Ontology-Driven Intelligent Learning Systems: Integrating Semantic Reasoning with Machine Learning for Performance Prediction

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Content

1 – Introduction

Title: *From Data to Meaning: Why Ontology Matters in AI for Education*

Points:

•Massive growth of data in online learning platforms

•Traditional AI models lack semantic understanding

•Ontologies enable *meaningful* representation and reasoning

•Aim: combine **Machine Learning (ML)** + **Ontology** + **SWRL rules** for transparent and transferable prediction

2 – Research Motivation

Title: *The Problem: Accurate but Opaque Models*

Points:

- ML models predict student performance but act as “black boxes”
- Educators need **explainable** and **interpretable** decisions
- Ontology bridges this gap by representing knowledge logically
- Supports *human-understandable reasoning*

3 – Research Objectives

Title: *Core Objectives*

Points:

- Develop ontology-driven prediction framework for e-learning.
- Integrate decision tree rules into SWRL.
- Enhance explainability and portability of predictive models.
- Validate using real learning analytics data (OULAD)

4. Methodology Overview

Title: Hybrid Framework Architecture
Visual Idea: simple flow diagram showing:
OULAD Dataset → Feature Selection (RFE + LR) → Decision Tree → Rule Extraction → SWRL Conversion → Ontology Integration → Reasoning & Classification

Short Text:
This multi-layer process ensures both *accuracy* and *semantic interpretability* in predictions

Dataset

Open University Learning Analytics Dataset (OULAD) is used [16]. The dataset contains the information about:

- 7 courses, 22 presentations, 32,593 students, and their assessment results.
- student clicks (10,655,280 entries)
- This dataset is available on http://www.kaggle.

Table 1. Module summary and domain information [17]

Module	Domain	Presentations	Students
AAA	Social Sciences	2	**748**
BBB	Social Sciences	4	**7,909**
CCC	STEM	2	**4,434**
DDD	STEM	4	**6,272**
EEE	STEM	3	**2,934**
FFF	STEM	4	**7,762**
GGG	Social Sciences	3	**2,534**

Table 2. The details of Demographic features of OULA Data

Demographic features:

Activity_type	Description
code_module	module identification code on which the student is registered
code_presentation	presentation identification code during which the student is registered on the module.
id_student	the unique student identification number
gender	student’s gender.
region	the geographic region, where the student lived while taking the module-presentation
highest_education	the highest student education level on entry to the module presentation.
imd_band	the IMD band of the place where the student lived during the module-presentation
age_band	a band of student’s age
num_of_prev_attempts	the number of how many times the student has attempted this module.
studied_credits	the total number of credits for the modules the student is currently studying
disability	indicates whether the student has declared a disability.
final_result	student’s final result in the module-presentation.

Table 3 The details of Behavioral features of OULA Datasets

Behavioral features:

Activity_type	Description
resource	usually contains pdf resources such as books
oucontent	represents content of assigments, which students should pass during presentation
url	contains links to external or internal resources or for example video/audio content
glossary	consist of basic glossary related to content of course
sharedsubpage	contains information shared among several courses and/or faculty
dualpane	the site is splitted to two parts - one containing information and second for activity related to the information
ouelluminate	online tutorial/live session
ouwiki	OU wikipedia content
homepage	course homepage
forumng	disscussion forum
questionnaire	questionares related to course
repeatactivity	usually points to content from previous weeks of course
subpage	points to other sites in the course together with basic instructions
oucollaborate	online video disscussion rooms (tutor - students)
page	contains informations and instructions related to course
folder	contations files relevant to course
dataplus	additional information/videos/audios/pdf
externalquiz	points to external quiz relevant to course (depending on course content is usually similar to quiz)
htmlactivity	interactive html page with learning content

Preprocessing

In this dissertation, many steps were followed to prepare the research data for the prediction model.

1- Data cleaning: In this step, features that were not useful in the prediction process such as ID number, code module, and code presentation were removed

2- Missing values. The assessment scores and the deprivation band (imd band) features in the used dataset have a few missing values. Instead of missing assessments, all -1s were issued following the Open University's allegation of negligence for all assessment values that students failed to complete.

3- Coding the categorical data. Encoding categorical data involves converting categorical variables into numerical representations that machine learning algorithms can use. Common encoding techniques that are used in this dataset are ordinal encoding for the highest education, age band, as well as nominal encoding for gender, region, and disability.

4- Normalization. Normalization aims to ensure that all features are in the same unit of measurement. Therefore, it is used to avoid the difference between the influence of small values and large values that dominate the results.

3.Feature generation

Based on the original features, eight new features are created which are, and

1. Total_precourse_activities: This feature combines the values of 20 behavioral features representing student interactions with the VLE before the course starts. The philosophy behind its calculation is that: Educational Theories: According to Self-Regulated Learning (SRL) Theory, proactive engagement and preparation before the course begins can lead to better academic outcomes as students set goals and plan their learning activities (17). Empirical Research: Early engagement with course materials is positively correlated with final grades (18). Equation 2 shows the calculation of this feature.

$$\text{Total\_precourse\_activities} = \sum(\text{BDataPlus} + \text{BDualPane} + \text{BOuCollaborate} + \text{BOuContent} + \text{BOuelluminate} + \text{BExternalQuiz} + \text{BFolder} + \text{BForumng} + \text{BGlossary} + \text{BHomePage} + \text{BOuWiki} + \text{BPage} + \text{BQuestionnaire} + \text{BQuiz} + \text{BBRepeatActivity} + \text{BResource} + \text{BSharedSubPage} + \text{BSubpage} + \text{BUrl}) \qquad (2)$$

