IS ROBOTICS IN EDUCATION THE RIGHT TOOL TO FACE THE FUTURE PIVOTAL CHALLENGES OF SOCIETY?

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Summary

• Background: Robotics in Education (RiE) is a broad area of robotics applications in education, but is it helpful to equip men and women with future critical competencies?

• Robotics in Education (RiE) or Educational Robotics (ER)?

• Educational Robotics: Challenges and outcomes

• Where is the learning system model?

• Can we use learning tools as sensors for collecting educational data?
Education is crucial for equipping men and women with the critical competencies that will enable them to understand the world, find employment and participate in future society. Understanding how a student learns (and what she needs to learn) is essential for enhancing the ability of teachers to guide her toward the desired outcome. New technologies can support this process by gathering information seamlessly and providing hints automatically. In addition, new technologies are an important part of the school renewal process when associated with innovative methodologies.

• **Background:** Robotics in Education (RiE) is a broad area of robotics applications in education, we know that it is helpful to equip men and women with future critical competencies.

• Robotics in Education (RiE) or Educational Robotics (ER)?

Even if some literature uses “Robotics in Education” and “Educational Robotics” as synonyms (Benitti, 2012; Eguchi, 2017), a distinction should be made between the two labels.
Robots in Education (RiE) or Educational Robotics (ER)

Educational Robotics (ER) is not R4E or RiE

Robots 4 Education (R4E)

- Robots that help students with relationship difficulties
- Robots that help children with physical impairments
- Robots used as educational tools to increase interest
- Robotic tools used in general for learning by educators
- Robotics / robotic tools to develop skills on a particular topic and transversal skills
- Robot as a mediator for learning STEM or other subjects

ER:

- Robots / robotic kits as a mediator for learning the basics of robotics
But how can we define ER?

It is not enough introducing robots in an educational setting to propose an ER activity (Scaradozzi, Screpanti & Cesaretti, 2019)!

ER is characterized by a workflow that allows students to **design**, **build** and **program** robotic artefacts, creatively solve problems and carry out meaningful projects.
Educational Robotics DEFINITION

- Educational Robotics (ER) builds on the work of Seymour Papert, Lev Vygotsky, Jean Piaget (Ackermann, 2001; Mevarech and Kramarski, 1993; Papert, 1980; Vygotsky, 1968) to bring not just robotics in education, but to understand Robotics since an early age.

- ER is made of robots allowing a construction/deconstruction and programming activity, teachers/experts facilitating the activity, methodologies enabling students to explore the subject, the environment, the content of the activity and their personal skills and knowledge.
• To benchmark ER activities, a framework is needed.

• Four different features can be identified to describe a RiE experience or project: the learning environment, the impact on students’ school curriculum, the integration of the robotic tool in the activity, the way evaluation is carried out.

• Regarding how the robotic tool is integrated into the activity we can distinguish ER as a subset of RiE.
Robotics in Education: classification of experiences

- **Learning environment** (formal/non-formal)
- **Type of activity** carried out: curricular/not curricular activities (organized and purposefully designed activities carried out regularly during an entire cycle of compulsory school/scattered activities inside or outside the classroom)
- **How to assess** performance and evaluate outcomes. V&V model. KPIs. Evaluation methods.
- **How robots are integrated in class:**
  - As a companion (socially assistive robotics) -> robots helping children with social impairments
  - As an aid for students with disabilities (assistive robotics) -> robots helping children with physical impairments
  - As a mediator for learning STEM or other subjects (educational assistive robotics) -> robots designed to help students learn other subjects than Robotics
  - As a mediator for learning STRem (educational robotics) -> robots designed to help students learn Robotics and other related subjects

Robotics in Education: classification of experiences

- Educational Kits
- Lesson Plans

Evaluation of activities
- Qualitative Methods
- Quantitative Methods
- Mixed Methods

Integration of the robotic tool
- Assistive Robots
- Socially Assistive Robots
- Social Robots

Non Curricular Activities carried out not regularly and not impacting the final evaluation on an educational path
- Curricular Activity carried out regularly impacting the final evaluation of the educational path

Impact on Curriculum

Learning Environment
- Formal Learning Environment
- Non Formal Learning Environment

Robotics in Education (RIE)
Why this research project?

