The Role of Natural Language Processing in Advancing Competency-Based Education and Mathematics Learning in Fourth Graders

19/04/23 (RELELA)

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UNIVERSIDAD DE CHILE
INSTITUTO DE ESTUDIOS
AVANZADOS EN EDUCACIÓN
IE

Abstract

La presente charla tiene como objetivo explorar cómo el procesamiento del lenguaje natural (NLP) puede ser utilizada para comprender la educación en la enseñanza primaria.

En la actualidad, las computadoras se han convertido en una herramienta esencial para el cálculo y la simulación, por lo que resulta importante desarrollar enfoques pedagógicos que mejoren la capacidad de comprensión y razonamiento de los estudiantes.

Para lograr este objetivo, se ha propuesto la utilización de técnicas de inteligencia artificial adecuadas para comprender cómo y dónde centrarse en la enseñanza.

En esta charla, presentaré gran parte de mi investigación sobre el impacto de la minería de datos, el aprendizaje automático y las técnicas de NLP en la investigación educativa, tanto pura como aplicada.

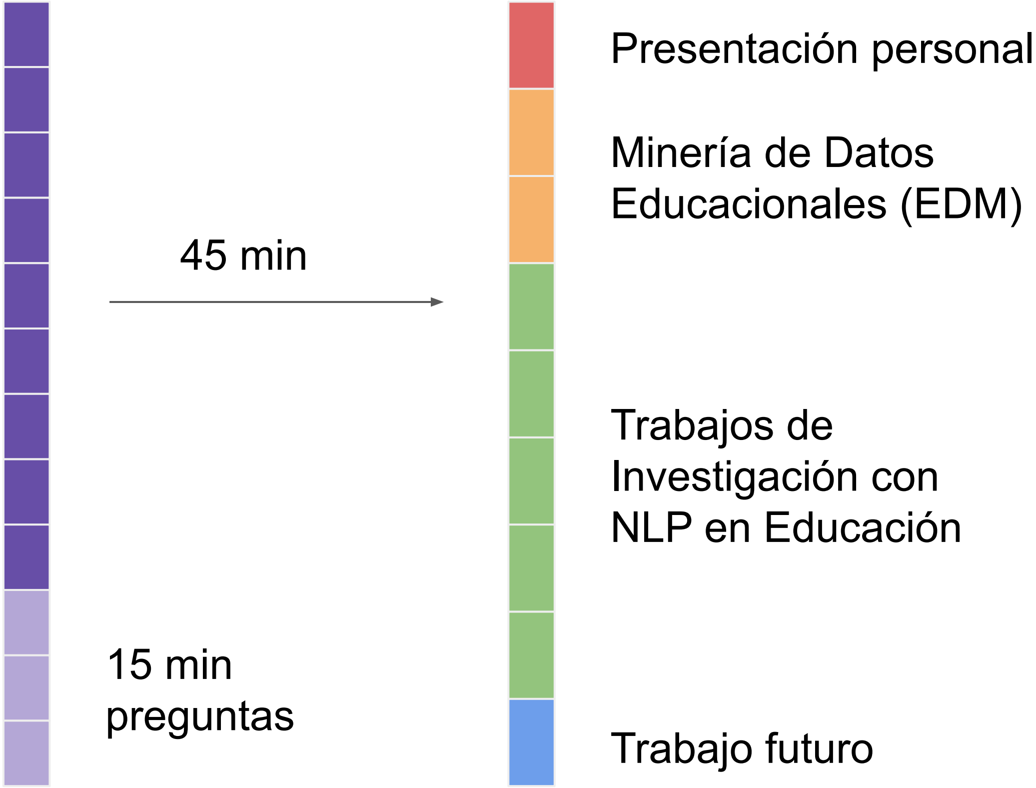
Ilustrare las principales tareas de NLP utilizadas en la minería de datos educativos y describiré los desafíos y los conocimientos adquiridos al proponer nuevos métodos y tareas de NLP en educación. Además, expondré la utilidad de NLP para descifrar las perspectivas actuales de la educación basada en competencias y demostrare el potencial de las técnicas de NLP para entender los desafíos de la argumentación en matemáticas en estudiantes de cuarto grado en Chile y su relación con la estimación del rendimiento en pruebas estandarizadas.

Explicare la parte metodológica y detallare los datos y técnicas de análisis utilizados. Presentare los resultados obtenidos de manera clara y discutiré las implicaciones prácticas de los hallazgos.

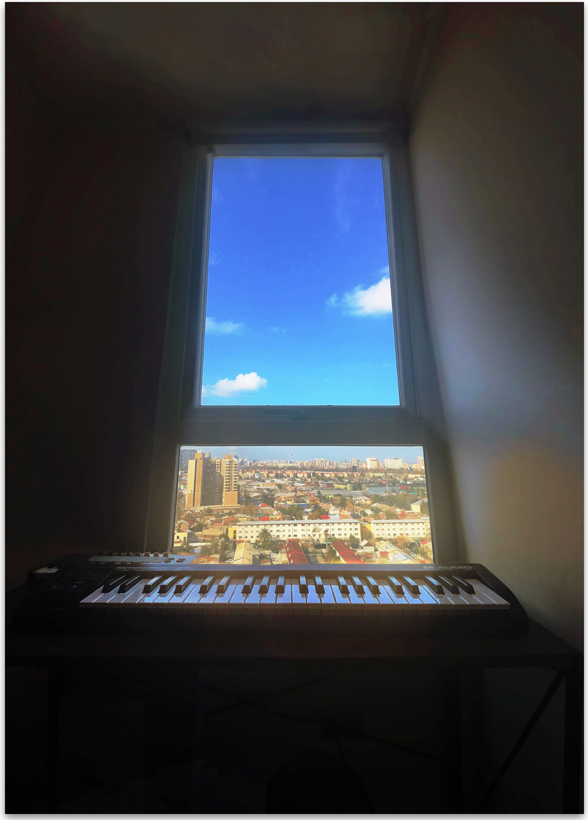
Finalmente, destacare la importancia del uso de NLP en educación para mejorar las competencias de los estudiantes y sugeriré posibles vías para futuras investigaciones.

Los asistentes a la charla tendrán la oportunidad de comprender el nuevo paradigma en NLP y conocer cómo conectar NLP con grafos del conocimiento, cuáles son los beneficios que nos aporta para construir IA explicables en contextos educativos y cómo podría ayudar a desarrollar una nueva técnica para comprender conceptos en educación.

Timeline


45 min
15 min
preguntas
Presentación personal
Minería de Datos
Educacionales (EDM)
Trabajos de
Investigación con
NLP en Educación
Trabajo futuro

Presentación personal



Presentación personal

Licenciado en Ciencias de la Ingenieria, mencion Matematicas

Estudiante

Ingeniería Matemática
FACULTAD DE CIENCIAS FÍSICAS Y MATEMÁTICAS
UNIVERSIDAD DE CHILE

Alumno regular
Ingeniería matemática, FCFM

dcc
CIENCIAS DE LA COMPUTACIÓN
UNIVERSIDAD DE CHILE

Alumno regular
Magister en Ciencias, mencion Computacion, FCFM

Investigador asistente

CiAE
CENTRO DE INVESTIGACIÓN AVANZADA EN EDUCACIÓN

Enero 2022 - Diciembre 2023

Araya, Roberto.

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

Abril 2022 - Abril 2023*

Mannonen, Joonas; Hämäläinen, Raija; Lehesvuori, Sami.

AEDIA

Co-fundador de Asociación de Ética en Datos e Inteligencia Artificial (AEDIA)

Source Reconstruction for Heat Equation

Noviembre 2022-hoy

Urrutia, Felipe &
Axel Osses

Theorem 1. *Exist β a real number different to $\gamma\lambda_k$, $V^{(\tau)}$ the Volterra operator (2), such that a control $v_k^{(\tau)}$ of the form*

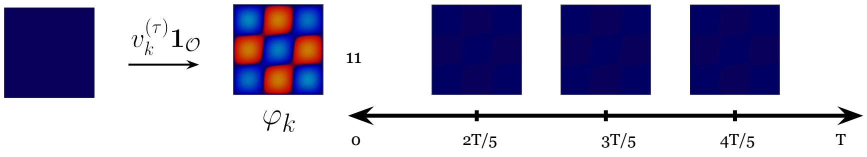
$$v_k^{(\tau)}(x,t) = c_k(\tau;\beta)\psi_k(x)V^{(\tau)}e^{\beta t} \tag{11}$$

satisfies that the function ϕ is a solution of the problem (9) and satisfies the initial temperature constraint (10). Moreover, $V^{(\tau)}e^{\beta t}$ is known (Lemma 1) and the c_k term is given by

$$c_k(\tau;\beta) = \frac{\gamma\lambda_k - \beta}{\beta\sigma(0)\left(e^{\beta\tau} - e^{\gamma\lambda_k\tau}\right) + \int_0^\tau \left(\sigma(s) + \beta\sigma'(s)\right)\left(e^{\beta\tau+\gamma\lambda_k s} - e^{\beta s+\gamma\lambda_k\tau}\right)ds}. \tag{12}$$

CMM
Center for Mathematical Modeling

$$\theta_k^{(\tau)}(x,t) = c_k(\tau;\beta_\tau)\psi_k(x)e^{\beta_\tau t}.$$



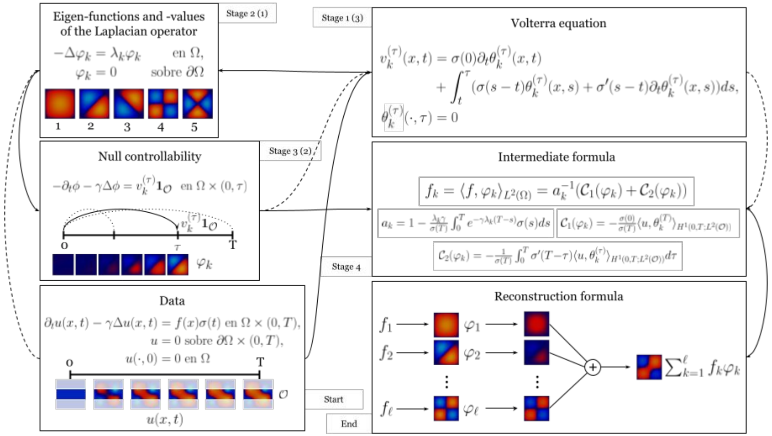


Figure 1. Illustration of our methodology for source reconstruction from known global measurements. **(Solid lines)** Sequence of steps of our method and **(Dashed lines)** sequence of steps of the [1] method.

