Investigación en Inteligencia Artificial

Dr. Pablo Moreno Ger

Dr. Ismael Sagredo Olivenza

Dr. Luis Miguel Garay Gallastegui

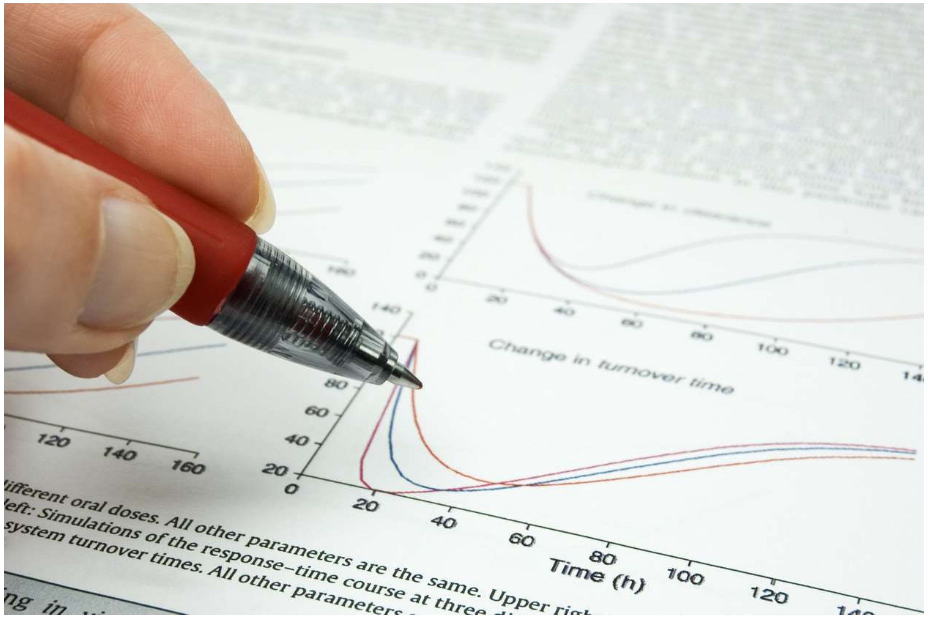
Tema 5 – Redacción científica

En la sesión anterior…

- Semana 5
  - Por qué publicar
  - Proceso publicaciones científicas

De qué vamos a hablar hoy…

- Tema 5
  - **Textos científicos**
    - Estilo
    - Estructura
  - **Herramientas**
  - **Redes difusión** conocimiento científico



Estilo

La forma ayuda a entender el fondo

Estilo redacción científica

Principios redacción científica

Comparison of Clustering Algorithms for Learning Analytics with Educational Datasets

Alvaro Martinez Navarro[1], Pablo Moreno-Ger[2] *

[1] Departamento de Ingeniería de Sistemas, Universidad Mariana, Pasto (Colombia)
[2] Escuela Superior de Ingeniería y Tecnología, Universidad Internacional de La Rioja, Logroño (España)

Received 3 November 2017 | Accepted 22 January 2018 | Published 9 February 2018

unir LA UNIVERSIDAD EN INTERNET

ABSTRACT

Learning Analytics is becoming a key tool for the analysis and improvement of digital education processes, and its potential benefit grows with the size of the student cohorts generating data. In the context of Open Education, the potentially massive student cohorts and the global audience represent a great opportunity for significant analyses and breakthroughs in the field of learning analytics. However, these potentially huge datasets require proper analysis techniques, and different algorithms, tools and approaches may perform better in this specific context. In this work, we compare different clustering algorithms using an educational dataset. We start by identifying the most relevant algorithms in Learning Analytics and benchmark them to determine, according to internal validation and stability measurements, which algorithms perform better. We analyzed seven algorithms, and determined that K-means and PAM were the best performers among partition algorithms, and DIANA was the best performer among hierarchical algorithms.