**Educational Robotics (ER)** is increasingly spreading in schools all over the world (Miller & Nourbakhsh, 2016), thanks to teachers and educators that are using this approach during the course of their standard lessons.

Angel-Fernandez and Vincze (2018) showed how the number of scientific papers using the words “robotics” and “education”, or the expression “ER” **has significantly increased** in the last two decades.


Summary

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- **Robotics in Education (RiE) or Educational Robotics (ER)?**

- **Educational Robotics**: Challenges and outcomes

  *(credits: Linda Daniela, Dean of the Faculty of Education, Psychology and Art, Chair of the Council for Promotion in Pedagogy of the University of Latvia)*
Educational Robotics: Challenges versus outcomes

- How to support knowledge improvement
- How to evaluate knowledge
- Where to use knowledge

Educational Robotics as a part of curriculum

Robotics as out of school activities

Educational Robotics

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Challenges for educational robotics activities

• For teachers
• For students
• For planning of learning activities
Challenges for educational robotics activities: teachers’ side

- How to ensure classroom management
- How to keep all students learning
- How to support knowledge development
- How to teach robotics (also remotely)

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Challenges for educational robotics activities: students’ side

- How to keep learning in own pace?
- How to understand what should be done?
- How to apply knowledge?
- How to conceptualize knowledge?
Challenges for educational robotics activities: planning new learning activities

1. How structure the learning environment?
2. How to ensure that all children can participate?
3. What kind of robotics kits are needed?
4. How to plan learning activities?

Organizational challenges (researchers)
Outcomes of educational robotics activities

INCLUSIVE EDUCATION

- Special needs
- Socio-economic status
- Cultural diversity
- Gender differences

ROBOTICS LEARNING MATERIALS

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Outcomes

Challenges for educational robotics activities

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• **Educational Robotics:** Challenges and outcomes

• Where is the learning system model?

• Can we use learning tools as sensors for collecting educational data?
Modelling learning systems

A system theory approach to Educational Robotics

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Modelling learning systems: the system theory approach

• A system is a group of interacting or interrelated entities that form a unified whole. It can be natural or artificial.

• A system is delineated by its spatial and temporal boundaries, surrounded and influenced by its environment, described by its structure and purpose and expressed in its timing or event functioning.
Modelling learning systems: the system theory approach

Four phases in modeling

• How can it be studied the learning process? What is learning? Which variables should be included in the model?

• Is it possible to establish the causality principle (i.e., given an input at a time t (or an event), we have a certain output at the time t (or a trigger))? 

• Metrology: how can we measure the intended variables?

• Cybernetics: how can we transform information on the output to determine which input to provide?
Model the learning process in an ER activity

Creating better innovation measurement practices
Errors and feedbacks
Success
Ethics

Educational Robotics
Model the learning process in an ER activity

Lesson topic

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Actions and Reactions

Learner’s development

Cyber-Human-Physical system Model of the Human Learning Interactions

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Model the learning process in an ER activity
Modelling learning systems: the system theory approach

- Learning is the process by which an individual assimilates information, ideas and values and thus acquires knowledge, know-how, skills and/or competences.
- Competence is the “combination of knowledge, skills and attitudes appropriate to the context”.
- Learning occurs through personal reflection, reconstruction and social interaction. It may take place in formal, non-formal or informal settings.


Modelling learning systems: the system theory approach

What is learning?

- Learning is the process by which an individual assimilates information, ideas and values and thus acquires knowledge, know-how, skills and/or competences.
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Modelling learning systems: the system theory approach

Conclusions of the study are strictly drawn from concretely empirical evidence.

Modelling learning systems: the system theory approach

Causality principle

Metrology

How can we measure learning?

• Development of the proper sensors to capture the variables of interest (Knowledge, Skills, Attitudes, Competences).

• Identification of the adequate sampling period and quantization.

• Demonstration of their validity and reliability.

