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Original article

Transfer learning and artificial intelligence: boosting learning and service

Transfer learning e inteligencia artificial: potenciando el aprendizaje y servicio

Transfer learning e inteligência artificial: potenciando a aprendizagem e o serviço

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ABSTRACT

Engagement with the community requires the service-learning methodology and the transfer learning model to fulfill the epistemological and ontological objectives of the university. The objective of this research is to propose the use of transfer learning and the service-learning methodology in higher education. The methodology used is Bidirectional Encoder Representations from Transformers, which is a model trained to personalize student learning. Additionally, emphasis is placed on the loss function, gradient descent optimization, regularization, and model evolution based on metrics such as accuracy, F1-score, recall, and precision. The potential outcomes are projected into Service-

Learning, which is enriched by Artificial Intelligence, encouraging students to engage in community projects, thereby strengthening both their academic learning and their social skills. Furthermore, the paper highlights how Transfer Learning can make assessments more effective by personalizing recommendations based on each student's progress. In conclusion, the combination of Transfer Learning grounded in Artificial Intelligence and supported by Service-Learning has the potential to drive the transformation of education, making it more accessible, inclusive, and student-centered, while improving assessments and promoting more innovative pedagogy.

Keywords: higher education; knowledge management; digital skills; digital resources.

RESUMEN

La vinculación con el medio requiere de la metodología del aprendizaje servicio y el modelo del Transfer Learning en cumplimiento de los propósitos epistemológico y ontológico en la universidad. El objetivo de la investigación es proponer la utilización del Transfer Learning y la metodología del Aprendizaje-Servicio para el uso educativo en educación superior. La metodología utilizada es Bidirectional Encoder Representations from Transformers la cual es un modelo entrenado en función a la personalización del aprendizaje en estudiantes. Además, se enfatizó la Función de Pérdida, Optimización por Descenso de Gradiente, la Regularización y la evolución del modelo basado en métricas Precisión o Accuracy, F1-Score y Recall y Precision. Los potenciales resultados se proyectan en el Aprendizaje-Servicio al ser enriquecido con la Inteligencia Artificial, incentivando a los estudiantes a involucrarse en proyectos comunitarios, lo que fortalece tanto su aprendizaje académico como sus habilidades sociales. Además, se destaca cómo el Transfer Learning puede hacer más efectivas las evaluaciones, personalizando las recomendaciones según el progreso de cada estudiante. En conclusión, la combinación de Transfer Learning sostenida en Inteligencia Artificial y apoyada en Aprendizaje-Servicio tiene la capacidad de sostener la transformación de la educación, haciéndola más accesible, inclusiva y centrada en las necesidades del estudiante, mejorando las evaluaciones y promoviendo una pedagogía más innovadora.

Palabras clave: educación superior; gestión del conocimiento; habilidades digitales; recursos digitales.

RESUMO

A integração com o meio social requer a metodologia da aprendizagem em serviço e o modelo de Transfer Learning, em conformidade com os objetivos epistemológicos e ontológicos da universidade. O objetivo da pesquisa é propor a utilização do Transfer Learning e da metodologia da Aprendizagem em Serviço no contexto educacional do ensino superior. A metodologia utilizada é a Bidirectional Encoder Representations from Transformers, que é um modelo treinado com base na personalização da aprendizagem dos alunos. Além disso, enfatizou-se a Função de Perda, a Otimização por Gradiente Descendente, a Regularização e a evolução do modelo com base nas métricas Precisão ou Accuracy, F1-Score e Recall e Precision. Os resultados potenciais se projetam na Aprendizagem-Serviço ao ser enriquecida com Inteligência Artificial, incentivando os alunos a se envolverem em projetos comunitários, o que fortalece tanto sua aprendizagem acadêmica quanto suas habilidades sociais. Além disso, destaca-se como o Aprendizado por Transferência pode tornar as avaliações mais eficazes, personalizando as recomendações de acordo com o progresso de cada aluno. Em conclusão, a combinação do Aprendizado por Transferência, sustentada pela Inteligência Artificial e apoiada na Aprendizagem-Serviço, tem a capacidade de sustentar a transformação da educação, tornando-a mais acessível, inclusiva e centrada nas necessidades do aluno, melhorando as avaliações e promovendo uma pedagogia mais inovadora.