KEYWORDS

Clustering Methods, Computer Languages, Data Analysis, Engineering Students, Performance Evaluation, Unsupervised Learning.

DOI: 10.9781/ijimai.2018.02.003

I. INTRODUCTION

SINCE the turn of the Century, researchers have been studying clustering methods and comparing them from different perspectives. These algorithms were the core of an emerging data mining discipline, which would soon explode along with the popularity of big data approaches in all fields. And when these ideas were applied to digital education, the field of Learning Analytics was born.

But the core of these approaches is still the use of adequate clustering algorithms for each scenario, and this problem has received a fair share of attention. Berkhin contrasted theoretically different algorithms [1], and indicated how to perform the most typical evaluations, data preparation and measurements. In [2], the authors studied 216 articles written between 2000 and 2011, classifying the literature in three author proposed specific analysis methods, and also studied the performance impact of different perturbations. In [6] the authors compared five grouping algorithms and used four different supervised automatic learning algorithms to analyze their performance. In [7] three algorithms were measured with four cluster validation indexes, using synthetic and real datasets. Other relevant works have conducted formal tests to determine the most appropriate data mining algorithms for specific fields such as classification [8] or text mining from RSS sources [9]. However, few experimental studies focused on analyzing performance using specifically educational datasets.

In turn, Learning Analytics (LA) research ranges from theoretical essays on the potential impact of LA in education [10] to very focused studies on how it is useful for establishing personalized feedback to improve academic performance [11]. There are also works proposing

https://www.ijimai.org/journal/node/2111

1. Precisión
2. Claridad
3. Brevedad
4. Formalidad

Estilo redacción científica

- ## Precisión

“El método 1 <u>distribuye</u> <u>mejor</u> los resultados que el método 2” ✗

– ¿Qué significar distribuir? Obtener, ordenar…

– ¿Qué significa mejor? Más rápidamente, uniformemente, menor error…

- ## Claridad

– El texto se lee y se entiende rápidamente. Oraciones bien construidas y cada párrafo desarrolla su tema siguiendo un orden lógico

Estilo redacción científica

- Brevedad

"Los resultados relacionados con la dispersión y la personalización en cada campaña de marketing estudiada nos permiten afirmar, de una manera general, que éstos no han presentado diferencias significativas…" ✗

"La dispersión y la personalización no variaron en las campañas de marketing estudiadas"

- Formalidad

  – "Tomamos <u>un montón</u> de muestras" ✗
  – "El método 1 converge <u>a toda prisa</u>" ✗