Typical measuring chain

SENSOR → TRANSDUCER → AMPLIFICATION STAGE → READING DEVICE

Students

Teachers

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Modelling learning systems: the system theory approach

Causality principle

Metrology

How can we measure learning?
The scientific method – empirical cycle

Conclusions of the study is strictly drawn from concretely empirical evidence

“verifiable” evidence
Modelling learning systems: the system theory approach

We must formulate hypotheses that are:
• empirically testable
• replicable
• objective
• transparent
• falsifiable
• logically consistent

To ensure the effectiveness, researchers need to be critical of their own studies and those of others; they should be open and transparent.
Modelling learning systems: the system theory approach

- **Causality principle**
  - How can we measure learning?
  - The scientific method – empirical cycle

- **Metrology**

- **Respect** for participant's autonomy
  - voluntary consent vs. coercion
  - Well-informed consent vs. deception (active – cover story or passive – omission, false feedback and perseverance effect)

- **Beneficience**
  - participants should not be harmed
  - cost/benefit for individuals and for society as a whole
  - Privacy (ex.: European GDPR)

- **Justice**
  - costs and benefits of research should be divided reasonably, fairly and equally over potential participants.
Modelling learning systems: the system theory approach

How can we measure learning?
A good research of Answers...

Quantitative
- Internal validity
- External validity
- Reliability
- Objectivity

Qualitative
- Credibility / Trustworthiness
- (Transferability)
- Confirmability, dependability
- Engagement, reflexivity

Causality principle
Metrology

Quantitative

Qualitative
Modelling learning systems: the system theory approach

Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Trustworthiness

• Member checks: recycling interpretation back to the key informants
• Searching for disconfirming evidence
• Triangulation; multiple data sources and multiple methods
• Thick description _ a thorough description of the context of the study

Qualitative

• Credibility / Trustworthiness
• (Transferability)
• Confirmability, dependability
• Engagement, reflexivity
Modelling learning systems: the system theory approach

**Confirmability**

- Data collection so that audit could be carried out (audio recordings, full transcripts of interview, …)
- Team approach
- Independent auditors

**Qualitative**

- Credibility / Trustworthiness
- (Transferability)
- **Confirmability**, dependability
- Engagement, reflexivity

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Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Reflexivity

• Document beliefs, framework, theories underlying approach to the problem before beginning the data collection

• Document reflections and limitations explaining how to overcome it

• Team analysis

Qualitative

• Credibility / Trustworthiness

• (Transferability)

• Confirmability, dependability

• Engagement, reflexivity
Modelling learning systems: the system theory approach

Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Internal validity

- How well an experiment is done, especially whether it avoids confounding (more than one possible independent variable [cause] acting at the same time).
- The less chance for confounding in a study, the higher its internal validity is.

Quantitative

- Internal validity
- External validity
- Reliability
- Objectivity
Modelling learning systems: the system theory approach

Causality principle

Metrology

How can we measure learning? A good research of Answers…

Quantitative

- Internal validity
- External validity
- Reliability
- Objectivity

External validity

- how well data and theories from one setting apply to another.
Modelling learning systems: the system theory approach

Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Quantitative
- Internal validity
- External validity
- Reliability
- Objectivity

Reliability
- In research, the term reliability means "repeatability" or "consistency". A measure is considered reliable if it would give us the same result over and over again (assuming that what we are measuring isn't changing!)
Modelling learning systems: the system theory approach

Causality principle

How can we measure learning?
A good research of Answers…

Metrology

Quantitative

- Internal validity
- External validity
- Reliability
- Objectivity

Objectivity

- In social research it is the principle drawn from positivism that, as far as is possible, researchers should remain distanced from what they study so findings depend on the nature of what was studied rather than on the personality, beliefs and values of the researcher.
Modelling learning systems: the system theory approach

- **Learning** is the process by which an individual assimilates information, ideas and values and thus acquires knowledge, know-how, skills and/or competences.
- **Competence** is the "combination of knowledge, skills and attitudes appropriate to the context".
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**What is learning?**

**Causality principle**

**Metrology**

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How can we measure learning?
A good measurement of constructs…

• We are measuring **constructs**: an explanatory variable which is not directly observable.

• For example, an object’s **centre of mass** is certainly a real thing, but it is a construct (not another object).