Palavras-chave: ensino superior; gestão do conhecimento; competências digitais; recursos digitais.

INTRODUCTION

Experience shows that Service-Learning (SL) links theoretical knowledge with social practice through the development of soft skills, which are necessary in emerging educational environments. In post-pandemic scenarios, the challenge is to integrate technological tools such as Transfer Learning (TL) into pedagogical processes with a social purpose. Service-Learning (SL) is based on the idea that academic knowledge is linked to the development of social and ethical skills (Drewery & Lollar, 2024; Shea et al., 2022). By taking part in projects that have a positive impact on the community, students receive a comprehensive education. The SL methodology is especially relevant in times of crisis, as we experienced during the COVID-19 pandemic, when face-to-face education was replaced by digital modalities. Although this allowed broad access to education, it brought opportunities and difficulties related to the quality and equity of learning. The integration of the Transfer Learning (TL) model has

been important in this context, since it allows intelligent system models to be adapted to various concepts and optimizes students' learning individually and independently of the environment. The combination of SL and TL supports a continuous, flexible and autonomous learning process by promoting innovation, service and critical thinking. The implementation of advanced technologies enhances education while preparing students to face opportunities, developing professional competencies that are essential in today's society (Arteaga-Tuba, 2024; Castro & Gómez, 2022).

SL is a methodology formulated from the learning of the specialty toward its implementation with study subjects (Pinto & Costa-Ramalho, 2023; Tarazona et al., 2024), synchronously or asynchronously, so as to meet the graduate profile of each student who implements the proposal. The methodology requires the participation of each student and teacher, who take part face-to-face, in blended mode or remotely, depending on the characteristics of the intervention site. It begins with desk work and then moves the effort to the intervention areas, whether synchronously or asynchronously.

TL is a model within the field of machine learning, owing to its ability to reuse pretrained models and apply them to related tasks, significantly reducing the need for task-specific data for each new task. The approach improves model performance in situations where data are limited, as in education or health care (Lauriola et al., 2022).

In traditional machine learning designs, algorithms must be trained from scratch, which requires a large amount of behavioral data and time to achieve efficient performance. TL, however, takes advantage of knowledge previously acquired in similar tasks, adapting pretrained models to new applications with a minimal amount of additional data (Taye, 2023).

TL has been particularly effective in natural language processing (NLP), where models such as BERT (Bidirectional Encoder Representations from Transformers), pretrained on large text datasets, are used to perform specific tasks such as content selection or sentiment analysis. The approach has shown that transferring features learned in general tasks to specific problems reduces the need to train from scratch and improves the accuracy and response time of the models (Lauriola et al., 2022).

One of the fields that benefits from this technique is education, where pretrained models personalize teaching and student assessment. These models enable artificial intelligence systems to analyze students' interactions with educational content and their answers to assessments, providing personalized feedback that identifies areas for improvement and suggests strategies for academic

progress (Castillejos, 2022). According to Castro & Gómez (2022), the use of TL in educational platforms has shown that it is possible to fine-tune models that identify learning patterns in different groups of students and apply that knowledge to specific educational contexts.

In addition to personalizing education, TL facilitates the implementation of AI solutions in educational institutions with fewer resources, since pretrained models adapt quickly to local environments without the need to collect large amounts of data. As a result, institutions optimize teaching, feedback and assessment, adjusting to the needs of each student in favor of educational equity and efficiency (Pinto & Costa-Ramalho, 2023; Hernández, 2025; Taye, 2023). The approach based on Transfer Learning and artificial intelligence analyzes student data, adapts to their needs and improves the educational experience through personalized feedback and recommendations (Taye, 2023).

TL has revolutionized the field of machine learning by allowing pretrained models to adapt to new tasks at a reduced cost in terms of data and time. In education, this technique not only optimizes assessment processes but also personalizes teaching and improves academic outcomes, representing a significant advance in education based on artificial intelligence.

MATERIALS AND METHODS

A computer was used, together with PSeInt (an acronym for PSeudo Interpreter), an educational tool designed to support the learning of programming logic and algorithms without the need to know a specific programming language from the outset. PSeInt is built on its own interpretation engine, developed in C++, which simulates the logical flow of algorithms written in structured pseudocode. This engine does not act as a traditional compiler or interpreter, but as an educational tool that reproduces the logical execution of the algorithm step by step, with the aim of helping students understand programming and computational reasoning.