Estilo redacción científica

- Otros aspectos a considerar

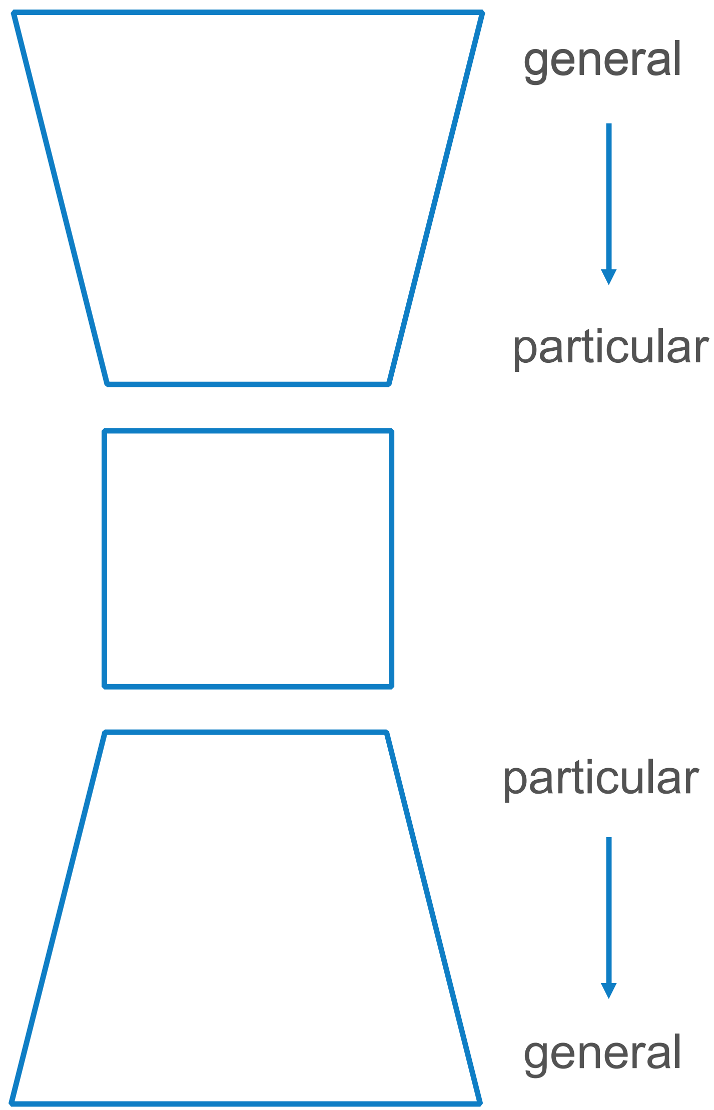
- Sintaxis
- Puntuación deficiente
- Faltas ortográficas
- Redundancia
- Vocabulario rebuscado
- Longitud de oraciones y párrafos
- Lenguaje informal…

Estructura

Todo en su sitio

Estructura artículo científico

- Introducción
- Motivación
- Estado del arte
- Marco Teórico
- Metodología experimental empleada
- Resultado de los experimentos
- Conclusiones
- Trabajos futuros
- Referencias



Estructura artículo científico

- Los descubrimientos científicos se comparten con la comunidad mediante artículos.
  - Se realizan artículos científicos donde:
    - **Se justifican** los objetivos
    - Se describe el **estado del arte** que ya existe sobre el tema
    - Se describe la **metodología** que se siguió para hacer la investigación.
      - Los datos que se emplean.
      - Los experimentos
    - Se discuten los resultados.
    - Se plantean conclusiones.
    - Formas de mejorar (trabajos futuros)

Estructura artículo científico

Comparison of Clustering Algorithms for Learning Analytics with Educational Datasets

Título

Alvaro Martínez Navarro[1], Pablo Moreno-Ger[2] *

Autores

[1] Departamento de Ingeniería de Sistemas, Universidad Mariana, Pasto (Colombia)
[2] Escuela Superior de Ingeniería y Tecnología, Universidad Internacional de La Rioja, Logroño (España)

Received 3 November 2017 | Accepted 22 January 2018 | Published 9 February 2018

unir LA UNIVERSIDAD EN INTERNET

Institución donde se realizó la investigación

Abstract

Learning Analytics is becoming a key tool for the analysis and improvement of digital education processes, and its potential benefit grows with the size of the student cohorts generating data. In the context of Open Education, the potentially massive student cohorts and the global audience represent a great opportunity for significant analyses and breakthroughs in the field of learning analytics. However, these potentially huge datasets require proper analysis techniques, and different algorithms, tools and approaches may perform better in this specific context. In this work, we compare different clustering algorithms using an educational dataset. We start by identifying the most relevant algorithms in Learning Analytics and benchmark them to determine, according to internal validation and stability measurements, which algorithms perform better. We analyzed seven algorithms, and determined that K-means and PAM were the best performers among partition algorithms, and DIANA was the best performer among hierarchical algorithms.

Keywords

Clustering Methods, Computer Languages, Data Analysis, Engineering Students, Performance Evaluation, Unsupervised Learning.

DOI: 10.9781/ijimai.2018.02.003

Resumen

I. Introduction

SINCE the turn of the Century, researchers have been studying clustering methods and comparing them from different perspectives. These algorithms were the core of an emerging data mining discipline, which would soon explode along with the popularity of big data approaches in all fields. And when these ideas were applied to digital education, the field of Learning Analytics was born.