2. Total_postcourse_activities ': This feature combines the values of 20 behavioral features in the original dataset from four different quarters epresenting student interactions with the VLE after the course starts. The philosophy behind its calculation is that: Educational Theories: The Engagement Theory posits that ongoing interaction with learning materials and activities is essential for effective learning (19). Empirical Research: High levels of student engagement post-course start are linked to better learning outcomes and higher retention rates (20). It calculates the sum of these 20 feature values as shown in Equation 3.

$$\text{Total\_postcourse\_activities} = \sum(\text{DataPlus} + \text{DualPane} + \text{OuCollaborate} + \text{OuContent} + \text{Ouelluminate} + \text{ExternalQuiz} + \text{Folder} + \text{Forumng} + \text{Glossary} + \text{HomePage} + \text{OuWiki} + \text{Page} + \text{Questionnaire} + \text{Quiz} + \text{RepeatActivity} + \text{Resource} + \text{SharedSubPage} + \text{Subpage} + \text{Url})) \qquad (3)$$

3. Average: It calculate the weighted average of individual assignment scores, where each score is associated with a specific weight as presented in Equation 4. The philosophy behind its calculation is that: Educational Theories: Assessment Theory emphasizes that weighted averages provide a fair representation of student performance by accounting for the varying importance of assignments [21]. Empirical Research: Research by Bloxham and Boyd [22] supports the use of weighted averages to accurately reflect students' academic abilities and overall performance.

$$Weighted\ Average = \frac{\sum(Scorei \times Weighti)}{\sum Weighti} \qquad (4)$$

where: Σ (sigma) represents the summation symbol. Score_i is the individual score for assignment i. Weight_i is the corresponding weight for assignment i.

4. Engagement: This feature is calculated based on assignment scores and total student activities on a VLE. Both academic performance and active participation (clicks) can signify engagement in online learning. The philosophy behind its calculation is that: Educational Theories: The Student Engagement Theory suggests that combining behavioral engagement (activities) and academic engagement (assignment performance) gives a comprehensive measure of overall student engagement [23]. Empirical Research: Students who are both behaviorally and academically engaged are more likely to achieve higher academic success [24]. The mean score measure of these two features is used to represent engagement (see Equation 5).

$$Engagement = \frac{(Assignment\ Scores + Total\ Student\ Activities)}{2} \quad (5)$$

5. Studying: This feature references all the actions about consulting resources. Studying is generated using five features in the original dataset (see Equation 6). The philosophy behind its calculation is that: Educational Theories: According to Information Processing Theory, frequent and diverse interactions with study materials enhance learning and retention [25]. Empirical Research: Engaging with various learning resources is crucial for deep understanding and improved academic performance [26].

$$Studying = \frac{Resource + Url + Page + Folder + Dataplus}{5} \quad (6)$$

6. Discussion: This feature represents students' communication actions as shown in Equation 7. The philosophy behind its calculation is that: Educational Theories: Social Constructivism emphasizes that learning occurs through social interaction and collaboration [27]. Empirical Research: Active participation in discussions is linked to better cognitive engagement and learning outcomes [28].

$$Discussion = \frac{ouelluminate+oucollaborate+Forumng}{2} \qquad (7)$$

7. Examining: This feature is about students' evaluation. This feature is generated based on questionnaire, externalquiz and quiz as shown in Equation 8. The philosophy behind its calculation is that: Educational Theories: Educational Theories: Formative Assessment Theory such as quizzes and questionnaires, play a critical role in the learning process. They provide ongoing feedback to students and teachers about student understanding and progress. underscores the role of regular evaluations in providing feedback and guiding learning [29]. Empirical Research: Regular self-assessment and feedback through quizzes and questionnaires improve student learning and self-regulation [30]. The mean score measure of these three features is used to represent the examination.

$$Examining = \frac{Questionnaire+ExternalQuiz+Quiz}{3} \qquad (8)$$

8. Working: This feature is about students' navigation through course pages as shown in Equation 9. The philosophy behind its calculation is that: Educational Theories: Educational Theories: Time Management Theory relates efficient navigation and use of course resources to better time management and organizational skills [31]. Empirical Research: Effective navigation and utilization of online course resources are associated with higher academic achievement [32].

$$Working = \frac{Homepage+Subpage+SharedSubpage}{3} \qquad (9)$$

5 . Ontology Design

Title: *Educational Ontology Structure*

Points:

- Classes: Student, Course, Activity, Performance
- Data properties: averageScore, engagementLevel, workingHours
- SWRL rules link behavioral patterns with performance outcomes

  Visual: simple class diagram (can add in Protégé screenshot if available)

6. SWRL Rules Example

Title: *From Decision Tree to SWRL Logic*

Example:

Rule_ID_05:

Student(?s) ∧ hasEngagement(?s, ?e) ∧ swrlb:greaterThan(?e, 0.75) ∧ hasAssessmentScore(?s, ?a) ∧ swrlb:greaterThan(?a, 60) → PredictedClass(?s, Successful)

Notes:

•Each DT leaf → one SWRL rule

•Enables logical inference within OWL ontology

7. Experimental Setup

Title: *Model Training and Evaluation*

Points:

•Dataset: Open University Learning Analytics (Social Sciences subset)

•Algorithms: Decision Tree with RFE + Logistic Regression

•150 epochs, batch size 32

•Evaluation metrics: Accuracy, Precision, Recall, F1-score

Ontology construction

.The ontology is developed from information gathered by domain experts and assigned to the ontology in the form of a set of concepts, relationships, and definitions . The proposed ontology was built using Protege 5.6.