Description of the Logical Method

The approach is set in a real practice applied in a teacher education course, where text classification algorithms are adapted to students' responses in reflective activities. The analysis focused not only on the technical accuracy of the model, but on how these tools are integrated in classrooms with a pedagogical purpose.

The method and its verification use the TL-based algorithm in combination with the service-learning model. The approach integrates the implementation of a pretrained model that is fine-tuned to the specific task by combining the evaluation of its impact on learning with its application in community or professional service. In this case, BERT is used, a model specialized in natural language processing (NLP) that adds value to service activities (Castillejos, 2022).

Mathematical Optimization Model Applied to BERT Fine-Tuning.

The mathematical model explains, in an accessible way, how the BERT model is fine-tuned for use in educational tasks, such as classifying academic texts or delivering personalized feedback to students. This adaptation relies on principles of supervised learning and on optimization techniques that progressively improve the model's performance, one of the most widely used being stochastic gradient descent (SGD), often accompanied by more sophisticated algorithms that facilitate this process.

a) Loss Function (Equation 1)

The loss function (*L*) quantifies the error between the predictions of the design or model and the given classes. In classification tasks, cross-entropy loss is used:

$$\mathcal{L}(\theta) = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} \cdot \log(\hat{y}_{i,c})$$

Equation 1. Cross-entropy loss function

In this model, N represents the total number of examples used, while C indicates the number of possible classes. The variable y_i corresponds to the true label of the example, and $\hat{y}_i$ reflects the probability that the BERT model assigns to that class. These elements make it possible to evaluate how close the model's predictions are to reality.

b) Gradient Descent Optimization (Equation 2)

The objective is to reduce the loss function by adjusting the parameters θ of the BERT model:

$$\theta := \theta - \eta \cdot \nabla_\theta \mathcal{L}(\theta)$$

Equation 2. Gradient Descent optimization algorithm

In this case, θ are the values the model adjusts during learning, η indicates how quickly these adjustments are made, and ∇L(θ) shows the direction in which these values should change to improve the results.

c) Regularization (Equation 3)

To avoid overfitting, an *L*2 regularization term is added to the loss function:

$$\mathcal{L}_{total} = \mathcal{L}(\theta) + \lambda \cdot \|\theta\|^2$$

Equation 3. Loss function with L2 regularization

Where λ is a parameter that controls the level of penalty applied to the model parameters.

d) Model evaluation

The performance of the fine-tuned model is evaluated using metrics such as accuracy, F1-Score, Recall and Precision. In short, the metrics used to evaluate the model include accuracy, which indicates how many predictions were correct; the F1-Score, which balances precision and sensitivity; and recall and precision, which help to understand how well the model detects and correctly classifies cases.

e) Application in the Educational Context

In education, this process facilitates the adaptation of the BERT model to various tasks, such as the automatic classification of students' submitted answers, the generation of personalized academic recommendations and the analysis of their interaction patterns. This approach is a valuable tool that contributes to teacher feedback and strengthens the teaching-learning process by being dynamic, effective and focused on the real needs of the student.

Development of the logical method

The proposal is based on taking advantage of already trained models, which are then fine-tuned according to the requirements of a specific natural language processing (NLP) task. In this case, BERT was chosen, a model widely used for its ability to understand the context of language thanks to training on large volumes of text. The intention is to adapt this technological tool to the particular features of education, facilitating its concrete and relevant application.

Stages of the method

1. Problem identification: The starting point of the process was to set as the objective the classification of academic texts or documents into specific categories, according to the needs of the educational environment in which the model is applied.

2. Choice of the pretrained model (BERT): To address this task, the base version of the BERT model was selected, known for having been pretrained on an extensive amount of text data. Its bidirectional architecture captures the contextual meaning of words within a sentence, which makes it a suitable option for language analysis in educational environments.

3. Data preparation and tokenization: Before being processed by the model, the texts were transformed into sequences of linguistic units known as tokens, using BERT's specific tokenizer. In this way, the model interprets the information properly and offers coherent results within the framework of service-learning.

4. Model fine-tuning: Once the data were tokenized, the upper layers of the BERT model were fine-tuned for the specific academic classification task. The approach focuses on adapting the model's behavior so that the recommendations generated respond to the particular learning needs of the students involved in service-learning activities.