But the core of these approaches is still the use of adequate clustering algorithms for each scenario, and this problem has received a fair share of attention. Berkhin contrasted theoretically different algorithms [1], and indicated how to perform the most typical evaluations, data preparation and measurements. In [2], the authors studied 216 articles written between 2000 and 2011, classifying the literature in three author proposed specific analysis methods, and also studied the performance impact of different perturbations. In [6] the authors compared five grouping algorithms and used four different supervised automatic learning algorithms to analyze their performance. In [7] three algorithms were measured with four cluster validation indexes, using synthetic and real datasets. Other relevant works have conducted formal tests to determine the most appropriate data mining algorithms for specific fields such as classification [8] or text mining from RSS sources [9]. However, few experimental studies focused on analyzing performance using specifically educational datasets.

In turn, Learning Analytics (LA) research ranges from theoretical essays on the potential impact of LA in education [10] to very focused studies on how it is useful for establishing personalized feedback to improve academic performance [11]. There are also works proposing

Introducción

Estructura artículo científico

trivial burdens on the data mining algorithms applied to make sense of how students are interacting with these open materials.

At the crossroads of these lines of research, our goal is to contribute experimental validation of the performance of different clustering techniques when specifically applied to educational datasets, thus providing a more solid foundation for further works focusing on practical aspects rather than back-office performance.

To achieve this goal, we have conducted a practical experiment using a real-world dataset provided by Universidad Mariana in Colombia, benchmarking different algorithms and configurations in terms of internal validations and stability measurements.

II. Materials and Methods

The experimental design is quite straightforward. We started with a literature review to select a representative set of clustering algorithms. Then, we organized a workflow for testing each algorithm and selected specific measurements for comparison, and finally we applied this workflow to all algorithms targeting an educational dataset provided by Universidad Mariana. This section details each of these steps.

A. Selecting the Algorithms to Be Benchmarked

The specific selection of algorithms was conducted after performing a literature review, with a heavy influence of related works from other fields ([1], [4], [16]) and trying to provide a wide perspective of the potential approaches.

The final selection of algorithms is summarized in Table I.

B. Experimental Platform

We employed different platforms and tools to create our experimental pipeline. We started with raw and cross-referenced data available on an Oracle 10g database server. We extracted different listings and used Microsoft Excel to review, perform basic cleaning (including anonymization) and saving as CSV (comma-separated values) files.

All statistical analyses and clustering algorithms were applied using the opensource platform R, for which we created our test scripts using the R Studio graphical interface. The platform was also used to create the different visualizations that helped in this study and that

TABLE I. Algorithm Selection

NAME	Description

are included in this article. In Table II we provide a summary of the different libraries that we used for the experiment.

C. Benchmarking Performance

In order to benchmark the performance of each algorithm, we focused on the facilities provided by the *clValid* library presented in [19] to measure internal and stability validations.

Internal validations are computed using intrinsic information from the datasets to assess the quality of the resulting clusters. We used the three main internal validation measurements offered by the validation library: *connectivity* (which provides a value in the $[0, \infty)$ range where lower is better), *silhouette width* (which proves values in the (-1,1) range where higher is better), and *Dunn index* (which provides a value in the $[0, \infty)$ range where higher is better).

In terms of stability measurement, we again selected the main measures from [19], all of them focused on inspecting each cluster and sequentially removing internal columns and checking whether the cluster remains valid. We employed APN (average proportion of non-overlap), AD (average distance between measurements), ADM (average distance between means) and FOM (figure of merit, focused on the average intra-cluster variance of the observations). All of them take values in the $[0, \infty)$ range where higher is better except APN, with values in the [0,1] range with preferred results close to zero.