• For example, the concepts of **intelligence** and **motivation** are used to explain phenomena in psychology, but neither is directly observable.
Modelling learning systems: the system theory approach

How can we measure learning?
A good measurement of constructs…

Are we measuring accurately?

Do our measurements reflect the construct we are interested in?

• The validity of an instrument or manipulation method is commonly referred to as measurement or construct validity.
Modelling learning systems: the system theory approach

How can we measure learning?
A good measurement of constructs…

How do we assess construct **validity**?

How do we determine if this score actually reflects the property?

- Face validity
- Predictive validity or criterion validity,
- Convergent and discriminant validity (multi trait and multi method matrix)
Modelling learning systems: the system theory approach

How do we assess construct reliability?

• **Measurement reliability** refers to the instrument’s consistency or stability or precision.

• A reliable instrument will result in highly similar scores if we repeatedly measure a stable property in the same person.

• There could be three types of consistency:
  • over time (test-retest reliability),
  • across items (internal consistency) -> split-halves reliability
  • across different researchers (inter-rater reliability).
  • over time for the same observer (intra-observer consistency)
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A good measurement of constructs
A systematically measure of a construct…

• What we want is true score from observed score

Reliability is influenced by random error

Systematic error

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In the Educational Robotics (ER) field researchers have identified **lack of quantitative analysis** on how robotics can improve skills and increase learning achievements in students (Benitti 2012; Alimisis, 2013).

The evaluation of designing and problem-solving activities could be difficult for teachers: what students learn thanks to the ER approach is hardly detected via analysing scores obtained through standard tests (Berland, Baker and Blikstein, 2014).

We need a **deep (quantitative) analysis** of ER activities!

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How can we measure learning? Classical Instruments (Sensors)

- 'Survey' is a general term that can refer to a list of questions asking about biographical information, opinions, attitudes, traits, behavior, basically anything. Surveys generally cover a variety of topics.

- ‘Questionnaire’ is used when the focus is on one construct, or a related set of constructs, usually psychological traits, emotional states or attitudes.

- ‘Test’ is used when the aim is to measure an ability, such as general intelligence or math proficiency.

- Surveys, test and questionnaires all consist of a series of questions. We refer to the questions as **items**, usually accompanied by a set of discrete **response options** or a continuous range to choose from.

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How can we collect educational data? (On-Line Sensors)

FROM CLASSIC APPROACH
(questionnaires, multiple choice questions, etc.)

ONLINE APPROACH
(recording log files during students’ activity)

Machine Learning in Education?
• Evaluation of complex activities → ER, programming, etc.
• Personalised paths and feedbacks

Which sensors?
ON-LINE?
Modelling learning systems: the system theory approach
Case Study: Research Questions

Applying data mining and machine learning methods to data collected from the educational environments can allow to predict and classify students’ behaviours and discover latent structural regularities to large educational dataset.

Our 3 research objectives:

- accurate prediction of students’ team final performance
- identification of different patterns in the students’ problem-solving trajectories
- correlation of the discovered patterns of students’ problem-solving with the evaluation given by the educators
Case Study: Research procedure

1. Software updated into Lego Mindstorms EV3 blocks

2. Data acquisition (ER activities in collaboration with 16 schools)

3. Algorithmic problem solving for input data transformation

4. Performance prediction and data clustering (problem-solving patterns analysis)

5. Cluster models’ validation

6. Correlation results (Cluster analysis vs. Student performance)
Case Study: Software update design

Parameters set by students

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Case Study: Data acquisition

Exercise A

Program the robot so that it covers a given distance (1 m), trying to be as precise as possible.

Constraints:
• the amount of time within students had to design and test their solution (15 - 20 minutes);
• the teams could test the programming sequence as many times as they wanted;
• they were allowed to use measuring instruments only to measure some robot’s parameters (for example the radius of the wheel).

EVALUATION
• if the error was < 4 cm, the educator considered the challenge completed;
• if the error was >= 4 cm the educator considered the challenge not completed.
Exercise B

Program the robot so that it stops at a given distance from the wall (25 cm), trying to be as precise as possible.