- Protege is a free, open-source ontology editor and a framework for managing information, established by the Biomedical Informatics Research Center of Stanford.
- The classification and validation is by applying ontology reasoners to check the ontology and extract knowledge, in order to make a knowledge base. We utilized the Stanford Protege ontology editor to develop an OWL ontology to represent the classes and properties of the model

Semantic Web Technology

- The foundation for the Semantic Web is the Resource Description Framework (RDF). RDF provides a language for describing information as graphs of triples called assertions that consis of a subject, property, and object.
- For example, WWW-Proposal hasAuthor Tim [36]. The nodes in an RDF graph are the subject (in this example WWW-Proposal), and the object (Tim) and the edges are the properties (hasAuthor). The nodes and edges are all represented via Uniform Resource Identifiers (URI) [37].

- A URI is a generalisation of the Uniform Resource Locator (URL) currently used to describe web addresses on the Internet. The difference is that URIs are not meant to be constrained to only Internet resources such as a web page but any resource includin data that would typically be stored in a database and used by a program but not necessarily viewed in a web browser.

- The mapping from the current Internet to RDF is straight forward: web pages are RDF nodes and links are RDF edges [37]. The language that provides rich semantic expressivity is the Web Ontology Language (OWL) [38]

SWRL rules and semantic reasoner

- The SWRL is the standard guideline language of the Semantic Web. SWRL can be used to express rules and logic, incorporating OWL DL or OWL Lite with a Rule Markup Language subset (RuleML). SWRL rules form as couples of antecedent–consequent[38]. The antecedent points to the body (rules), and the subsequent part is referred to as the head.
- OWL reasoner such as Pellet, HermiT, ELK, and FaCT++ is the most common in ontology for executing SWRL rules and inferring new ontology axioms [41].

Ontology Experimentation Approach

The methodology used in our experimentation consisted of these steps:

- Firstly, OULA dataset have to be pre-processed in order to obtain numerical datasets according to the format expected in the data mining tool to be used.
- Secondly, for each course dataset, the algorithm DT is run in order to obtain a general prediction model of 7 courses to be used in portability experiments. In this step, we obtained one prediction model for each course. According to the result obtains in python course A has a higher accuracy than other courses in social science courses (B and G courses) and course F has a higher accuracy than other courses in STEM science courses (C, D, and E courses).
- Then, 7 courses are grouped according to two different grouped called social science courses and STEM science courses.
- Next, We selected the prediction model obtained in one course (course A in social science course and course F in STEM course) and then applied the prediction model for one course over the other datasets of all the other courses in the same group.
- Next, courses are in social science courses conduct four types of prediction experiments of course A and course F; for the first experiment is predicting by using the original features before generating the new features and without using the random search optimizer; for the second experiment is predicting by using the optimized features selection after generating the new features and using the random search optimizer; for the third experiment is predicting by using the generated new feature; for the forth experiment is predicting by using the generated new features and unused features in the generation process.
- Finally, we obtained the values of the four evaluation metrics that we used (Accuracy- precision- recall –f1 course).