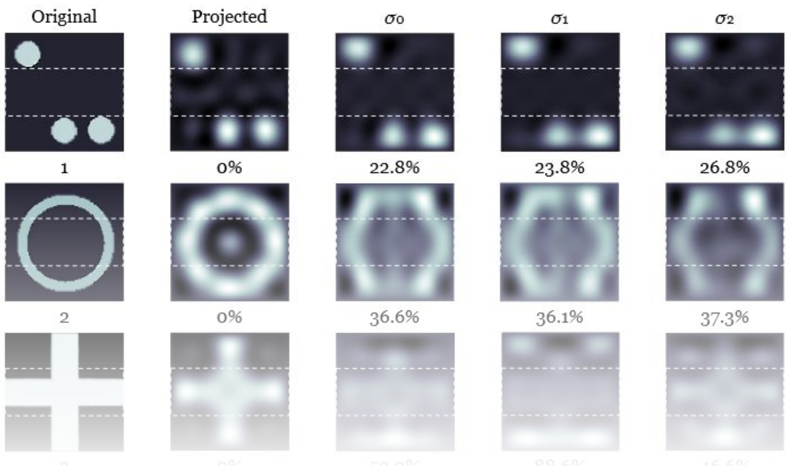


Figure 3. The given figure depicts the process of reconstructing various sources, represented by the function $f(x)$, where x belongs to a two-dimensional region denoted by $\Omega = (0,1)^2$. The reconstruction is done based on the local measurements taken from the observatory denoted by $\mathcal{O} = (0,1)\times(0.3,0.7)$, which is bounded by dotted lines. The measurements are affected by centered-Gaussian noise (with 0.5 standard deviation). The accuracy of the reconstructions is evaluated by computing the L^2 relative error relative to the first 45 eigen-functions of the projected source. Three different cases are considered, as represented in the third, fourth, and fifth columns of the figure, where σ takes the values σ_1, σ_2, and σ_3, respectively (see Figure 2).

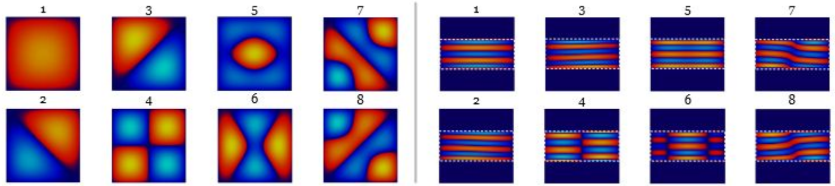
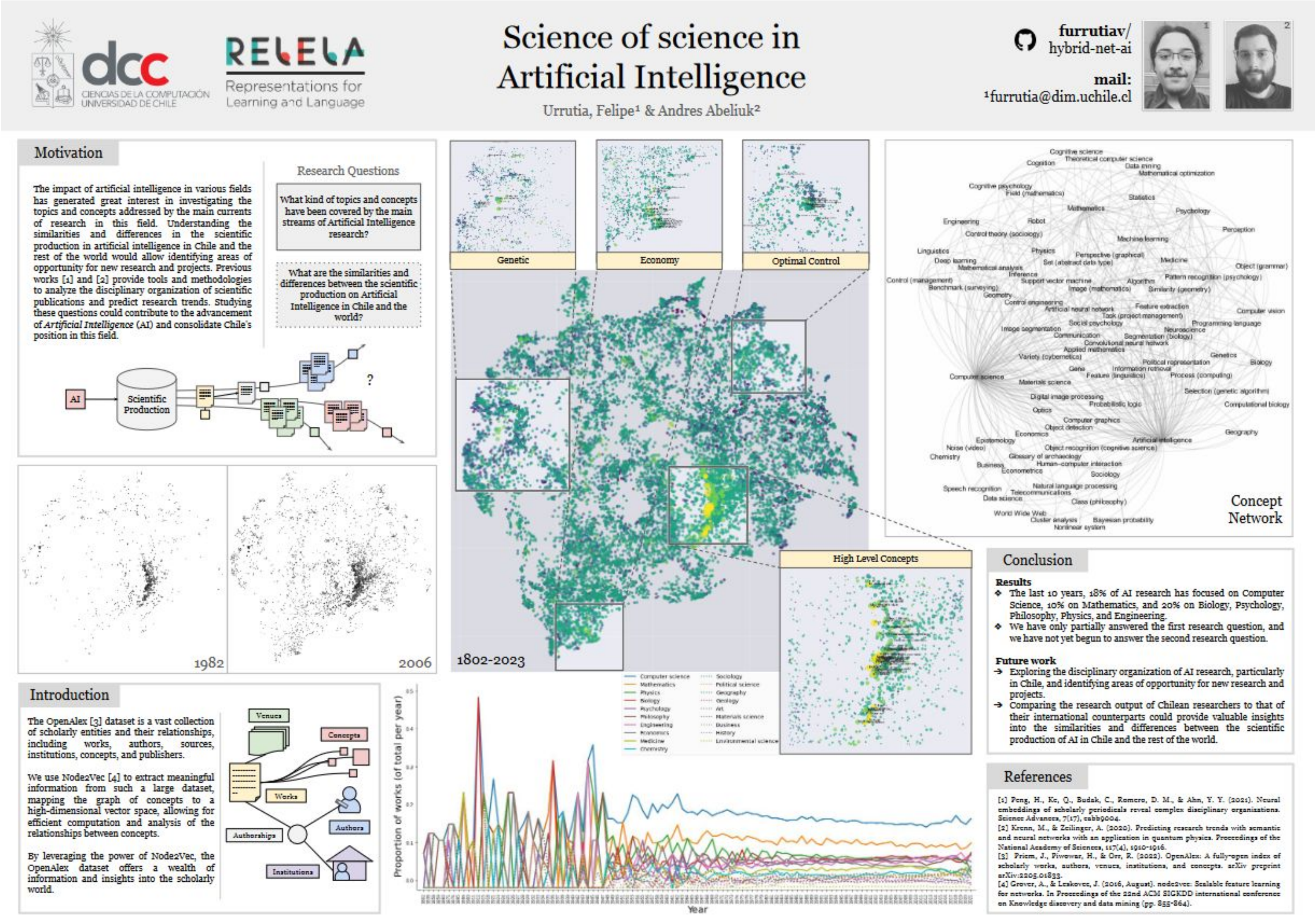


Figure 4. Sample of the first eight eigen-functions of the Laplacian operator together with their associated pseudo-functions. **(Left)** Eigen-functions. **(Right)** Pseudo-functions.

Ciencia de la ciencia en IA

Enero 2023-hoy

Urrutia, Felipe & ***Andres Abeliuk***



RL5 / Human-centric AI

CENIA

CENTRO NACIONAL DE INTELIGENCIA ARTIFICIAL

Minería de Datos Educacionales (EDM)

Minería de Datos Educacionales

Datos Edu. + Herramientas + Objetivos

1. Elementos
2. Grupos de actores
3. Tareas

Educational data mining: a review of the state of the art

2010
Romero, Cristóbal & Sebastián Ventura.
IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 40(6), 601-618.

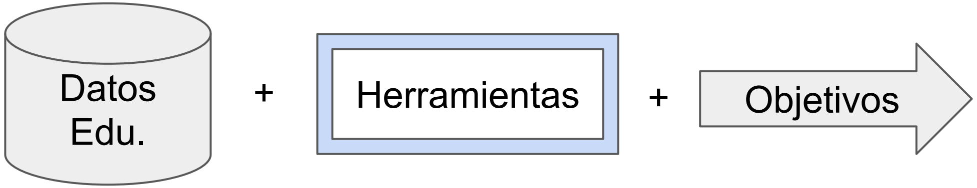
Minería de Datos Educacionales

- Respuestas en ejercicios
- Grabaciones de clases
- Redes sociales
- Libros de contenido para clases

- Contabilidad de recursos
- Mallas curriculares
- Variables de comportamiento
- Planificación de clases

Romero, C.; Ventura, S. (**2010**). *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 40(6), 601-618.*

Minería de Datos Educacionales



Algoritmos estadísticos
- Análisis de correlaciones

Aprendizaje de máquinas
- Regresión
- Clasificación
- Clustering

Minería de datos
- Reglas de asociación

Romero, C.; Ventura, S. (**2010**). *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 40(6), 601-618.*

Minería de Datos Educacionales

Investigación **pura**

- *Entendimientos* de fenómenos educativos
- *Descubrimiento* de nuevos fenómenos educativos

Investigación **aplicada**

- Mejorar procesos de aprendizaje
- Guiar el aprendizaje del estudiante
- Apoyar a los profesores con herramientas

Romero, C.; Ventura, S. (**2010**). *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 40(6), 601-618.*

Minería de Datos Educacionales

Grupos de actores

- Estudiantes
- Educadores
- Investigadores educativos
- Directores

Tareas

- Recomendaciones para estudiantes
- Modelado de estudiantes
- Desarrollo de mapas conceptuales
- Predecir el desempeño del estudiante

Romero, C.; Ventura, S. (**2010**). *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 40(6), 601-618.*

Trabajos de Investigación con NLP en Educación

Araya, R.; Ulloa, O.; Jimenez, A.; Mannonen, J.; Lehesvuori, S.; Hämäläinen, R.