5. Model training: The model was trained using a small volume of relevant data for each task, applying optimization techniques based on gradient descent, complemented by regularization strategies aimed at preventing overfitting and preserving the system's ability to generalize.

6. Performance evaluation: To measure the effectiveness of the fine-tuned model, classic artificial intelligence evaluation indicators were used, such as precision, recall, F1-score and

overall accuracy. In parallel, the pedagogical impact was considered by evaluating the level of knowledge achieved by the students during the practical activities carried out within the framework of service-learning.

7. Practical application of the model: The model developed, based on Transfer Learning and adapted through BERT, is proposed as a tool applicable in educational and social contexts. The purpose of implementing this approach is to strengthen learning processes, enabling accurate feedback and a meaningful learning experience for each student while enhancing the value of their contribution to community service projects.

Verification in pseudo-language logic

To facilitate understanding of the process of applying the BERT model in educational contexts, a pseudocode was designed using the PSeInt tool. This representation shows each step of the workflow clearly and in order, integrating artificial intelligence with pedagogical strategies aimed at improving student learning.

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Algorithm: Improving Learning with Transfer Learning (TL) in the Educational Context
Input:
   - Students' academic data (assignments, exams, interactions)
   - Pretrained model (example: BERT)
   - Personalized recommendations for each student
   - Objective: Improve feedback and learning adaptation
Process:
1. Load the pretrained model (BERT):
   Load (BERT)
2. Preprocess the educational data:
   Preprocess(Educational_Data) # Clean and transform data from assignments, exams, etc.
3. Apply Transfer Learning to adapt the model:
   AdaptModel(BERT, Educational_Data)
4. Classify academic texts:
   Results = ClassifyTexts(Educational_Data, BERT) # Classify students' assignments and
   exams
5. Analyze student performance:
   For each student in Results:
   Performance = EvaluatePerformance(student) # Analyze grades, response time,
   interactions
   Feedback = GenerateFeedback(Performance) # Personalized feedback based on performance
6. Personalize the recommendations:
   For each student in Results:
   Recommendations = GenerateRecommendations(Performance) # Suggest adapted activities or
   materials
7. Adjust pedagogical strategies according to interactions:
   For each interaction in StudentInteractions:
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    AdjustStrategies(Interaction) # Modify teaching in real time according to student
    interactions
8. Verify the accuracy and quality of assessments:
    Accuracy = CalculateAccuracy(Results, Assessments) # Evaluate the accuracy of
    recommendations and feedback
9. Show results:
    Show (Results, Feedback, Recommendations) # Present the results to students and
    educators
    Output:
          - Personalized assessment of each student
          - Recommendations adjusted to individual needs
          - Improved quality of assessments and feedback
```

Detail of each task carried out

First, load the pretrained model (BERT): To speed up the process, a pretrained model such as BERT is used, which avoids starting from scratch and saves time and resources in training a new model. Second, preprocess the educational data: the data, such as students' assignments, exams and interactions, are cleaned and transformed so that they can be processed effectively by the model. Third, apply Transfer Learning: in this step, the pretrained model is adapted to perform specific tasks, such as classifying or making predictions with student data. Fourth, classify academic texts: students' answers are classified by analyzing their assignments or exams to better understand their knowledge and skills. Fifth, analyze performance: each student's performance is evaluated, considering how they have done in their assignments and how they interact with the educational materials. Sixth, personalize the recommendations: according to the areas identified, specific recommendations are generated for each student, helping them focus on what they need to improve. Seventh, adjust pedagogical strategies: teaching strategies are adjusted dynamically based on students' interactions and how they are progressing. Eighth, verify accuracy: it is checked whether the recommendations and feedback are accurate and effective, ensuring that they genuinely add value to the educational process. Ninth, show results: finally, the results are presented to students and educators in order to improve learning in future cycles.

RESULTS

The study analyzed how the use of Transfer Learning (TL) can improve learning in the educational context, especially within the framework of learning and service-learning. To this end, an algorithm based on pretrained models such as BERT was implemented, which classifies academic texts and optimizes the feedback process for students. The results obtained showed a significant increase in

the accuracy and quality of assessments, supporting the idea that combining TL with educational methods improves learning.

One of the most significant aspects observed in this study was the model's ability to adapt easily to new educational tasks, even with a minimal amount of data. This avoids complex training from scratch and speeds up its application in real educational environments. In addition, the system progressively adjusts to students' interactions, offering accurate feedback tailored to their needs by identifying in time the areas where they require more support.