TABLE II. R Libraries

Library	Description
cluster	It allows clustering analysis by implementing hierarchical and partition algorithms. Details in: https://cran.r-project.org/web/packages/cluster/index.html
ggplot2	It builds visualizations using the information of the data meaning. Details in: https://cran.r-project.org/web/packages/ggplot2/index.html
factoextra	It offers different easy-to-use functions to extract and visualize the results of multivariate analyzes, it simplifies clustering analysis and its graphical representations. Details in: https://cran.r-project.org/web/packages/factoextra/index.html
readr	It provides fast and friendly mechanisms to read files in csv, tsv and fwf formats. Details in: https://cran.r-project.org/web/packages/readr/index.html
	It provides color schemes to be used with various types of

Material y métodos

Responde a la pregunta "cómo se ha hecho el estudio"

Descripción del diseño de la investigación

Explicación de cómo se llevó a la práctica, justificando la elección de métodos y técnicas de forma tal que el lector pueda repetir el estudio

Estructura artículo científico

Number of clusters k

Fig. 2. Optimal K presented by the gap statistic.

III. Results

A. Pre-processing

The first step in our test pipeline was the conduction of relatively simple cleanup tasks, mostly focused on removing instances where some grades were missing (this may happen either due to an administrative issue or an error in the grade reporting system).

After this step, we analyzed for each variable different comparison statistics, averaging their maximum, minimum, average and mean values. We determined that their standard deviation and variances were minimal, therefore making it possible to work directly with the original data without requiring a previous normalization.

We also analyzed the dataset to validate its clusterability, using two approaches: first, we used the *Hopkins statistic* method from [20], with a resulting value of 0.2036606 (<0.5) which shows that the values are potentially groupable. We also validated this notion visually, by representing the tendency of the data to be grouped. This is achieved by (1) calculating the dissimilarities between all datapoints and storing them in a dissimilarity matrix according to their Euclidean distances, (2) sorting the matrix so that similar objects are closer together and (3) displaying the matrix to check the presence of high values along the diagonal of the matrix (Fig. 1).

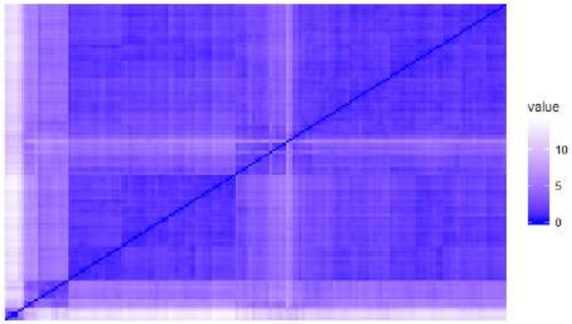


Fig. 1. Data clustering trend where we can observe dark blue rectangles aligned with the diagonal line, which can be interpreted as a potential clustering amenability of the data.

Given this partially unsatisfactory result, we also looked at the nbClust R package, which analyses 30 separate indexed to determine the optimal K. We ran this analysis for values of K in the [2,10] range, with full clustering and all indexes included. As observed in Fig. 3, this yielded an optimal number of clusters of K=3.

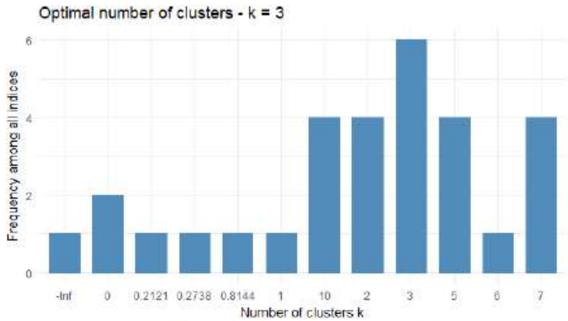


Fig. 3. Optimal K reported by nbClust.

C. Algorithm Execution with Optimal K Value

All seven algorithms were run on the data using K=3 in order to study their behavior and performance.