Research

Do Written Responses to Open-Ended Questions on Fourth-Grade Online Formative Assessments in Mathematics Help Predict Scores on End-of-Year Standardized Tests?

2022
Urrutia, F., & Araya, R.
Journal of Intelligence, *10*(4), 82.

Automatically Detecting Incoherent Written Math Answers of Fourth-graders

2023
Urrutia, F., & Araya, R.
(pre-print) Educational Studies in Mathematics

Who's the Best Detective? LLMs vs. MLs in Detecting Incoherent Fourth Grade Math Answers

2023
Urrutia, F., & Araya, R.
(pre-print) Journal of Educational Computing Research

A Methodology for Enhanced Explanations of Incoherence Detection in Fourth Grade Student Writing
2023
Urrutia, F., & Araya, R.
MKR 2023 (submitted)

Untangling Incoherent Argumentation in Fourth Graders' Written Answers to Open-ended Math Questions
202?
Urrutia, F., & Araya, R.

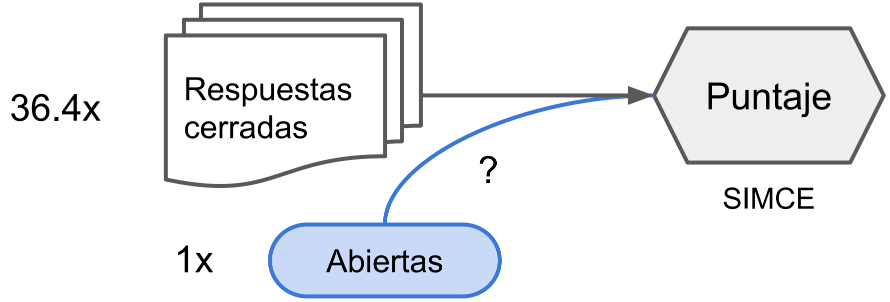
Mapping the main streams and foci of competence-based education research: A review with direct citation network analysis and topic modeling with latent semantic analysis
2023
Mannonen, J., Urrutia, F., Lehesvuori, S., Hämäläinen, R., & Araya, R.
(proofreading) Educational Research Review

Urrutia, F.; Araya, R. J. Intell. 2022, 10, 82.

Do Written Responses to Open-Ended Questions on Fourth-Grade Online Formative Assessments in Mathematics Help Predict Scores on End-of-Year Standardized Tests?

2022
Urrutia, F., & Araya, R.
Journal of Intelligence, *10*(4), 82.

RQ: ¿En qué medida las respuestas cortas y escritas de los estudiantes a las preguntas abiertas diseñadas por el profesor en las pruebas formativas semanales en línea ayudan a mejorar las predicciones del rendimiento en las evaluaciones nacionales estandarizadas de opción múltiple de final de año?



Urrutia, F.; Araya, R. J. Intell. 2022, 10, 82.

Do Written Responses to Open-Ended Questions on Fourth-Grade Online Formative Assessments in Mathematics Help Predict Scores on End-of-Year Standardized Tests?

2022
Urrutia, F., & Araya, R.
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Respuestas a preguntas abiertas

1

María y su marido cocinaron ayer una tortilla, la adición en 6 partes iguales. María se comió 2/6 y su marido 3/6. 3/6. ¿Qué fracción de la tortilla quedó?

1/6

2

Catalina compró 12 cebollas. De las 12 cebollas, utilizó 1/4 de ellas para hacer unas deliciosas empanadas. ¿Cuántas cebollas utilizó para las empanadas? Explica cómo supiste el resultado

Necesito 3 y lo sé porque he dividido 12:4=3x1=3

3

Camilo tiene que recoger 60 bolas. Hasta ahora ha recogido 23. Para saber cuántas bolas le quedan por recoger, restan 23 de 60. ¿Es correcto el ejercicio de Camilo? Justifica tu respuesta

está bien porque he añadido 37+23 y medio 60

4

Pablo tarda 5 horas en viajar de Santiago a La Serena. Su amigo Pedro viajó de La Serena a Santiago y tardó 300 minutos. ¿Cuál de los dos niños tardó menos? Explica tu respuesta

ambos tomaron el mismo tiempo porque he multiplicado 5x60=300 y 300 minutos son 5 horas

5

¿Qué es una línea de simetría? Explica con tus propias palabras y dame un ejemplo

una línea de simetría es una línea que separa dos imágenes iguales edades

0

Pamela tiene 25 flores y su amiga le regala 17 flores. Escribe con palabras el número total de flores que tiene Pamela

cuarenta y dos

Urrutia, F.; Araya, R. J. Intell. 2022, 10, 82.

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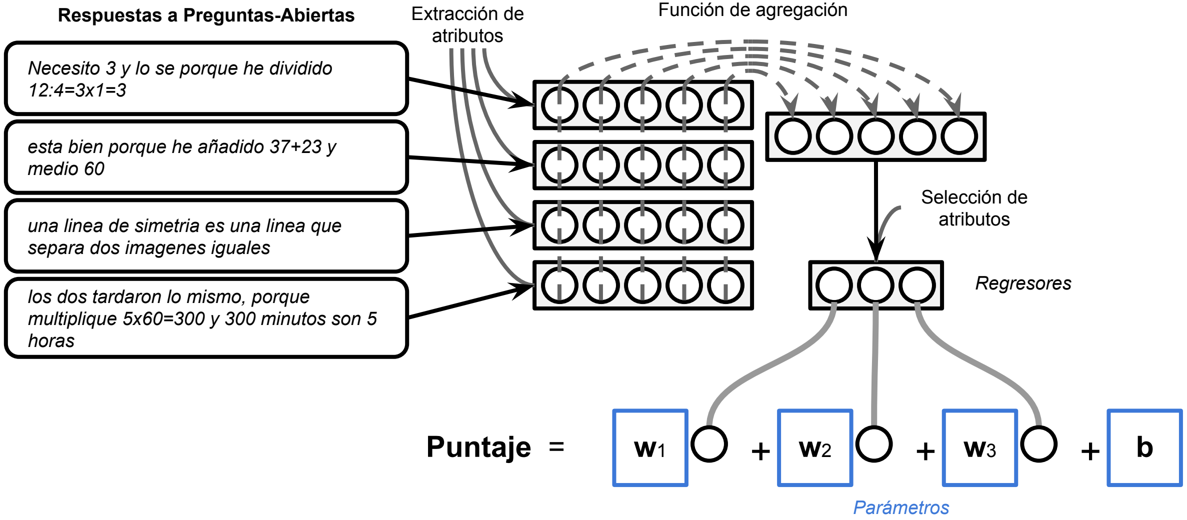
Modelo Open-ended



Basado en Fig. 1. Urrutia, F.; Araya, R. *J. Intell.* **2022**, *10*, 82.

Urrutia, F.; Araya, R. J. Intell. 2022, 10, 82.

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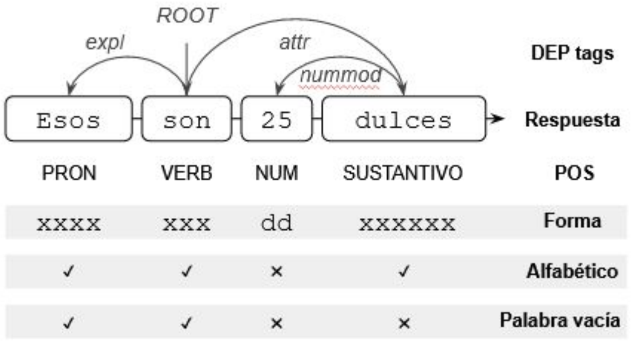
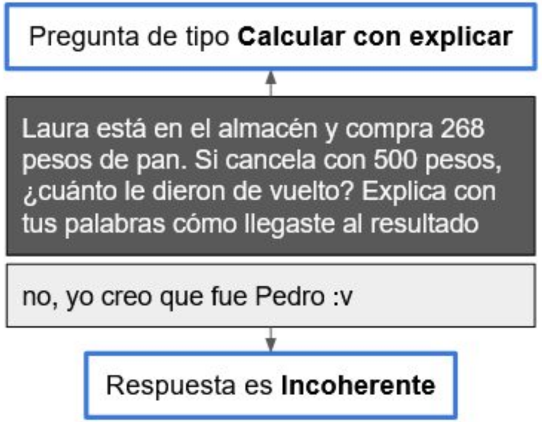
Variables basadas en respuesta abiertas





Basado en el ejemplo "Linguistic features". Urrutia, F.; Araya, R. *J. Intell.* **2022**, *10*, 82.