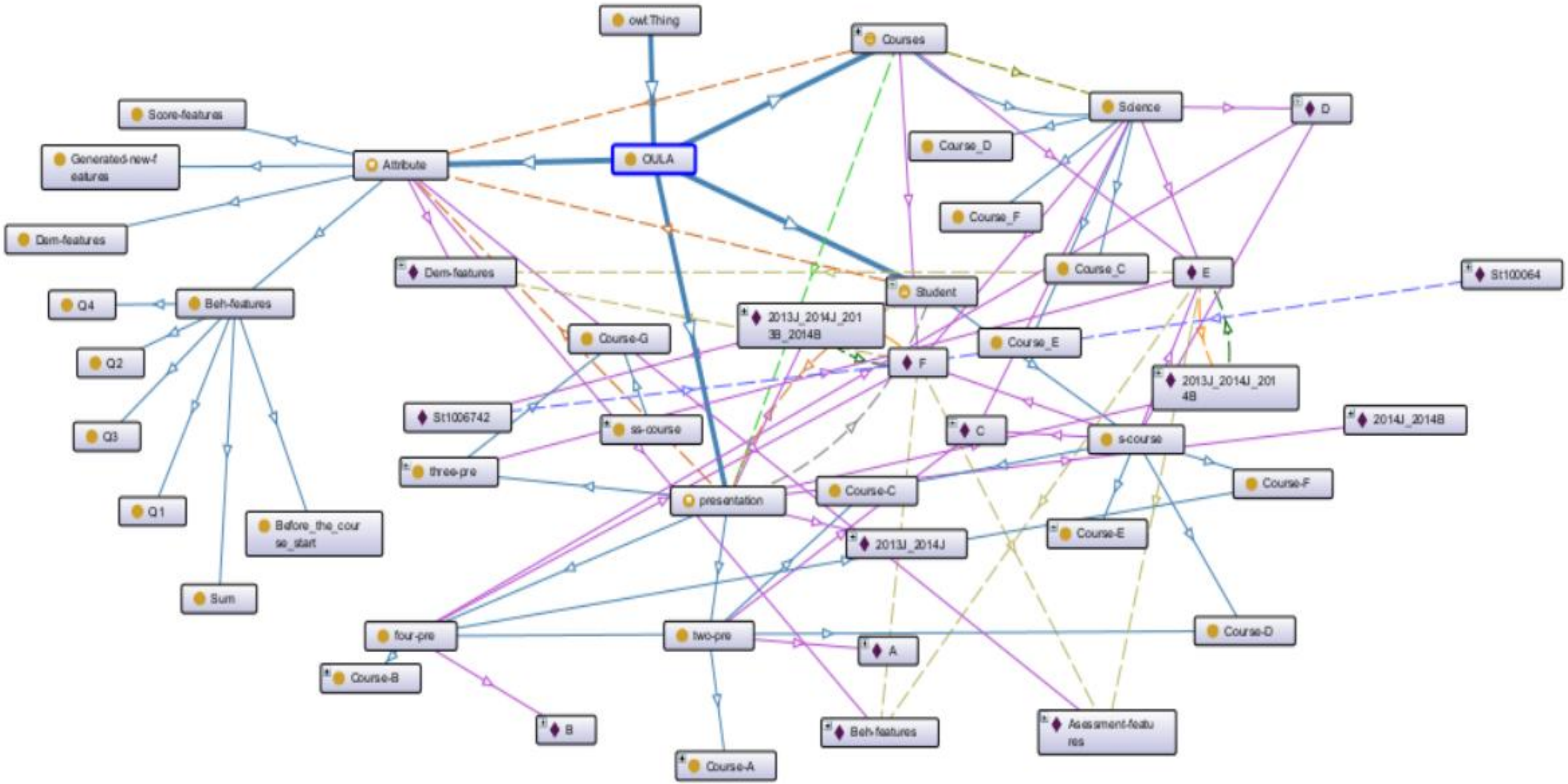


Figure 1. The classes hierarchy of student performance classification Ontology.

To predict student performance using the integration of machine learning (Decision Tree) with engineering ontology for social science courses

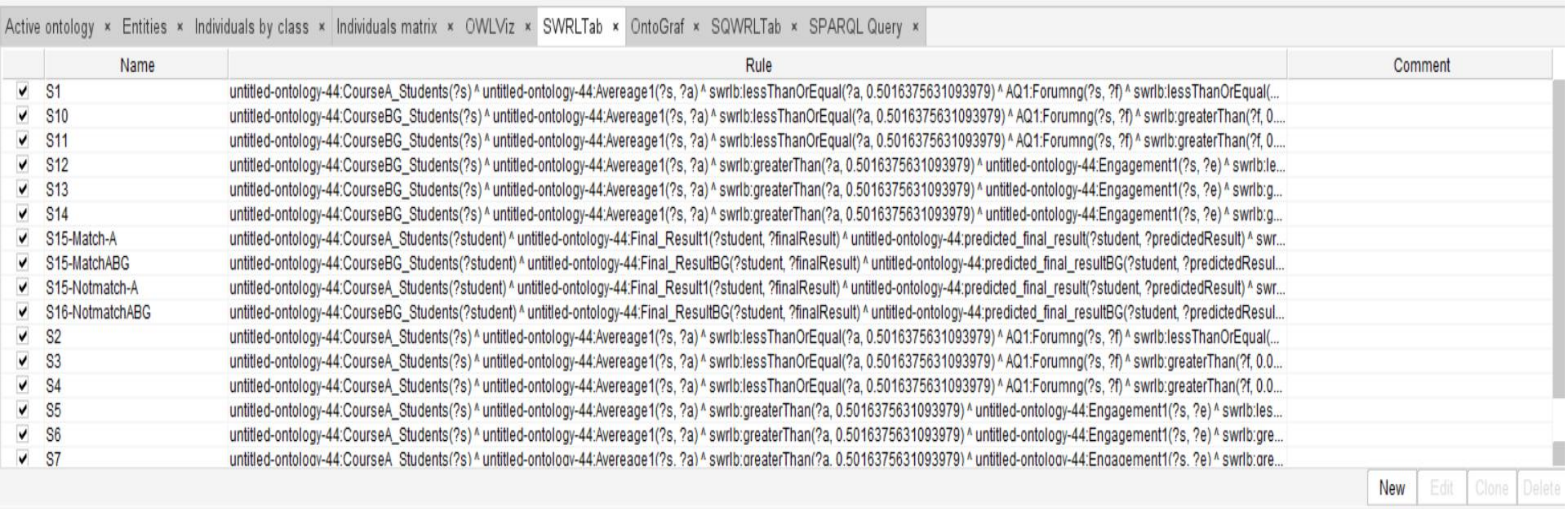
```
Decision Tree Rules:
    |--- num_of_prev_attempts <= 0.5000000000000000
        |--- AQ1:OuContent <= 0.0878712870180607
            |--- region <= 0.4583333283662796
                |--- class: 1
            |--- region >  0.4583333283662796
                |--- class: 1
        |--- AQ1:OuContent >  0.0878712870180607
            |--- AQ1:OuCollaborate <= 0.9583333432674408
                |--- class: 1
            |--- AQ1:OuCollaborate >  0.9583333432674408
                |--- class: 0
    |--- num_of_prev_attempts >  0.5000000000000000
        |--- AQ1:Subpage <= 0.0895196534693241
            |--- class: 0
        |--- AQ1:Subpage >  0.0895196534693241
            |--- imd_band <= 0.0001247024156328
                |--- class: 1
            |--- imd_band >  0.0001247024156328
                |--- class: 0
```