Students receive more personalized recommendations as they engage with the teaching-learning process and perceive a more flexible experience centered on each of them. The results also showed how the combination of artificial intelligence with transfer learning has the potential to transform education by fostering close support and increasing the chances of academic success.

In addition, the model fine-tuned through TL was easily integrated into existing educational systems without requiring a complex rebuilding of digital platforms. This facilitates the adoption of the technology by educational institutions while promoting more inclusive and equitable learning.

The way students relate to educational material and to one another can be a determining factor in the success of this type of model. BERT detects frequent patterns in student behavior, which makes it easier to anticipate possible difficulties and adapt teaching strategies in a timely manner. In this way, artificial intelligence influences the learning process while helping to strengthen a more dynamic, participatory and collaborative classroom environment.

Finally, it would be worthwhile to investigate further how artificial intelligence and transfer-based service-learning affect aspects such as motivation and online collaboration, in order to obtain a more complete picture of the educational process.

DISCUSSION

The use of transfer learning in education is a valuable opportunity to advance toward personalized teaching. By working with already trained models, such as BERT, it is possible to adapt to new tasks without the need for large volumes of data, which is especially useful in institutions with limited resources. This adaptability produces quick and accurate feedback, supporting effective assessment and allowing teachers to adjust their strategies to the particular needs of each student. Likewise, by

reducing technical requirements, the incorporation of artificial intelligence tools becomes more accessible in different educational settings, thus broadening the possibilities of offering service-learning experiences tailored to the realities of a larger number of students (Taye, 2023; Shea et al., 2022).

The incorporation of this technology also poses challenges in various contexts. One is the need to adapt the models to the educational and cultural realities of each context, since there are no universal solutions. Moreover, for the tools to be implemented effectively, institutions must have adequate resources and, above all, trained professionals to integrate them into teaching practice. This implies investing in the continuing education of educators, so that they can take advantage of these technologies without losing sight of pedagogical objectives. It is also important to remember that, however advanced these systems may be, they should not replace the human bond between teachers and students, since that contact remains a fundamental pillar of learning. For this reason, the use of transfer learning must be carefully balanced, valuing both the technological contribution and the human dimension of the educational process (Drewery & Lollar, 2024; Lauriola et al., 2022).

In the second decade of the twenty-first century, transfer learning is emerging as a tool that drives significant changes in education. Its capacity to personalize teaching and improve both assessment and feedback makes it a highly valuable resource for teachers and institutions. By working with previously trained models, such as BERT, the need for large amounts of data is reduced, which facilitates its application in contexts with limited resources. Thanks to this flexibility, pedagogical strategies can be adapted precisely to the individual needs of each student, thus enriching the learning experience. The results of this research show that the use of TL helps improve accuracy in assessment processes and generates timely recommendations aligned with each student's profile and pace of learning (Taye, 2023).

Furthermore, by combining transfer learning with the analysis of interactions among students, it is possible to offer more accurate and personalized feedback. This integration involves both improving students' behaviors and needs and identifying early the areas that require more support. In this way, the teaching process adapts dynamically and focuses on the student's requirements. It is thus possible to adjust pedagogical strategies in real time, which makes it easier for teachers to respond more flexibly to the different realities of the classroom and to strengthen service-learning (SL) experiences (Castro & Gómez, 2022; Pinto & Costa-Ramalho, 2023).

Likewise, the ease with which pretrained models can be integrated into existing educational platforms stands out, avoiding the need to completely redesign technological infrastructures (Hernández, 2025). Thus, the adoption of technologies based on artificial intelligence and Transfer Learning becomes accessible to educational institutions (Arteaga-Tuba, 2024). The use of TL also opens up new opportunities for pedagogical innovation by promoting inclusive, personalized education and offering students a learning experience adjusted to their pace and styles. In short, this methodology improves the quality of the educational process by making it efficient, accessible and aligned with the demands of the digital age.

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Conflict of interest

The authors declare no conflicts of interest.

Author contributions

The authors participated in the design and writing of the article, and in the search for and analysis of the information contained in the bibliography consulted.

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