Urrutia, F.; Araya, R. J. Intell. 2022, 10, 82.

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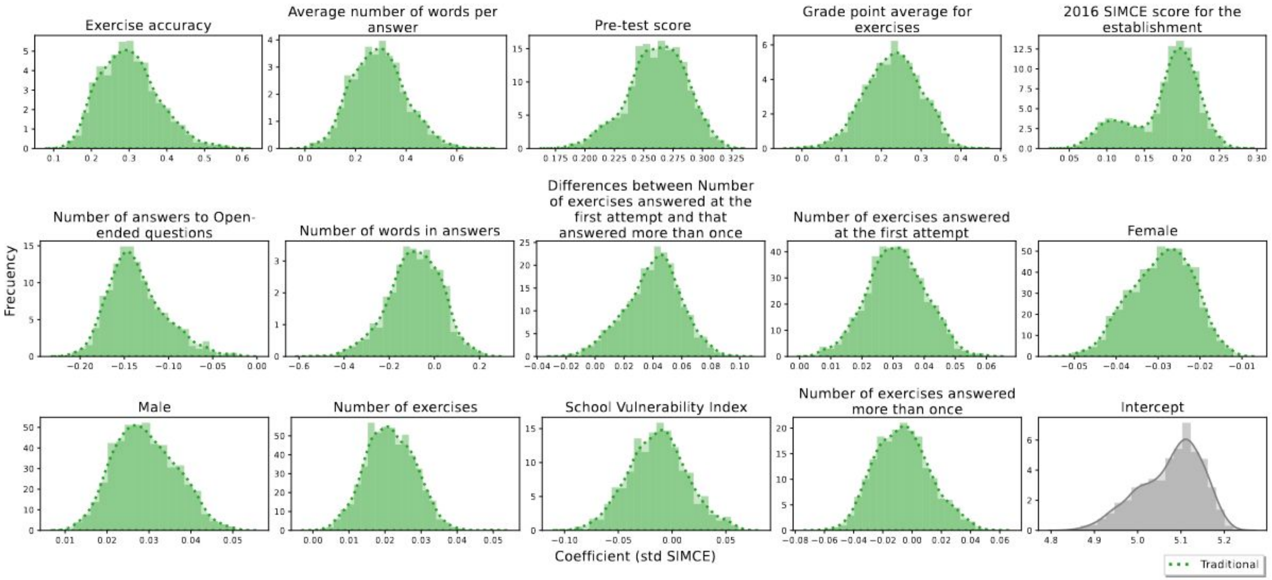

Figure 2. Distribution of each coefficient (std SIMCE) for the baseline model. These are obtained from 250 four-fold cross-validations. (Green) Traditional regressors.

Urrutia, F.; Araya, R. J. Intell. 2022, 10, 82.

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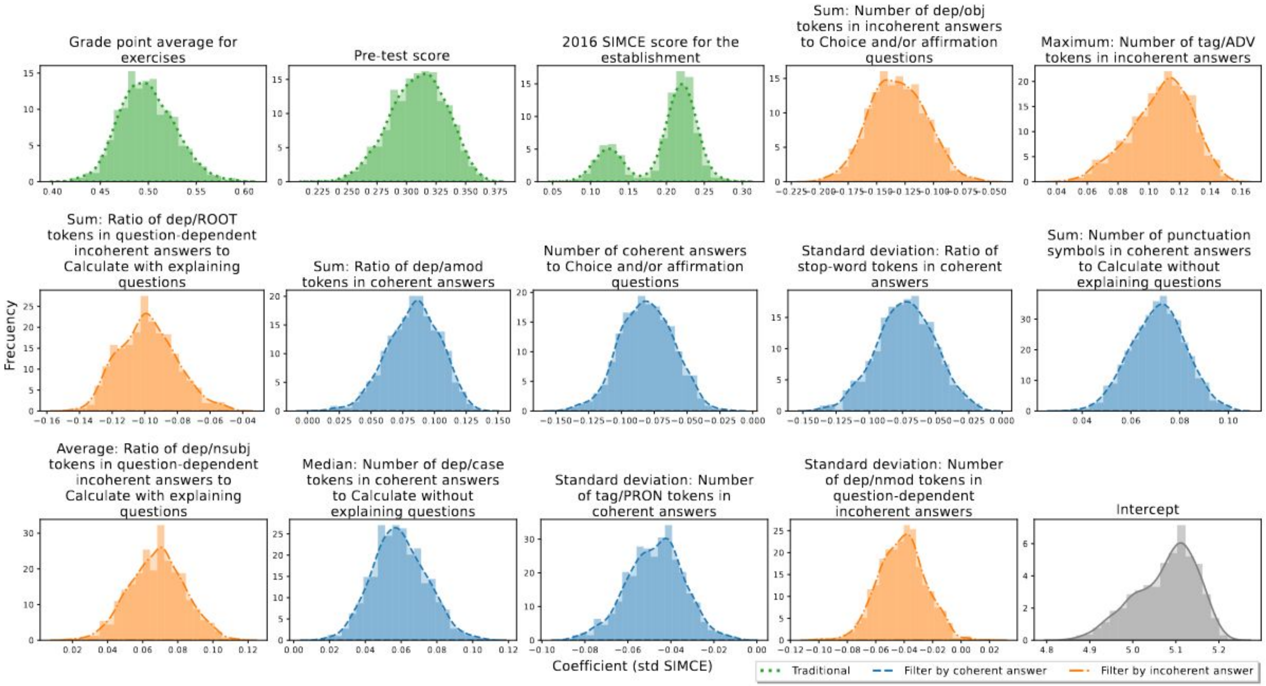

Figure 3. Distribution of each coefficient (std SIMCE) for the Open-ended model. These are obtained from 250 four-fold cross-validations. (Green) Traditional regressors. (Blue) Filter by coherent answers. (Orange) Filter by incoherent answers.

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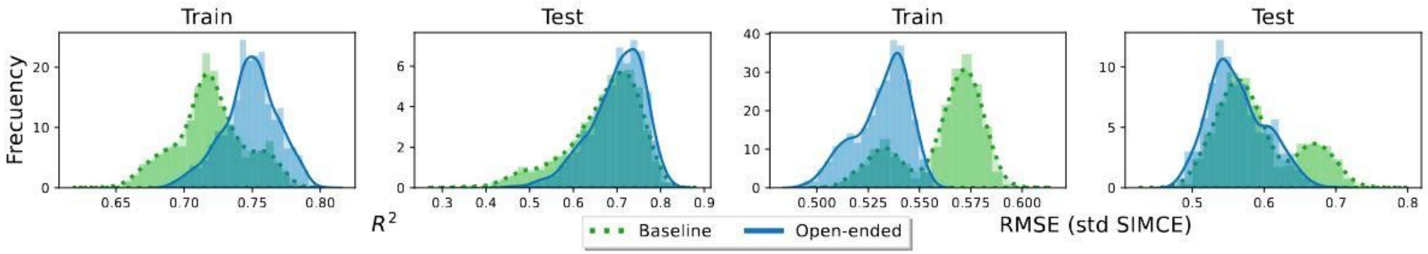
Set	$R^2_{adjusted}$		R^2			RMSE (std SIMCE)			Support
	Baseline	Open-Ended	Baseline	Open-Ended	%	Baseline	Open-ended	%	
Test	0.65 ± 0.09	0.69 ± 0.07	0.67 ± 0.08	0.70 ± 0.06	83.5	0.59 ± 0.06	0.56 ± 0.04	83.5	116 ± 13
Train	0.71 ± 0.03	0.74 ± 0.02	0.72 ± 0.03	0.75 ± 0.02	100	0.56 ± 0.02	0.53 ± 0.01	100	348 ± 13



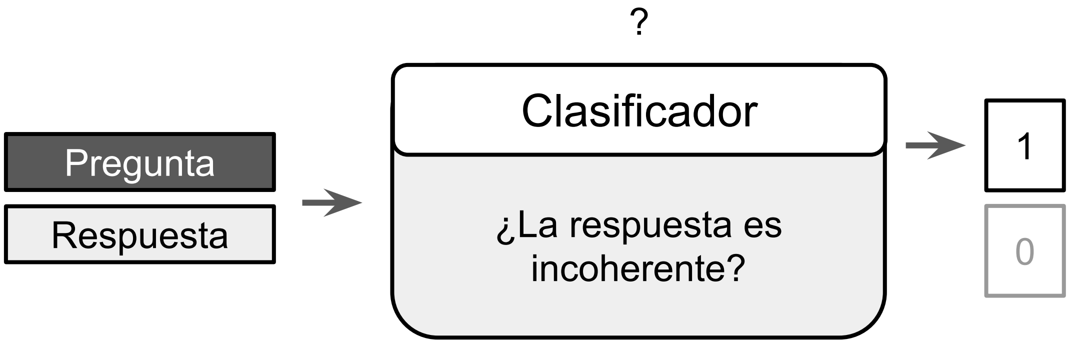
Tab. 5 y Fig. 5. Urrutia, F.; Araya, R. *J. Intell.* **2022**, *10*, 82.