Figure 2. The decision tree for course A by using the original features

Table 4. The SWRL testing rules are crated from existing facts from course A

Rule	SWRL rules
1	CourseA_Students(?s) ^ num_of_prev_attempts(?s, ?npa) ^ swrlb:lessThanOrEqual(?npa, 0.5) ^ AQ1_OuContent(?s, ?oc) ^ swrlb:lessThanOrEqual(?oc, 0.0878712870180607) ^ region(?s, ?r) ^ swrlb:lessThanOrEqual(?r, 0.4583333283662796) -> predicted_final_result(?s, 1)
2	CourseA_Students(?s) ^ num_of_prev_attempts(?s, ?npa) ^ swrlb:lessThanOrEqual(?npa, 0.5) ^ AQ1_OuContent(?s, ?oc) ^ swrlb:lessThanOrEqual(?oc, 0.0878712870180607) ^ region(?s, ?r) ^ swrlb:greaterThan(?r, 0.4583333283662796) -> predicted_final_result(?s, 1)
3	CourseA_Students(?s) ^ num_of_prev_attempts(?s, ?npa) ^ swrlb:lessThanOrEqual(?npa, 0.5) ^ AQ1_OuContent(?s, ?oc) ^ swrlb:greaterThan(?oc, 0.0878712870180607) ^ AQ1_OuCollaborate(?s, ?ocb) ^ swrlb:lessThanOrEqual(?ocb, 0.9583333432674408) -> predicted_final_result(?s, 1)
4	CourseA_Students(?s) ^ num_of_prev_attempts(?s, ?npa) ^ swrlb:lessThanOrEqual(?npa, 0.5) ^ AQ1_OuContent(?s, ?oc) ^ swrlb:greaterThan(?oc, 0.0878712870180607) ^ AQ1_OuCollaborate(?s, ?ocb) ^ swrlb:greaterThan(?ocb, 0.9583333432674408) -> predicted_final_result(?s, 0)
5	CourseA_Students(?s) ^ num_of_prev_attempts(?s, ?npa) ^ swrlb:greaterThan(?npa, 0.5) ^ AQ1_Subpage(?s, ?sp) ^ swrlb:lessThanOrEqual(?sp, 0.0895196534693241) -> predicted_final_result(?s, 0)
6	CourseA_Students(?s) ^ num_of_prev_attempts(?s, ?npa) ^ swrlb:greaterThan(?npa, 0.5) ^ AQ1_Subpage(?s, ?sp) ^ swrlb:greaterThan(?sp, 0.0895196534693241) ^ imd_band(?s, ?ib) ^ swrlb:lessThanOrEqual(?ib, 0.0001247024156328) -> predicted_final_result(?s, 1)
7	CourseA_Students(?s) ^ num_of_prev_attempts(?s, ?npa) ^ swrlb:greaterThan(?npa, 0.5) ^ AQ1_Subpage(?s, ?sp) ^ swrlb:greaterThan(?sp, 0.0895196534693241) ^ imd_band(?s, ?ib) ^ swrlb:greaterThan(?ib, 0.0001247024156328) -> predicted_final_result(?s, 0)

Then developed an SWRL rule to represent the decision tree rules



Active ontology × | Entities × | Individuals by class × | Individuals matrix × | OWLViz × | SWRLTab × | OntoGraf × | SQWRLTab × | SPARQL Query ×