Constraints:

- the amount of time within students had to design and test their solution (20 minutes for secondary school classes, 30 minutes for primary school classes);
- during the available time the teams could test the programming sequence as many times as they wanted.

EVALUATION

- if the error was < 3 cm, the educator considered the challenge completed;
- if the error was >= 3 cm the educator considered the challenge not completed.
Case Study: Data acquisition

Students from sixteen Italian primary and secondary schools, located in the Emilia Romagna, Lazio and Marche regions. The total number of students involved in this study is 455. The experimentation was carried out from March 2018 to October 2019.
Modelling learning systems: the system theory approach

Case Study: Input data transformation

Students’ teams designed 2187 programming sequences to solve the Exercise A and 4252 programming sequences to solve the Exercise B. At first, for each programming sequences in each log files we calculated these 13 parameters:

- **Motors**: the number of Motor blocks in the sequence
- **Loops**: the number of Loop blocks in the sequence.
- **Conditionals**: the number of Conditional and Sensors blocks in the sequence.
- **Others**: the number of blocks in the sequence belonging to different categories than Motors, Loops and Conditionals.
- **High Values**: the number of Motors blocks in the sequence with a Rotations parameter ≥ 20, or with a Seconds parameter ≥ 15.
- **Added**: the number of blocks added, compared to the previous sequence;
- **Deleted**: the number of blocks deleted, compared to the previous sequence;
- **Changed**: the number of blocks changed, compared to the previous sequence;
- **Equal**: the number of the same blocks, compared to the previous sequence;
- **Delta Motors**: amount of change in Motor blocks parameters (first, second or third parameter), compared to the previous sequence (calculated only for blocks of the “Changed” category);
- **Delta Loops**: amount of change in Loop blocks parameters, compared to the previous sequence;
- **Delta Conditionals**: amount of change in Conditional blocks parameters, compared to the previous sequence;
- **Delta Others**: amount of change in Other blocks parameters, compared to the previous sequence.
Thanks to the Log-files produced by the students, it is possible to extract the data useful for the development of the project:

→ Data-mining process extrapolated

→ 1113 code sequences relating to Exercise A
→ 1785 code sequences relating to Exercise B

→ The final evaluation expressed by the teacher for each of the two tests was used as a label for the subsequent data-labeling process
LOG-FILES AND DATA MINING

The log-files of the student groups were collected, the various datasets were grouped to train and refine the machine learning algorithms:

- **LR** - Logistic Regression
- **SVM** - Support Vector Machine
- **KNN** - K-nearest neighbor classifier
- **RF** - Random Forest

The project authors adopted two different approaches in data analysis:

- Supervised Approach
- Mixed Approach

**The Supervised Approach** creates a matrix of characteristics by manipulating data based on what the authors consider relevant.

**The Mixed Approach**, thanks to the preliminary division into clusters, attempts to focus attention on the presence of homogeneity between elements or specific intrinsic patterns in the composition of the dataset.

The Mixed Approach, initially released from any conditioning, lays the foundations for a second interpretation (this time supervised) of the data, producing a matrix of characteristics very different from that proposed by the supervised approach.
Analyzing the code sequence produced by the students, the authors of the experiment identified 12 indicators, thus managing to synthesize the elaborate of each group as a vector of the characteristics of 12 components.

Since each group of students produced a log-file for each of the two exercises, it was possible to calculate the mean and standard deviation of each indicator thus obtaining a two-dimensional sample.

The dataset that will be provided as input to the learning algorithms is therefore composed of the two-dimensional samples of each group of students.