Urrutia, F.; Araya, R. (pre-print) ESM. 2023

Automatic detection of incoherent written responses to open-ended mathematics questions of fourth graders

2023
Urrutia, F., & Araya, R.
(pre-print) Educational Studies in Mathematics

RQ: ¿Hasta qué punto se puede construir un clasificador automático que detecte en tiempo real las respuestas incoherentes dadas por los alumnos de cuarto grado a las preguntas abiertas de matemáticas diseñadas y escritas al momento por el profesor en una plataforma online?



Urrutia, F.; Araya, R. (pre-print) ESM. 2023

Automatic detection of incoherent written responses to open-ended mathematics questions of fourth graders

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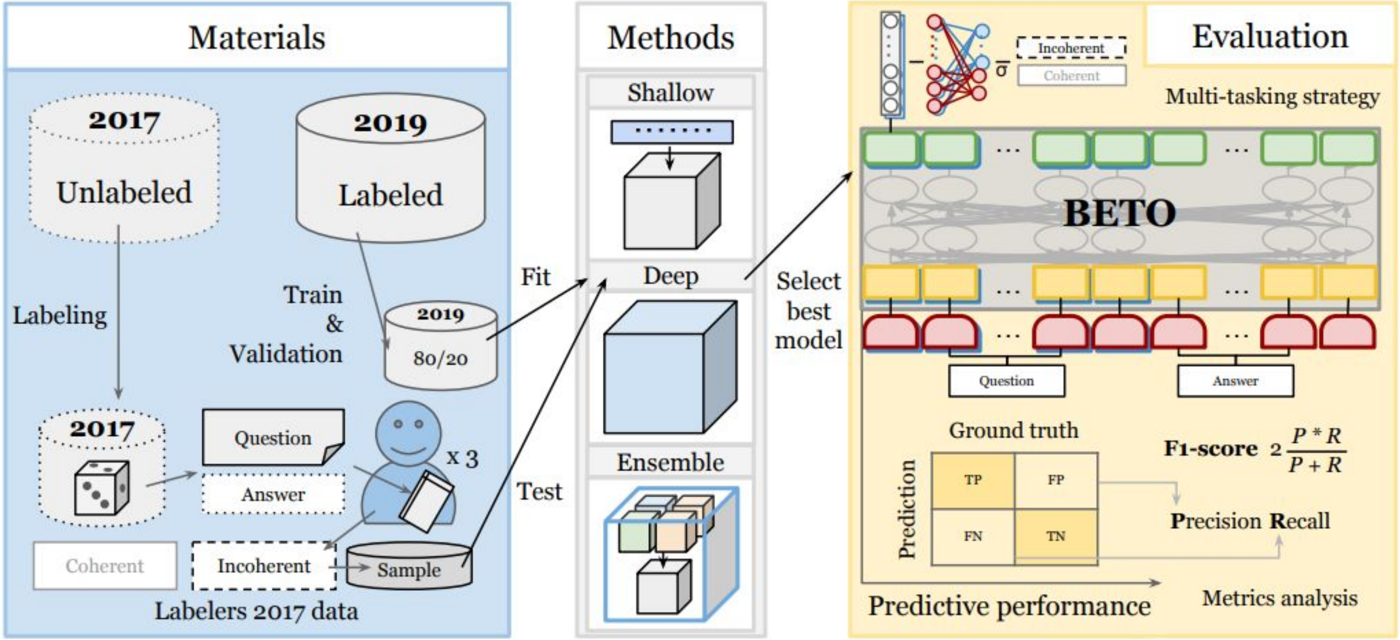

Fig. 1 (**Left**) Datasets and labeling. (**Center**) Three types of ML algorithms. (**Right**) Performance evaluation.

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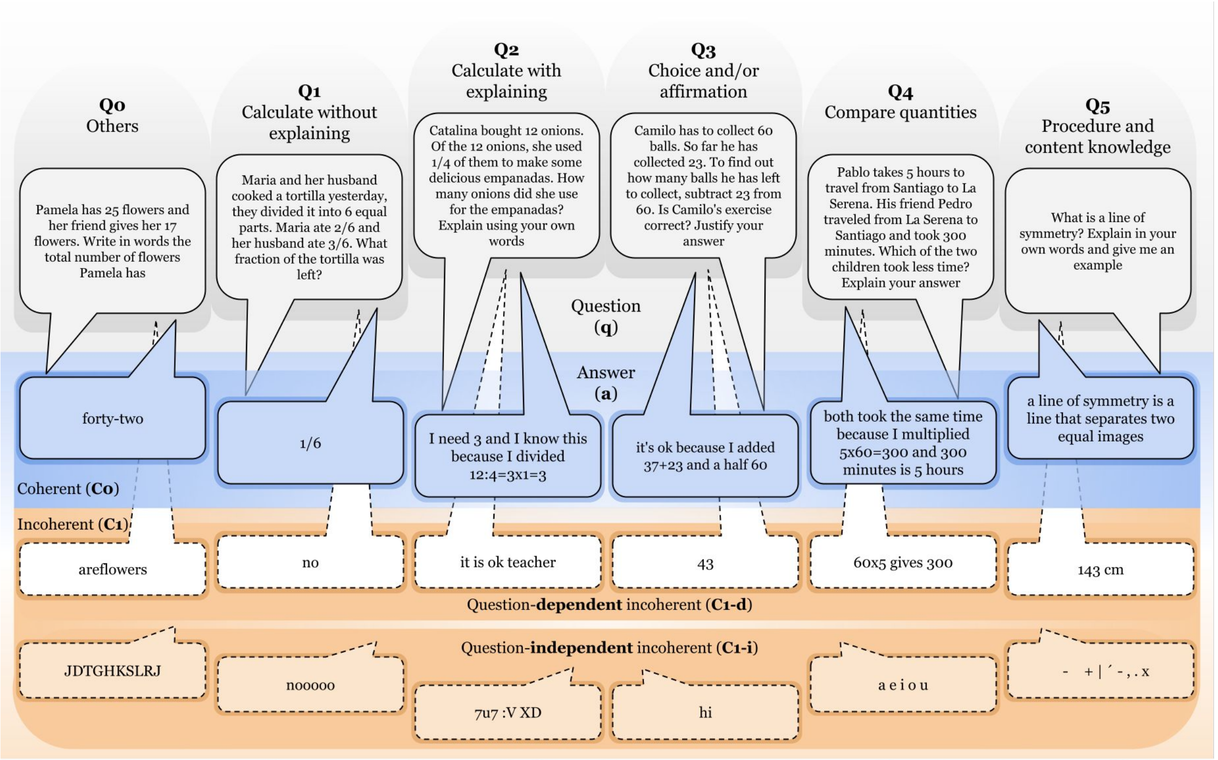

Fig. 2 Example of open-ended math exercise questions and fourth graders answers. The first row contains the questions, separated by type and indexed with Q_i, where i is a number between 0 and 5. The second row has coherent answers, and the third row has incoherent answers dependent on the question. The fourth row contains incoherent answers that are independent of the question. Note: Examples originally in Spanish.

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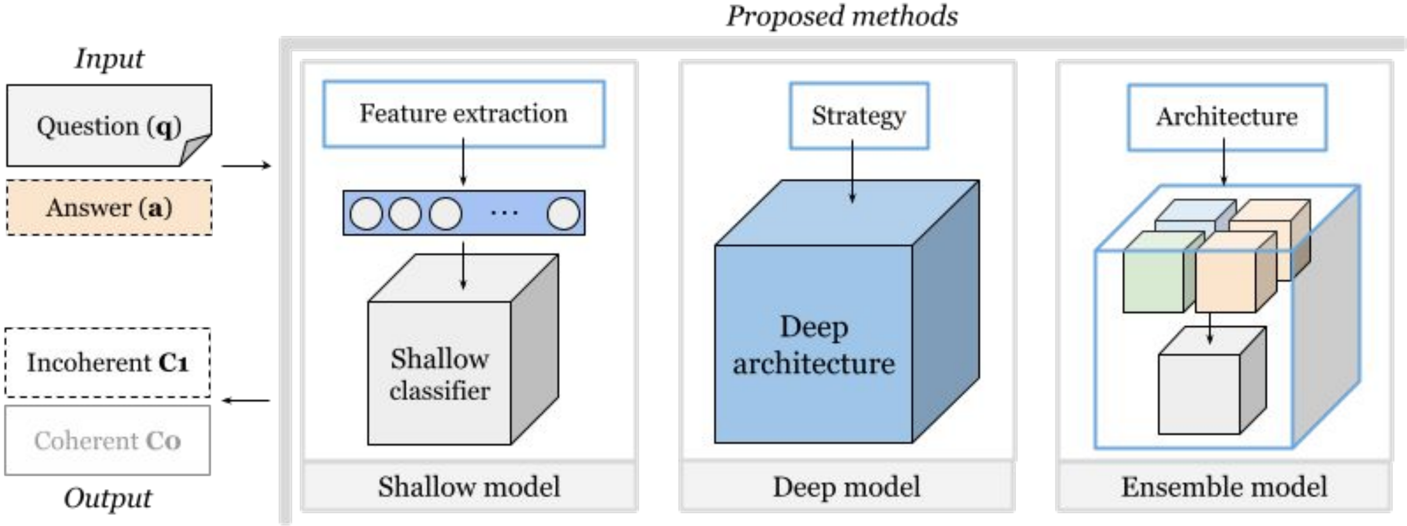

Fig. 3 Shallow models are low complexity and suitable for simple tasks with limited data, capturing only shallow patterns. Deep models are more complex, capturing more intricate patterns. Ensemble models use a combination of shallow and deep models, depending on the task.