Regarding the set of partition algorithms, Fig. 4a shows the dispersion and cluster charts produce by the K-means, CLARA and PAM algorithms (all three produced the same output), while Fig. 4b shows the results for the FANNY algorithm, which displayed a significantly worse performance.

These results were validated through a silhouette inspection, which measures the adequacy of each observation for each cluster representing the average distance between groups. Fig. 5 shows the results of these inspections. The K-means, CLARA and PAM algorithms yielded an average silhouette width of 0.55 while the FANNY algorithm yielded 0.29. This indicates a good result for the first three algorithms, while the FANNY algorithm even had a cluster with negative average width, representing a large number of incorrectly assigned instances.

Resultados

Presentar resultados del estudio mencionando los hallazgos relevantes (incluso los contrarios a la hipótesis), incluyendo detalles suficientes para justificar las conclusiones

Estructura artículo científico

```
             Silhouette    0.5549  0.2151  0.2301  0.2435
pam          Connectivity  5.7167 58.4603 75.7325 76.1421
             Dunn          0.3721  0.0485  0.0485  0.0781
             Silhouette    0.5549  0.2168  0.2262  0.2345
fanny        Connectivity      NA      NA      NA      NA
             Dunn              NA      NA      NA      NA
             Silhouette        NA      NA      NA      NA
hierarchical Connectivity  8.6151 11.9484 13.7079 16.6579
             Dunn          0.3883  0.3883  0.4338  0.4338
             Silhouette    0.5450  0.5377  0.5513  0.5524
agnes        Connectivity  8.6151 11.9484 13.7079 16.6579
             Dunn          0.3883  0.3883  0.4338  0.4338
             Silhouette    0.5450  0.5377  0.5513  0.5524
diana        Connectivity  8.6151 10.3746 28.6325 31.9659
             Dunn          0.3883  0.4338  0.1209  0.1466
             Silhouette    0.5450  0.5586  0.4156  0.4083

Optimal Scores:

             Score  Method       Clusters
Connectivity 5.7167 kmeans       3
Dunn         0.4338 hierarchical 5
Silhouette   0.5586 diana        4
```

Fig. 10. Internal validation scores for all algorithms.

```
Clustering Methods:
 kmeans clara pam fanny hierarchical agnes dia

Cluster sizes:
 3 4 5 6

Validation Measures:
                       3      4      5      6

kmeans       APN  0.0350 0.1462 0.0524 0.0345
             AD   2.4473 2.4391 2.2072 2.0718
             ADM  0.2036 0.5720 0.4537 0.3029
             FOM  0.6958 0.6866 0.6907 0.6690
clara        APN  0.0758 0.1308 0.1661 0.1674
             AD   2.4425 2.1941 2.0620 1.9967
             ADM  0.2482 0.3520 0.4425 0.5323
             FOM  0.6917 0.6630 0.6674 0.6680
pam          APN  0.0476 0.1499 0.1706 0.2969
             AD   2.4014 2.2172 2.0254 1.9934
             ADM  0.1323 0.4477 0.3421 0.5667
             FOM  0.6957 0.6676 0.6585 0.6578
fanny        APN      NA     NA     NA     NA
             AD       NA     NA     NA     NA
             ADM      NA     NA     NA     NA
             FOM      NA     NA     NA     NA
hierarchical APN  0.0187 0.0525 0.0049 0.0071
             AD   2.7104 2.6614 2.2709 2.2316
             ADM  0.1080 0.2569 0.1111 0.1171
             FOM  0.7016 0.6912 0.6787 0.6715
agnes        APN  0.0187 0.0525 0.0049 0.0071
             AD   2.7104 2.6614 2.2709 2.2316
             ADM  0.1080 0.2569 0.1111 0.1171
             FOM  0.7016 0.6912 0.6787 0.6715
diana        APN  0.0350 0.0265 0.0176 0.0161
             AD   2.7106 2.3175 2.2031 2.0415
             ADM  0.1729 0.1330 0.4379 0.1834
             FOM  0.7015 0.6873 0.6765 0.6598

Optimal Scores:

    Score  Method       Clusters
APN 0.0049 hierarchical 5
AD  1.9934 pam          6
ADM 0.1080 hierarchical 3
FOM 0.6578 pam          6
```

Fig. 11. Stability scores for all algorithms.