<table>
<thead>
<tr>
<th>Name of the indicator</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motors</td>
<td>The number of Lego Motor blocks in the sequence</td>
</tr>
<tr>
<td>Loops</td>
<td>The number of Lego Loop blocks in the sequence</td>
</tr>
<tr>
<td>Conditionals</td>
<td>The number of Lego Conditional and Sensors blocks in the sequence</td>
</tr>
<tr>
<td>Others</td>
<td>The number of Lego blocks in the sequence belonging to different categories than Motors, Loops and Conditionals</td>
</tr>
<tr>
<td>Added</td>
<td>The number of Lego blocks added in sequence i+1 if compared to the sequence i</td>
</tr>
<tr>
<td>Changed*</td>
<td>The number of Lego blocks in sequence i+1 that has different parameters if compared to the sequence i</td>
</tr>
<tr>
<td>Deleted**</td>
<td>The number of Lego blocks deleted in sequence i+1 if compared to the sequence i</td>
</tr>
<tr>
<td>Equal</td>
<td>The number of the unchanged Lego blocks, compared to the previous sequence</td>
</tr>
<tr>
<td>Delta Motors***</td>
<td>The amount of change in Motor blocks parameters (first, second or third parameter) in sequence i+1 if compared to the sequence i</td>
</tr>
<tr>
<td>Delta Loops***</td>
<td>The amount of change in Loop blocks parameters in sequence i+1 if compared to the sequence i</td>
</tr>
<tr>
<td>Delta Conditionals***</td>
<td>amount of change in Conditional blocks parameters in sequence i+1 if compared to the sequence i</td>
</tr>
<tr>
<td>Delta Others***</td>
<td>amount of change in Other blocks parameters in sequence i+1 if compared to the sequence i</td>
</tr>
</tbody>
</table>

*how many blocks with same Block Name and same Block Option, but different comparing two contiguous sequences.

**how many blocks in a specific sequence have been deleted in the next sequence as "Changed".

***only for blocks of the "Changed" category.
In this case, the code sequence present in the log-files has been clustered using the **K-means method**, supported by the **Elbow method**.

The clustering algorithm has identified precise patterns within the documents of the various groups of students by grouping the data into optimal subsets.

### Esercizio A:

<table>
<thead>
<tr>
<th>Name</th>
<th>Number of sequences</th>
<th>%</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SMALL MOTORS PARAMETERS CHANGE</td>
<td>231</td>
<td>20,7</td>
<td>The team is refining its Motors parameters.</td>
</tr>
<tr>
<td>STRATEGY CHANGE</td>
<td>17</td>
<td>1,5</td>
<td>The team is changing its strategy (1 block is deleted, 1 block is added).</td>
</tr>
<tr>
<td>TEST MOTORS SEQUENCE</td>
<td>799</td>
<td>71,8</td>
<td>The team is testing the same previous programming sequence (with only Motors blocks).</td>
</tr>
<tr>
<td>HIGH MOTORS PARAMETERS CHANGE</td>
<td>30</td>
<td>2,7</td>
<td>The team is strongly changing its Motors parameters.</td>
</tr>
<tr>
<td>OTHERS BLOCKS CHANGE</td>
<td>1</td>
<td>0,1</td>
<td>The team is changing something not connected to the challenge.</td>
</tr>
<tr>
<td>SMALL LOOP PARAMETERS CHANGE</td>
<td>2</td>
<td>0,2</td>
<td>The team is refining its Loop parameters.</td>
</tr>
<tr>
<td>TEST LOOP SEQUENCE</td>
<td>21</td>
<td>1,9</td>
<td>The team is testing the same programming sequence (with Loop and Motors block).</td>
</tr>
<tr>
<td>TEST OTHERS BLOCKS SEQUENCE</td>
<td>12</td>
<td>1,1</td>
<td>The team is testing the same programming sequence (with Others and Motors blocks).</td>
</tr>
</tbody>
</table>