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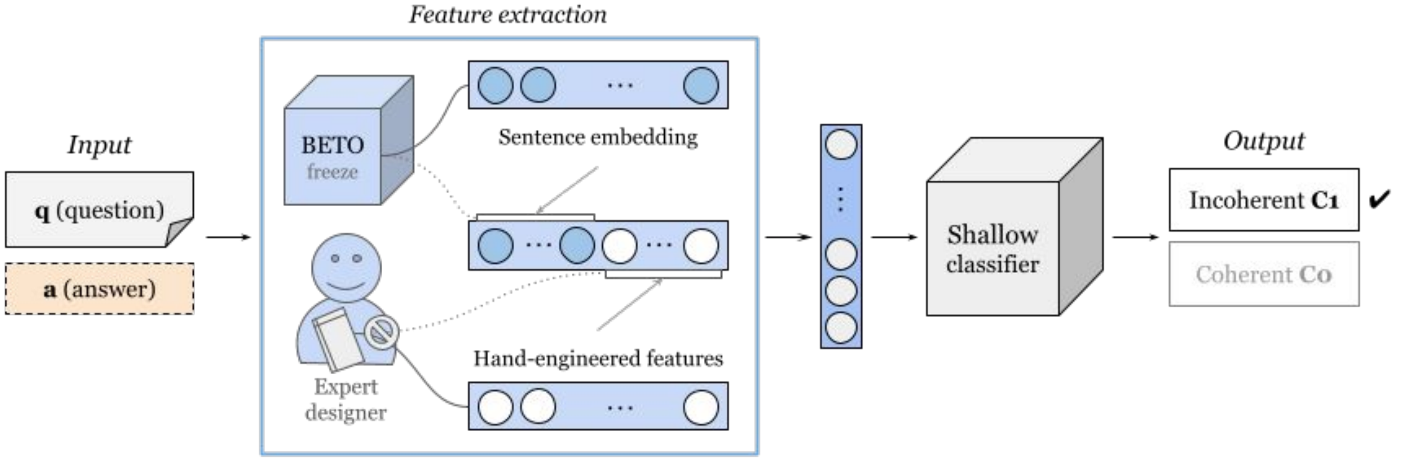

Fig. 4 Classify incoherence in open-ended answers using various feature extraction methods, including handcrafted features and word embeddings. Interpretable features such as word count, question-answer overlap, and linguistic knowledge were used to identify incoherence (Table 4). The study utilized the Spanish version of BERT (BETO) for vector representations of text (Figure 5) and two classification models, Support Vector Machines (SVMs) and eXtreme Gradient Boosting (XGBoost). We evaluate the model and fit the parameters following Tables 1 and 3.

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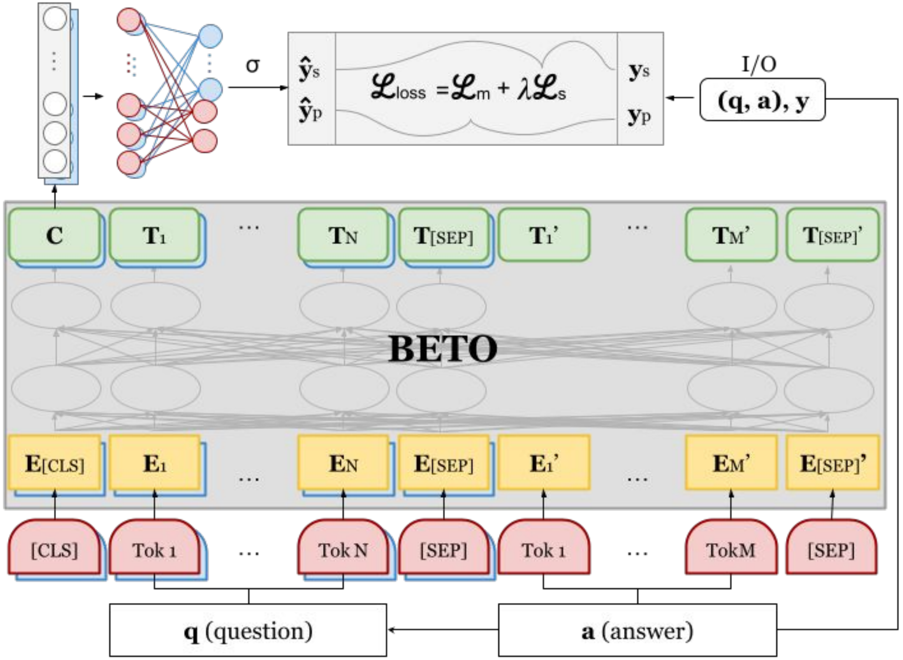

Fig. 5 The BETO model was trained to classify incoherence in open-ended question answers using Multi-Tasking and Fine-Tuning strategies with a fixed λ = 0. The model was pre-trained on two self-supervised tasks, Masked language model and Next sentence prediction, using the sources of the OPUS Project and Spanish Wikipedia datasets. Fine-Tuning involved adjusting the pre-trained model by adding a last linear layer, while Multi-Tasking trained the model on multiple tasks simultaneously. Further Pre-Training involved retraining the model with intrinsic tasks specific to the domain of the main task data. For the BETO Multi-Tasking experiment, a BETO model was trained directly without further pre training [44], using specific parameters (Table 2).

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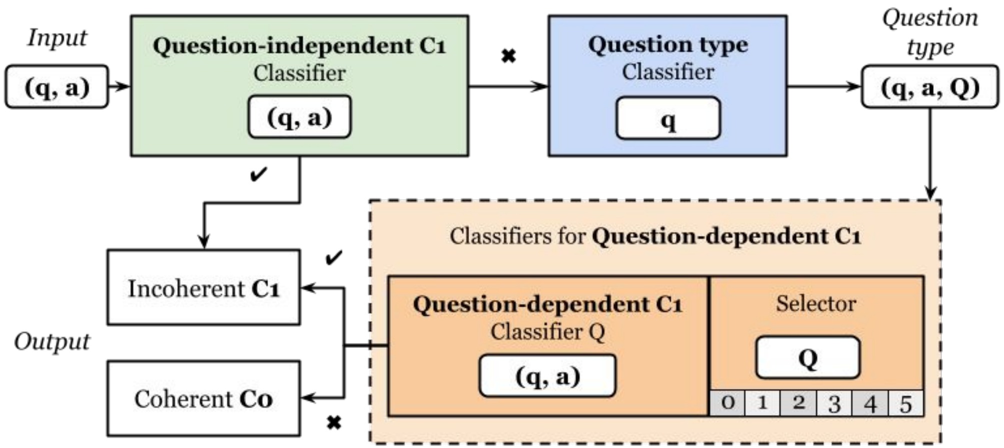

Fig. 6 The Logical architecture is an ensemble model consisting of eight classifiers designed to identify incoherent answers to different types of questions. Question-dependent incoherence (C1-d) requires further analysis than question-independent incoherence (C1-i). The model includes a C1-i classifier, a Question type classifier (QT), and a C1-d classifier per type of question. The QT classifier is a BETO model trained with fine-tuning strategy, while the C1-i and C1-d classifiers are XGBoost models using hand-crafted features and BETO sentence embeddings. By considering the type of question, the Logical architecture can determine whether an answer is coherent or not.

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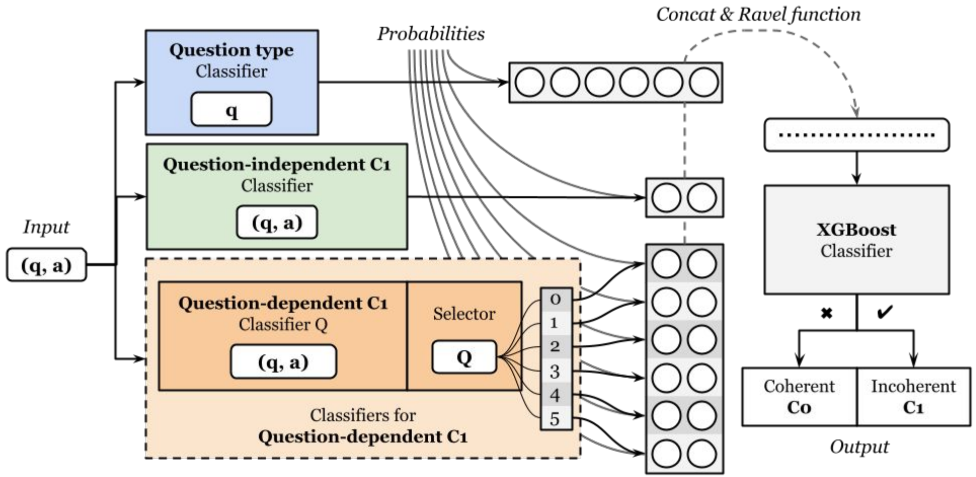

Fig. 7 The General architecture incorporates the same classifiers as the Logical architecture but requires additional training to properly integrate them. This approach uses the probabilities associated with each classifier to generate a large probability vector, which is then inputted into a tree-based model to make the best decision and determine whether the answer is coherent with the question. The General architecture is an ensemble model that includes the same eight classifiers as the Logical architecture (Figure 6). To optimize the XGBoost model's parameters (Table 3), we use a grid search method over the validation set to choose the best generalizing model.