	Name	Rule	Comment
✔	S1	untitled-ontology-44:CourseA_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:lessThanOrEqual(?a, 0.5016375631093979) ^ AQ1:Forumng(?s, ?f) ^ swrlb:lessThanOrEqual(...	
✔	S10	untitled-ontology-44:CourseBG_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:lessThanOrEqual(?a, 0.5016375631093979) ^ AQ1:Forumng(?s, ?f) ^ swrlb:greaterThan(?f, 0....	
✔	S11	untitled-ontology-44:CourseBG_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:lessThanOrEqual(?a, 0.5016375631093979) ^ AQ1:Forumng(?s, ?f) ^ swrlb:greaterThan(?f, 0....	
✔	S12	untitled-ontology-44:CourseBG_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:greaterThan(?a, 0.5016375631093979) ^ untitled-ontology-44:Engagement1(?s, ?e) ^ swrlb:le...	
✔	S13	untitled-ontology-44:CourseBG_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:greaterThan(?a, 0.5016375631093979) ^ untitled-ontology-44:Engagement1(?s, ?e) ^ swrlb:g...	
✔	S14	untitled-ontology-44:CourseBG_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:greaterThan(?a, 0.5016375631093979) ^ untitled-ontology-44:Engagement1(?s, ?e) ^ swrlb:g...	
✔	S15-Match-A	untitled-ontology-44:CourseA_Students(?student) ^ untitled-ontology-44:Final_Result1(?student, ?finalResult) ^ untitled-ontology-44:predicted_final_result(?student, ?predictedResult) ^ swr...	
✔	S15-MatchABG	untitled-ontology-44:CourseBG_Students(?student) ^ untitled-ontology-44:Final_ResultBG(?student, ?finalResult) ^ untitled-ontology-44:predicted_final_resultBG(?student, ?predictedResul...	
✔	S15-Notmatch-A	untitled-ontology-44:CourseA_Students(?student) ^ untitled-ontology-44:Final_Result1(?student, ?finalResult) ^ untitled-ontology-44:predicted_final_result(?student, ?predictedResult) ^ swr...	
✔	S16-NotmatchABG	untitled-ontology-44:CourseBG_Students(?student) ^ untitled-ontology-44:Final_ResultBG(?student, ?finalResult) ^ untitled-ontology-44:predicted_final_resultBG(?student, ?predictedResul...	
✔	S2	untitled-ontology-44:CourseA_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:lessThanOrEqual(?a, 0.5016375631093979) ^ AQ1:Forumng(?s, ?f) ^ swrlb:lessThanOrEqual(...	
✔	S3	untitled-ontology-44:CourseA_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:lessThanOrEqual(?a, 0.5016375631093979) ^ AQ1:Forumng(?s, ?f) ^ swrlb:greaterThan(?f, 0.0...	
✔	S4	untitled-ontology-44:CourseA_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:lessThanOrEqual(?a, 0.5016375631093979) ^ AQ1:Forumng(?s, ?f) ^ swrlb:greaterThan(?f, 0.0...	
✔	S5	untitled-ontology-44:CourseA_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:greaterThan(?a, 0.5016375631093979) ^ untitled-ontology-44:Engagement1(?s, ?e) ^ swrlb:les...	
✔	S6	untitled-ontology-44:CourseA_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:greaterThan(?a, 0.5016375631093979) ^ untitled-ontology-44:Engagement1(?s, ?e) ^ swrlb:gre...	
✔	S7	untitled-ontology-44:CourseA_Students(?s) ^ untitled-ontology-44:Avereage1(?s, ?a) ^ swrlb:greaterThan(?a, 0.5016375631093979) ^ untitled-ontology-44:Engagement1(?s, ?e) ^ swrlb:gre...	

New | Edit | Clone | Delete

Figure 3. SWRL implemented rules for OULA Social Science courses- A-course

To predict student performance using the integration of machine learning (Decision Tree) with engineering ontology for STEM Courses

```
Decision Tree Rules:
    |--- AQ1:HomePage <= 0.0101256985217333
        |--- AQ1:HomePage <= 0.0059357541613281
            |--- AQ1:Subpage <= 0.0293650794774294
                |--- class: 0
            |--- AQ1:Subpage >  0.0293650794774294
                |--- class: 0
        |--- AQ1:HomePage >  0.0059357541613281
            |--- AQ1:Quiz <= 0.0124033074826002
                |--- class: 0
            |--- AQ1:Quiz >  0.0124033074826002
                |--- class: 0
    |--- AQ1:HomePage >  0.0101256985217333
        |--- AQ1:Questionnaire <= 0.0892857164144516
            |--- AQ1:Quiz <= 0.0310749532654881
                |--- class: 0
            |--- AQ1:Quiz >  0.0310749532654881
                |--- class: 1
        |--- AQ1:Questionnaire >  0.0892857164144516
            |--- AQ1:OuContent <= 0.0714956559240818
                |--- class: 1
            |--- AQ1:OuContent >  0.0714956559240818
                |--- class: 1
            |--- AQ1:Forumng >  0.0301135275512934
                |--- class: 1
```

Figure 4. The decision tree for course F by using the original features

Table 5. The SWRL testing rules are crated from existing facts from course F by using the raw features

Rule	SWRL rules
1	CourseF_Students(?s) ^ Avereage(?s, ?avg) ^ swrlb:lessThanOrEqual(?avg, 0.4414357542991638) ^Examining(?s, ?exam) ^ swrlb:lessThanOrEqual(?exam, 0.0390111785382032) ^ swrlb:lessThanOrEqual(?exam, 0.0318658519536257) ->predicted_final_result(?s, 0)
2	CourseF_Students(?s) ^ Avereage(?s, ?avg) ^ swrlb:lessThanOrEqual(?avg, 0.4414357542991638) ^Examining(?s, ?exam) ^ swrlb:greaterThan(?exam, 0.0390111785382032) ^ Total_number_of_clicks_Befor(?s, ?clicksBefore) ^ swrlb:lessThanOrEqual(?clicksBefore, 0.3017341494560242) ->predicted_final_result(?s, 1)
3	CourseF_Students(?s) ^ Avereage(?s, ?avg) ^ swrlb:lessThanOrEqual(?avg, 0.4414357542991638) ^Examining(?s, ?exam) ^ swrlb:greaterThan(?exam, 0.0390111785382032) ^ Total_number_of_clicks_Befor(?s, ?clicksBefore) ^ swrlb:greaterThan(?clicksBefore, 0.3017341494560242) ->predicted_final_result(?s, 0)
4	CourseF_Students(?s) ^ Avereage(?s, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^Total_number_of_clicks_Befor(?s, ?clicksBefore) ^ swrlb:lessThanOrEqual(?clicksBefore, 0.0853973627090454) ^Avereage(?s, ?avg2) ^ swrlb:lessThanOrEqual(?avg2, 0.7632241845130920) ->predicted_final_result(?s, 0)
5	CourseF_Students(?s) ^ Avereage(?s, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^Total_number_of_clicks_Befor(?s, ?clicksBefore) ^ swrlb:greaterThan(?clicksBefore, 0.0853973627090454) ^Avereage(?s, ?avg2) ^ swrlb:lessThanOrEqual(?avg2, 0.6612090468406677) ->predicted_final_result(?s, "1")
6	Avereage(?s, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ Total_number_of_clicks_Befor(?s, ?clicksBefore) ^ swrlb:greaterThan(?clicksBefore, 0.0853973627090454) ^Avereage(?s, ?avg2) ^ swrlb:greaterThan(?avg2, 0.6612090468406677) ->predicted_final_result(?s, 1)
7	CourseF_Students(?s) ^ Avereage(?s, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^Total_number_of_clicks_Befor(?student,