### Esercizio B:

<table>
<thead>
<tr>
<th>Name</th>
<th>Number of sequences</th>
<th>%</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TEST COMPLETE SEQUENCE (WITH LOOPS)</td>
<td>393</td>
<td>22,02</td>
<td>The team is testing the same previous programming sequence (with Motors, Loops and Conditional blocks).</td>
</tr>
<tr>
<td>SMALL CONDITIONALS PARAMETERS CHANGE (NO LOOPS)</td>
<td>676</td>
<td>37,87</td>
<td>The team is refining its conditional parameters, in the Wait block (there aren't Loops blocks in these clusters).</td>
</tr>
<tr>
<td>HIGH CONDITIONAL PARAMETERS CHANGE</td>
<td>48</td>
<td>2,69</td>
<td>The team is strongly changing its Conditional (Wait or Switch block) parameters.</td>
</tr>
<tr>
<td>DOUBLE PARAMETERS CHANGE (OTHERS AND MOTORS)</td>
<td>6</td>
<td>0,34</td>
<td>The team is changing Others and Motors parameters.</td>
</tr>
<tr>
<td>LOOPS PARAMETERS CHANGE</td>
<td>1</td>
<td>0,06</td>
<td>The team is changing its Loops parameters.</td>
</tr>
<tr>
<td>HIGH MOTORS PARAMETERS CHANGE</td>
<td>32</td>
<td>1,79</td>
<td>The team is strongly changing its Motors parameters.</td>
</tr>
<tr>
<td>TEST COMPLETE SEQUENCE (NO LOOPS)</td>
<td>234</td>
<td>13,11</td>
<td>The team is testing the same previous programming sequence (with Motors and Conditional blocks (Wait block), and without Loops blocks).</td>
</tr>
<tr>
<td>TEST COMPLEX COMPLETE SEQUENCE</td>
<td>103</td>
<td>5,77</td>
<td>The team is testing the same previous and complex programming sequence (with Loops, Motors, Others, and Conditional blocks).</td>
</tr>
<tr>
<td>ADDING BLOCKS</td>
<td>85</td>
<td>4,76</td>
<td>The team is adding some blocks in the sequence.</td>
</tr>
<tr>
<td>SMALL CONDITIONALS PARAMETER CHANGE (WITH LOOPS)</td>
<td>136</td>
<td>7,62</td>
<td>The team is refining its Conditional (Switch) parameters (with also Motors and Loops blocks in the sequence).</td>
</tr>
<tr>
<td>DELETING BLOCKS</td>
<td>71</td>
<td>3,98</td>
<td>The team is deleting some blocks in the sequence.</td>
</tr>
</tbody>
</table>
MIXED APPROACH AND PROBLEM SOLVING STYLES

The difference in the number of clusters is due to the nature of the exercises themselves: the former is less complex than the latter and requires a simpler code sequence. **By analyzing the data in this way**, the presence of each type of cluster within the files produced for each of the two exercises was assessed at a percentage level, thus obtaining a one-dimensional sample. The dataset that will be provided as input to the learning algorithms is therefore composed of the one-dimensional samples of each group of students.

The authors of the experiment, in collaboration with the same teachers who participated in the project, associated key elements present in each cluster to a specific type of "problem-solving".

- **Mathematical / planning**: reduced number of tests with minimal changes to the product code; the robot parameters were derived analytically.
- **Tinkering with refining**: the robot parameters are assigned in a heuristic way, refining them on the basis of the feedback generated by the robot itself.
- **Tinkering with significantly high changes**: the robot parameters are assigned in a heuristic way, but there is a high number of tests and a distortion of the code due to an incorrect interpretation of the robot feedback.
MIXED APPROACH AND PROBLEM SOLVING STYLES: I result

- Distribution of the different types of problem-solving in the two assigned exercises (upper part);
- distribution of successes and failures related to the different types of problem-solving (lower part).

Using the mixed approach as an exploitation of a clustering method for data manipulation (typical of the unsupervised approach) and combining it with the observation-interpretation of the results (typical of the supervised approach), thus relating cluster and classification of the problem-solving.
After preparing the datasets according to the two approaches, we move on to training the machine learning models to make them able to predict the "success" or "failure" of a group of students in solving an ER exercise.

**Goal:**

- **decree which of the four methods is more accurate in predicting the final result** of the single exercise;

- **performances** of each individual model in relation to the two different dataset management approaches, establishing which feature space is best in the training phase.
MACHINE LEARNING TECHNIQUES AND PERFORMANCE FORECAST

Learning algorithms used and results:

- The **Support Vector Machine**, which features a high degree of accuracy.
- The **Logistic Regression**, with good performance in terms of speed of prediction.
- The **K-nearest neighbor**, based on storage and characterized by low to medium computational complexity
- The **Random Forest**, with a clear interpretation of the data provided as output
PERFORMANCES OF MACHINE LEARNING TECHNIQUES

SVM, LR, K-NN, and RF are evaluated on the basis of four parameters:

→ **Accuracy**: the ratio of correct predictions to total predictions.