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Table 5 Predictive performance of the models on the test set, validation set, and train set. The category column corresponds to baselines and the three families of proposed models: shallow, deep, and ensemble models. The model column refer to the names of the experiment models, and the numerical values are the metrics associated with each dataset and model.

Category	Model	Test set			Validation set			Train set		
		P	R	F	P	R	F	P	R	F
Baseline	Dummy (most frequent)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Dummy (stratified)	20.24	12.50	15.45	15.06	15.72	15.38	13.48	13.57	13.53
	Dummy (uniform)	21.65	52.21	30.60	13.57	49.48	21.30	13.00	48.90	20.54
	NB+BOW	100.00	2.21	4.32	60.99	28.61	38.95	80.06	55.00	**65.20**
	Rule-based	69.79	49.26	**57.76**	50.46	56.96	**53.51**	48.07	53.38	50.58
Shallow	XGBoost + HF	70.00	72.06	71.01	89.63	80.15	84.63	94.80	92.40	93.59
	XGBoost + Mix	70.92	73.53	**72.20**	93.97	84.28	**88.86**	99.93	99.74	**99.84**
	SVM + BETO embeddings	60.78	68.38	64.36	88.05	72.16	79.32	93.27	80.13	86.20
Deep	BETO fine-tuning	74.83	78.68	76.70	81.23	84.79	82.98	98.21	99.94	**99.07**
	BETO multi-tasking	76.19	82.35	**79.15***	84.50	84.28	**84.39**	96.25	100.00	98.09
Ensemble	Logical	66.45	75.74	70.79	88.25	90.98	89.59	92.67	98.51	95.50
	General (XGBoost)	78.79	76.47	**77.61**	94.49	92.78	**93.63**	99.93	99.74	**99.84**

Note: Precision (P), Recall (R), F1-score (F); Support: 136 (test), 388 (val), 1540 (train).

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RQ1: How do LLMs fare in detecting incoherent fourth-graders responses to typical math word problems?

RQ2: How does the incoherence detection performance of LLMs compare to that of ML classifiers?

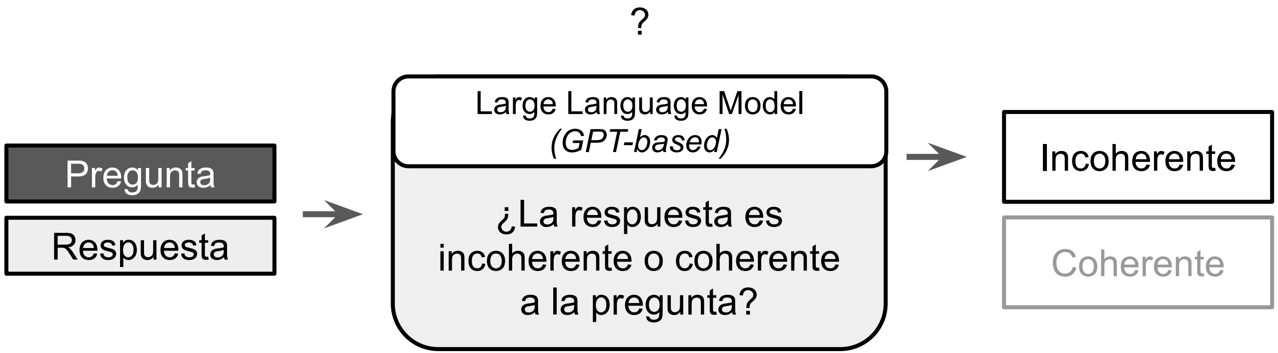

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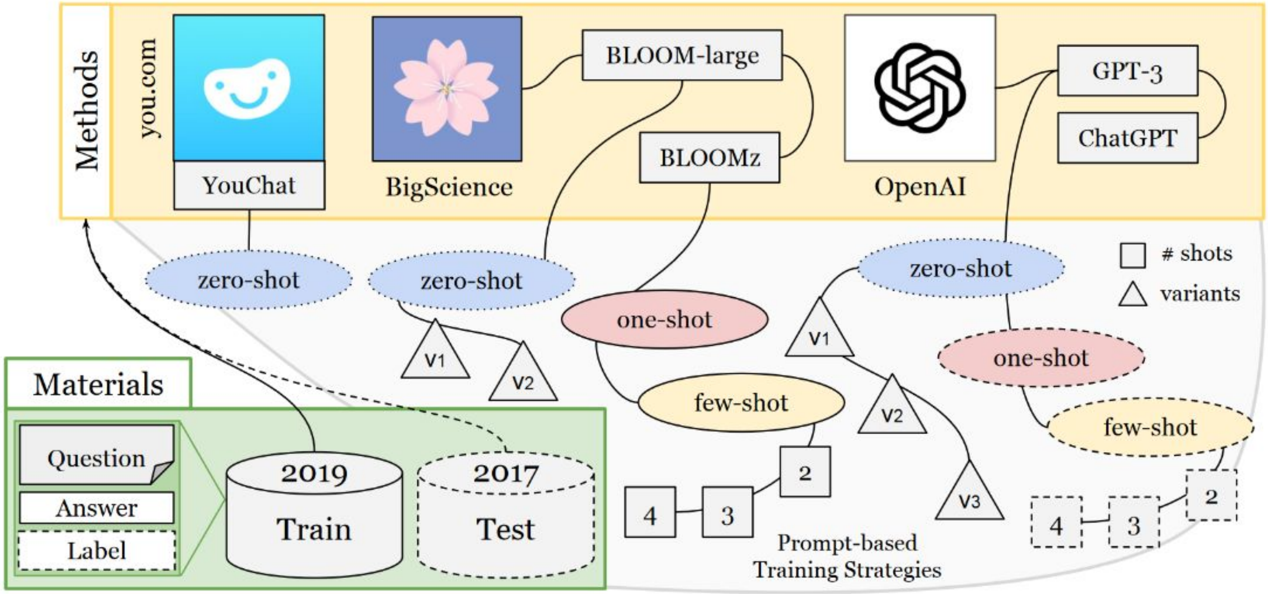
Figure 1. The four LLMs used in this study. Three of them with prompting of zero, one, two or three shots. Below are the two databases with questions and answers. Those of 2019 will be used to train the ML models. The 2017 one is used for testing.



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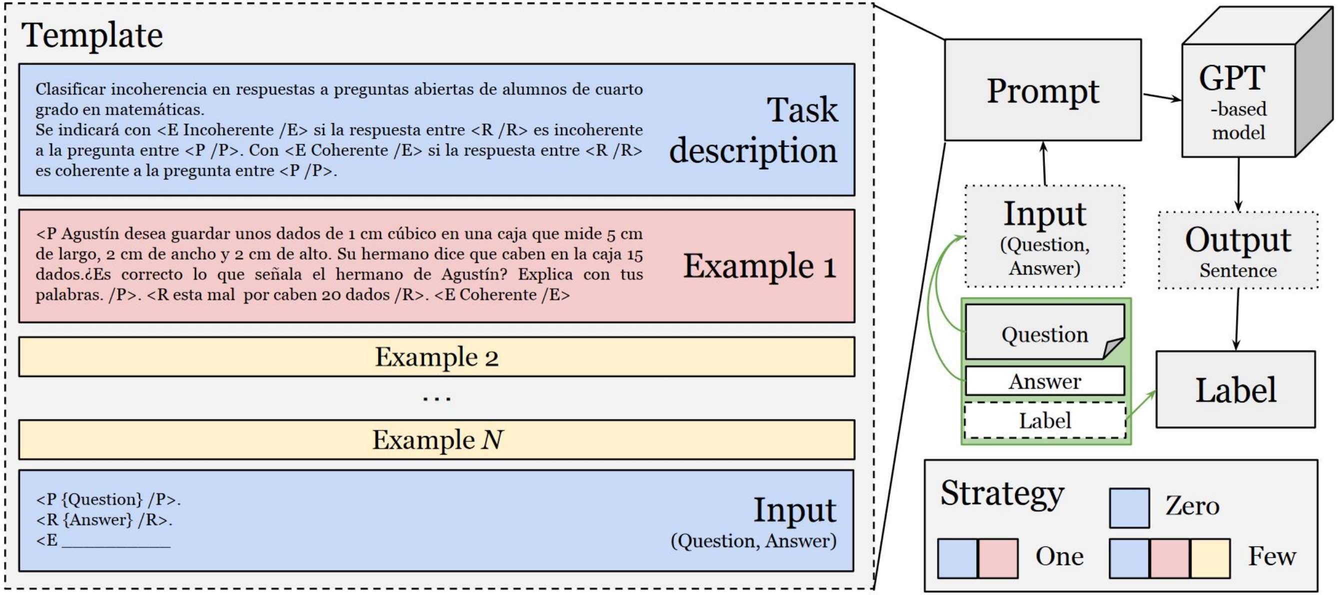

*Figure 2. (**Left**) Structure of the Prompt-based Training Strategies. (**Right**) Input to the GPT and*