Then developed an SWRL rule to represent the decision tree rules

Active ontology × Entities × Individuals by class × Individuals matrix × OWLViz × OntoGraf × SWRLTab × SQWRLTab × SPARQL Query ×

	Name	Rule	Comment
✔	S1	untitled-ontology-44:CourseF_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:lessThanOrEqual(?avg, 0.4414357542991638) ^ untitled-ontology-44:Examining(?student, ?exam) ^ swrlb:lessThanOrEqual(?exa...	
✔	S10	untitled-ontology-44:CourseCDE_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:lessThanOrEqual(?avg, 0.4414357542991638) ^ untitled-ontology-44:Examining(?student, ?exam) ^ swrlb:greaterThan(?exam,...	
✔	S11	untitled-ontology-44:CourseCDE_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:lessThanOrEqual(?avg, 0.4414357542991638) ^ untitled-ontology-44:Examining(?student, ?exam) ^ swrlb:greaterThan(?exam,...	
✔	S12	untitled-ontology-44:CourseCDE_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrl...	
✔	S13	untitled-ontology-44:CourseCDE_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrl...	
✔	S14	untitled-ontology-44:CourseCDE_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrl...	
✔	S15	untitled-ontology-44:CourseCDE_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrl...	
✔	S16	untitled-ontology-44:CourseCDE_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrl...	
✔	S2	untitled-ontology-44:CourseF_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:lessThanOrEqual(?avg, 0.4414357542991638) ^ untitled-ontology-44:Examining(?student, ?exam) ^ swrlb:greaterThan(?exam, 0.0...	
✔	S3	untitled-ontology-44:CourseF_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:lessThanOrEqual(?avg, 0.4414357542991638) ^ untitled-ontology-44:Examining(?student, ?exam) ^ swrlb:greaterThan(?exam, 0.0...	
✔	S4	untitled-ontology-44:CourseF_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrlb:le...	
✔	S5	untitled-ontology-44:CourseF_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrlb:le...	
✔	S6	untitled-ontology-44:CourseF_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrlb:gr...	
✔	S7	untitled-ontology-44:CourseF_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrlb:gr...	
✔	S8	untitled-ontology-44:CourseF_Students(?student) ^ untitled-ontology-44:Avereage(?student, ?avg) ^ swrlb:greaterThan(?avg, 0.4414357542991638) ^ untitled-ontology-44:Total_number_of_clicks_Befor(?student, ?clicksBefore) ^ swrlb:gr...	

New Edit Clone Delete

Figure 5. SWRL implemented rules OULA STEM courses- F-course

The proposed ontology approach for predicting students' academic performance falls into two successive stages. In the first stage, two data properties were generated for STEM courses, the first one called ***predicted_final_result*** used to show the predictive result of ontology, and the second data property called ***matchedfinalresultCDE*** *(like loss function)* used for matching the result between ***predicted_final_result*** and the actual result. If the individuals result is matched, ***matchedfinalresultCDE*** will be true, and if not, it will be false as shown in Figure 15

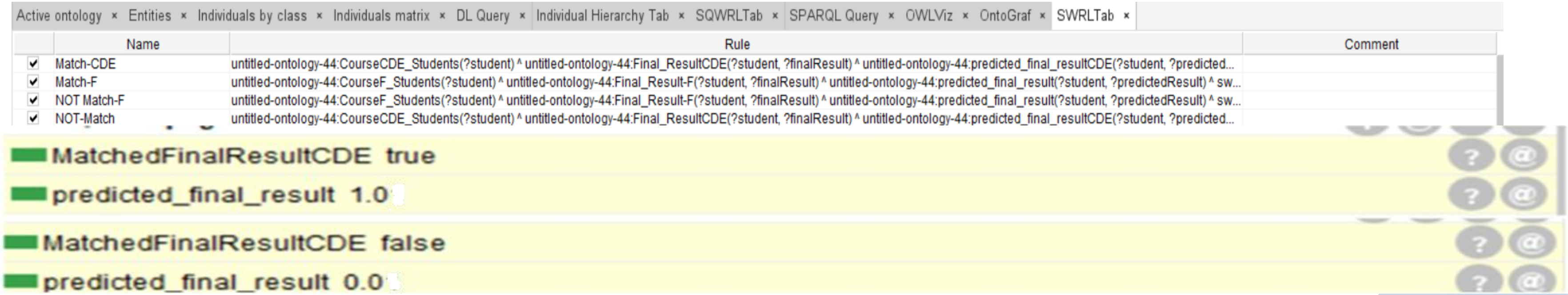


Figure 6. Inferred result for STEM course.