→ **Mean Precision**: the average value between the precision in establishing a student’s success and his or her failure.

→ **Mean Recall**: the average value between recall in predicting a student’s success and his or her failure. The term recall indicates the percentage of samples classified correctly with respect to the total number of samples belonging to that same class.

→ **Mean F1-score**: the mean value of the F1-score of each prediction, that is a parameter that depends on the precision and recall of each sample.

For each of the methods, through a **10-fold cross-validation method**, the mean and standard deviation are determined and the results obtained by the four machine-learning methods subjected to the two different data analysis approaches are compared.
**Performances** in the predictions of the four Machine Learning algorithms relating to **Exercises A and B**, obtained by applying the Supervised Approach (left) and the Mixed Approach (right).

The **Support Vector Machine** features a high degree of accuracy.
PERFORMANCES OF MACHINE LEARNING TECHNIQUES

<table>
<thead>
<tr>
<th></th>
<th>SVM (supervised)</th>
<th>SVM (mixed)</th>
<th>SVM (supervised) Ex. B</th>
<th>SVM (mixed) Ex. B</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accuracy</strong></td>
<td>0.80</td>
<td>0.82</td>
<td>0.83</td>
<td>0.84</td>
</tr>
<tr>
<td><strong>Mean Precision</strong></td>
<td>0.76</td>
<td>0.80</td>
<td>0.77</td>
<td>0.82</td>
</tr>
<tr>
<td><strong>Mean Recall</strong></td>
<td>0.72</td>
<td>0.76</td>
<td>0.76</td>
<td>0.79</td>
</tr>
<tr>
<td><strong>Mean F1 Score</strong></td>
<td>0.71</td>
<td>0.76</td>
<td>0.75</td>
<td>0.79</td>
</tr>
</tbody>
</table>

To obtain these results a **repeated 10-fold cross validation** was performed, so that the average value and standard deviation of the four indicators (Accuracy, Precision, Recall, F1 Score) repeating the 10-fold validation multiple times were calculated.
Conclusions

1- For the first time an experimentation involving a fair number of students (455) has been conducted gathering programming sequences designed by students during Educational Robotics activities and automatically analysing them, using machine learning techniques (Scaradozzi, Cesaretti, Screpanti & Mangina, 2020).

2- We consider very important from a pedagogical point of view the recall indicator for the students’ groups who showed a negative performance. Recognizing in advance those teams with difficulties in the exercise resolution could allow teachers to give them some suggestions to solve the challenge; the MLP neural network algorithm reached very high performance also for this indicator (Ex. A = 0.92, Ex. B = 0.97):
We are quite close to identify each students’ group that is struggling with the Educational Robotics challenge, and this result is very important for further developments of the system, implementing a real-time use of the tool by teachers and educators.

3- The results presented our research project seem to show connections with previous research, in terms of problem-solving patterns.

Further developments

Some planned improvements are:

• Applying our approach to a **larger set of Robotics exercises** (in order to obtain more general results).

• Including **time tracking** in the log files generated by the system.

• Using **recurrent neural network**, in particular the long short-term memory autoencoders (a structure specifically designed to support sequences of input data), in order to translate the programming sequences created by students into fixed-length vectors (compress representation of the input data), maintaining high level of information content.

• Performing a **sequential analysis** (lag sequential analysis, sequential pattern mining) of the programming sequences created by the participants.

• Updating the current system design with a **personalised e-learning system**.
Thank you! Questions?

- Nihil est in intellectu quod prius non fuerit in sensu
- Nihil est in intellectu quod prius non fuerit in sensu nisi intellectus ipse.

(Nouveaux Essais, II, 1, 2) <Leibniz>

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Related work

Journal:


Related work

International conference:


DiveSafe: Co-funded by the EMFF programme of the European Union
RoboPISCES, E-Tech: Co-funded by the Erasmus+ programme of the European Union
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Other types of publication:

- **Book chapters:**

- **INDIRE National platform for teachers’ training:**