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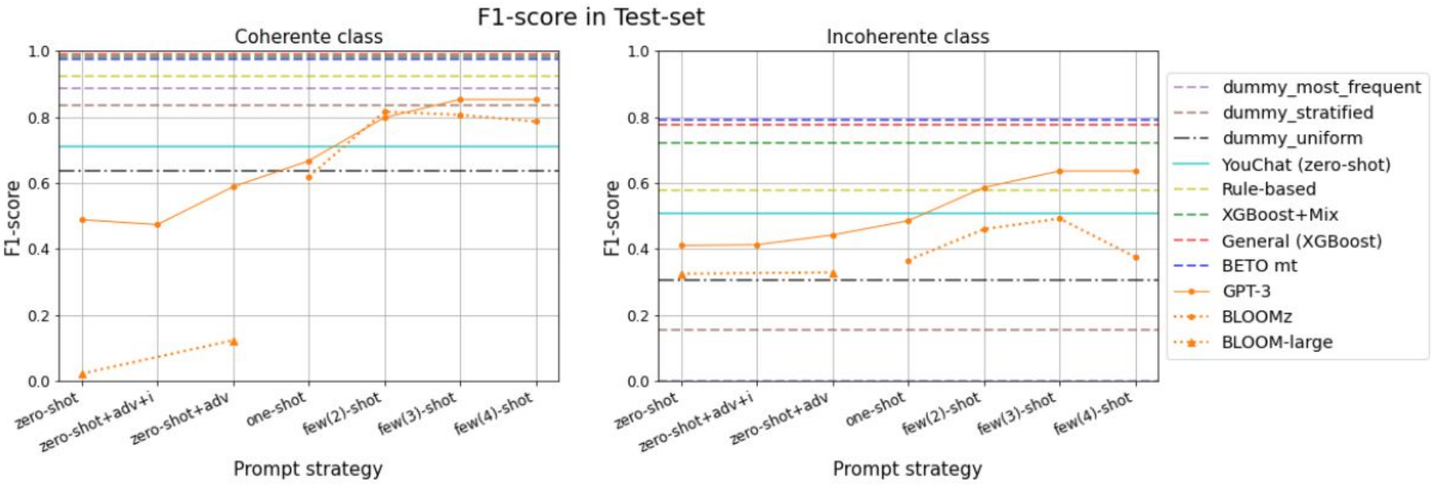
*Figure 3. Comparison of performance between GPT and ML models. (**Left**) F1-score of the Coherent class. (**Right**) F1-score of the Incoherent class.*



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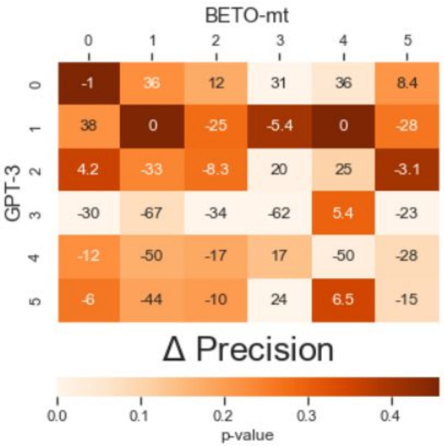
Recursivity



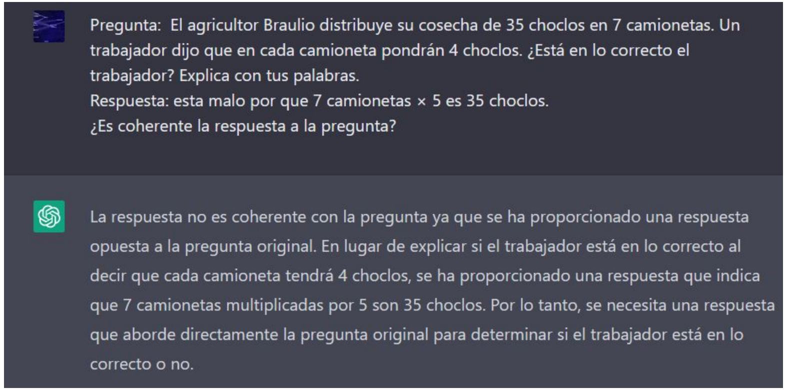


*Figure 4. Differences between Precision for the Incoherent class. (**Diagonal**) Difference of Precision between GPT-3 and BETO-mt models for each question type. (**Under diagonal**) Differences of Precision between questions for the GPT-3 model. (**Over diagonal**) Differences of Precision between questions for the GPT-3 model and BETO-mt model.*

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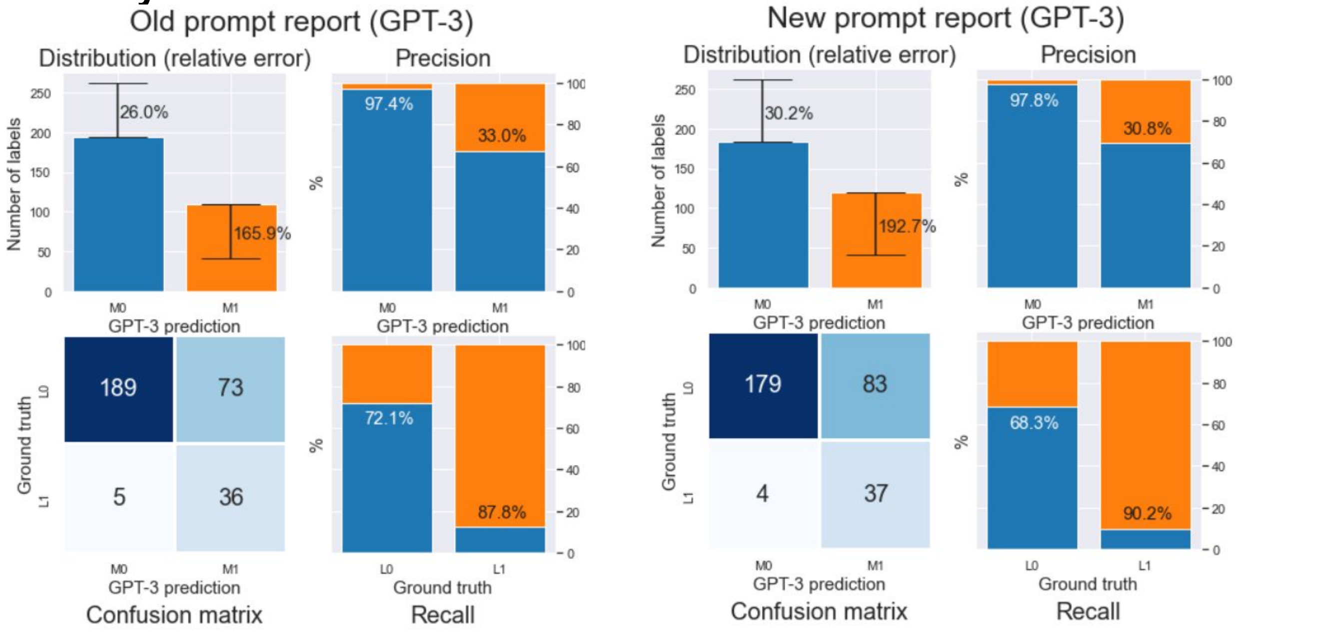

*Figure 5. Comparison of results of the GPT-3 model in question type Q3. (**Left**) GPT-3 with 4 shots. (**Right**) GPT-3 with new three-question zero-shot prompt.*

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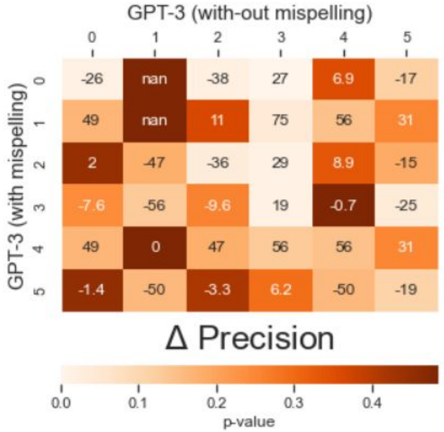
Kids' misspelling



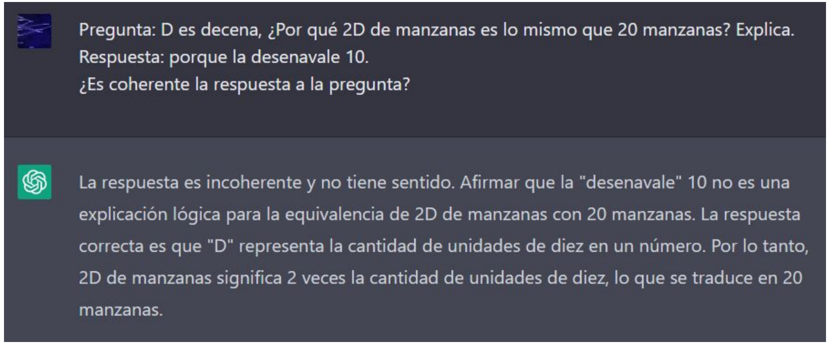


*Figure 6. Differences between Precision for the Incoherent class. (**Diagonal**) Difference of Precision between GPT-3 with and with-out misspellings for each question type. (**Under diagonal**) Differences of Precision between questions for the GPT-3 model in answers with misspellings. (**Over diagonal**) Differences of Precision between questions for the GPT-3 model in answers with-out misspellings.*

Parte 1 …

to be continued …

The Role of Natural Language Processing in Advancing Competency-Based Education and Mathematics Learning in Fourth Graders

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