (Figure 25). Thus, every prompt and the focus table is linked to a Connection. Moreover, the other traces tables are also linked to a subject (Figure 26). We can finally easily get the whole process of logs only by knowing a participation.

## 7.2 Prompts

In this section, we show and describe our prompts with more details.

### 7.2.1 Interface

The interface was realized with Bootstrap's framework and CSS/SASS stylesheets. It is purified but style warm-full for a high school audience. We have three types of data such that :

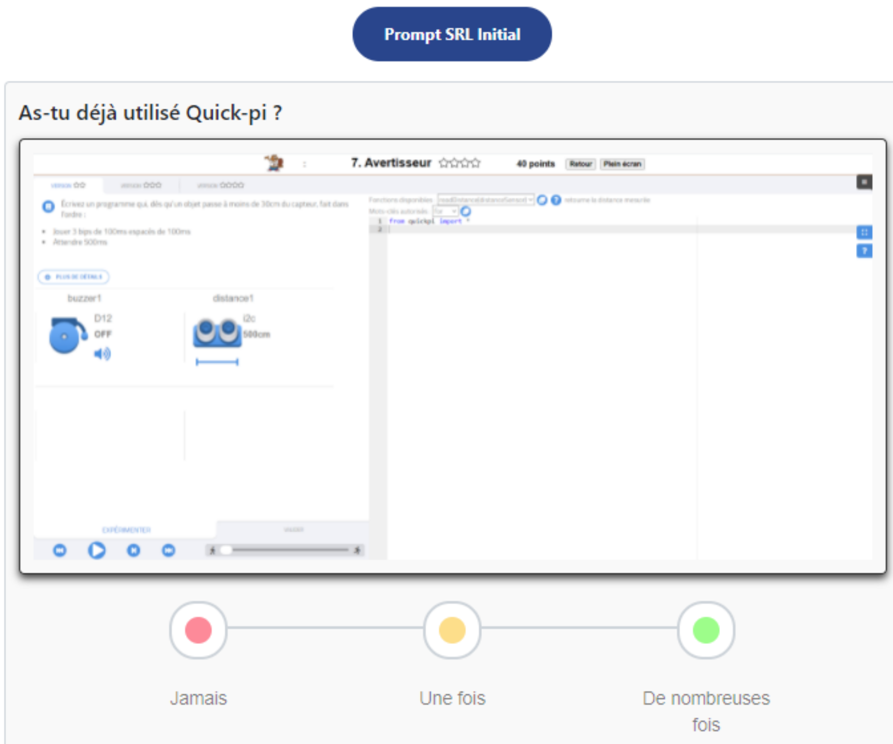


Figure 27: Ordinal Non-Feelings Question : Num 1

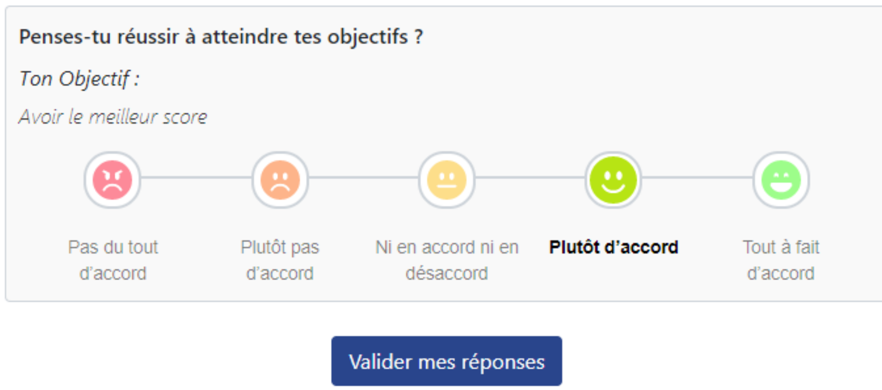


Figure 28: Ordinal 5-Likert Question : Num 9

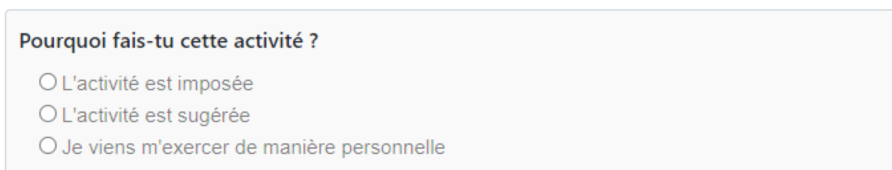


Figure 29: Categorical Question : Num 5

### 7.2.2 Answers Description

We describe here in a more accurate way our prompts' answers. We also added conditional questions.

- **1** : Have you already used quick-pi ?
  - Never
  - One time
  - Several Times
- **2** : Have you ever programmed ?
  - Never
  - One time
  - Several Times
- **3** : Where do you practice this activity ?
  - At home

  - At school

- **4** : Is there someone to help you ?
  - I'm in total autonomy
  - Very rarely
  - Sometimes
  - Often
  - Very frequently
- **5** : What is the reason for you doing this activity ?
  - This activity has been imposed to me
  - This activity has been suggested to me
  - I want to train myself
- **6** : What is your goal ?
  - I don't have any goal
  - Get the best final score
  - Having a good grade to my course
  - Having fun
  - Improving my coding skills
  - Learn to code a connected object
- **7** : Are you motivated and interested in this activity ?
  - I Totally disagree
  - I disagree
  - I am neutral
  - I agree
  - I Totally agree
- **8** : How do you handle your time ?
  - Really badly
  - badly
  - I am neither good or bad
  - well
  - Very well
- **9** : Do you think you can reach your goal ?
  - I Totally disagree

– I disagree
– I am neutral
– I agree
– I Totally agree

If question 6 was set to "I don't have any goal", we change the 9th question by the 6th.

- **10** : How have you handled your time ?
  – Really badly
  – badly
  – I am neither good or bad
  – well
  – Very well
- **11** : What do you think about your strategy in order to reach your goal ?
  – Really bad
  – bad
  – neither good or bad
  – good
  – Very good
- **12** : Have you reach your goal ?
  – I Totally disagree
  – I disagree
  – I am neutral
  – I agree
  – I Totally agree

  If question 6 and 9 was set to "I don't have any goal", we automatically set the answer to "I Totally disagree".

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