For social science course courses two data properties were generated the first one called ***predicted_final_resultBG*** and used to show the predictive result of ontology, and the second data property called ***matchedfinalresultBG*** used for matching the result between ***predicted_final_resultBG*** and the actual result. If the individuals result is matched, ***matchedfinalresultBG*** will be true, and if not, it will be false as shown in Figure 16

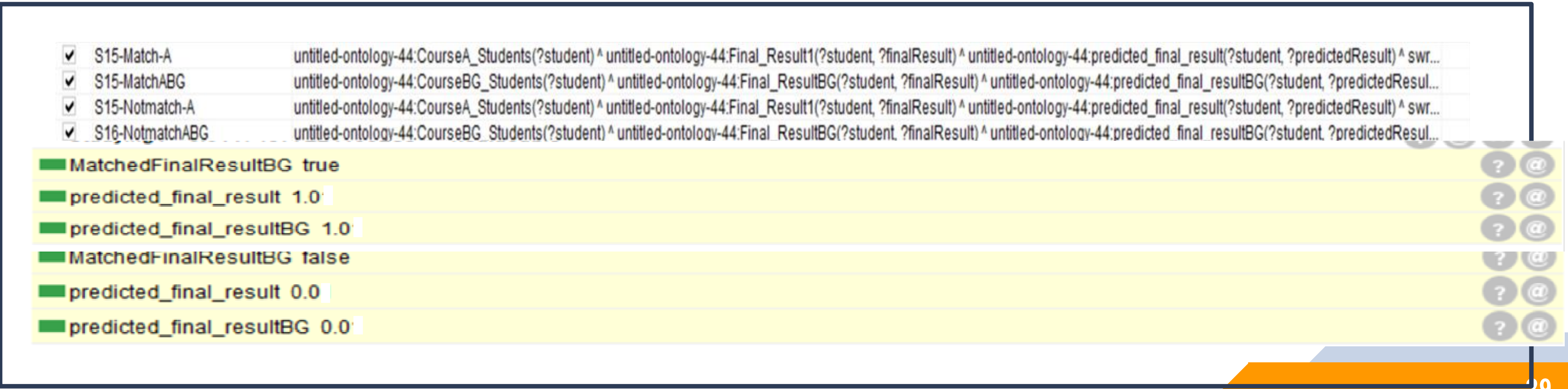


Figure 7 Inferred result social science course.

8 . Results and Discussion

Title: *Performance and Interpretability*

Points:

•Model Accuracy: **98%**

•Confusion Matrix shows strong balance between classes

•Ontology reasoning confirms logical consistency

•Explainability improved → educators can trace reasoning path

Table 6. Ontology result prediction for social science and STEM courses at Q1 and Q2

Course	Prediction stage for a group	Quarters	Accuracy
Social science courses	First: Ontology prediction accuracy is obtained based on the original features of the dataset as a baseline	Q1	Correctly classified instances 10,403 (0.92%) and incorrectly classified instances 684.
		Q2	Correctly classified instances 10,527 (0.93%) and incorrectly classified instances 663.
	Second: Ontology prediction accuracy is obtained based on the generated attributes, a feature selection approach to choose the best features, and also apply the random search optimizer.	Q1	Correctly classified instances 10,960 (0.97%) and incorrectly classified instances 176.
		Q2	Correctly classified instances 10,982 (0.98%) and incorrectly classified instances 123.
	Third: The ontology accuracy is obtained based on the features generated	Q1Q2	Correctly classified instances 10,522 (0.94%) and incorrectly classified instances 668.
	Fourth: The ontology accuracy is obtained by using the features that are generated and unused features in the generation process in the two quartiles	Q1Q2	Correctly classified instances 10,527 (0.94%) and incorrectly classified instances 663.

STEM courses			
	Ontology prediction accuracy is obtained based on the original features of the dataset as a baseline	Q1	Correctly classified instances 19,802 (0.92%) and incorrectly classified instances 1598.
		Q2	Correctly classified instances 19,878 (0.93%) and incorrectly classified instances 1522.
	Ontology prediction accuracy is obtained based on the generated attributes, applied a feature selection approach to choose the best features, and also apply the random search optimizer.	Q1	Correctly classified instances 10,960 (0.96%) and incorrectly classified instances 1055.
		Q2	Correctly classified instances 20,595 (0.98%) and incorrectly classified instances 805.
	The ontology accuracy is obtained based on the features generated	Q1Q2	Correctly classified instances 20,322 (0.94%) and incorrectly classified instances 668.
	The ontology accuracy is obtained by using the features that are generated and unused features in the generation	Q1Q2	Correctly classified instances 20,345 (0.95%) and incorrectly classified instances 1055.

9 . Applications and Implications

Title: *Practical Implications*

Points:

- Early detection of at-risk students
- Adaptive feedback and personalized learning
- Explainable AI for educational decision-making
- Extendable to other domains (e.g., fraud detection, cybersecurity)

10 . Conclusions & Future Work

Title: *Conclusions and Future Research*

Points:

•Ontology + ML = Hybrid Explainable AI

•Enhanced transparency and semantic portability

•Future work:

- Extend ontology to cross-institutional datasets
- Integrate neural reasoning (Neuro-Symbolic AI)
- Apply in real-time LMS environments

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“Thank you for your attention – I look forward to your questions.”