IV. Discussion

One of the most relevant (although reasonably expected) observations is that no algorithm is a clear and obvious winner across all measurements and potential K values.

In terms of internal validation, K-means, CLARA and PAM achieved the best overall scores with K=3, although CLARA and PAM experienced a worst degradation as the K value increased. However, the hierarchical and AGENS algorithms also achieve very significant Dunn scores when K=4.

If we focus on K=3 (our selected optimal value), the worst performers in connectivity were the three hierarchical algorithms, although they achieved better Dunn index scores. However, they also presented more incorrect assignments, and therefore can be considered worst performers overall.

However, as we increased the K value, partition algorithms degraded their performance quickly, while hierarchical algorithms remained more stable and actually improved some scores.

In terms of stability, again there is no single algorithm that achieves the best score in all four measurements. PAM exhibited good AP and FOM behavior at K=6, hierarchical achieved very good APN with K=5 and very good ADM with K=3.

Again, if we focus on K=3, the worst performer in terms of APN and ADM was CLARA, while DIANA and AGNES performed poorly in AD and FOM respectively.

The pattern of degradation as we increased the K value exhibited by partition algorithms was also apparent when looking at stability measurements, yielding a consistent conclusion of the better behavior of hierarchical algorithms for higher number of clusters.

The FANNY algorithm failed to produce significant clusters and was therefore deemed as poorly fit for our specific dataset.

V. Conclusion and Future Works

Open education is bound to push the boundaries of how we analyze our educational datasets. And as the scope of our research actions Learning Analytics becomes more and more specialized, the specific underlying techniques, including the selection of a particular clustering algorithm, are bound to receive less attention than appropriate.

This study aims to provide researchers with insights into how the different algorithms exhibit different performance patterns depending on specific measurements and variation in K values, especially when the dataset is highly driven by a set of grades in different courses.

This is achieved through a detailed and highly practical experiment,

Discusión

Se discuten los resultados logrados mediante los experimentos y las observaciones realizadas. Comparar o contrastar resultados obtenidos con otros estudios para extraer similitudes, mejoras o diferencias

Conclusiones y trabajo futuro

Establecer conclusiones infiriendo o deduciendo una verdad, respondiendo a la pregunta de investigación planteada en la introducción

Recomendaciones evolución trabajo investigación

Estructura artículo científico

REFERENCES

[1] P. Berkhin, "A Survey of Clustering Data Mining Techniques", *Grouping Multidimensional Data. Springer*, no. c, pp. 25–71, 2006.

[2] S. H. Liao, P. H. Chu, and P. Y. Hsiao, "Data mining techniques and applications - A decade review from 2000 to 2011", *Expert Systems with Applications*, vol. 39, no. 12, pp. 11303–11311, 2012.

[3] Q. Hen, "A Review of Clustering Algorithms as Applied in IR", *Technical Report IUIUCLIS--1999/6+IRG*, pp. 1–33, 1999.

[4] G. Sreenivasulu, S. V. Raju, and N. S. Rao, "Review of Clustering Techniques", *Proceedings of the International Conference on Data Engineering and Communication Technology Advances in Intelligent Systems and Computing 468*, pp. 523–535, 2017.

[5] G. W. Milligan and M. C. Cooper, "Methodology Review: Clustering Methods", *Applied Psychological Measurement*, vol. 11, no. 4, pp. 329–354, 1987.

[6] L. Candillier, I. Tellier, F. Torre, and O. Bousquet, "Cascade evaluation of clustering algorithm", *Springer Verlag. 17th European conference on machine learning*, pp. 574–581, 2010.

[7] U. Maulik and S. Bandyopadhyay, "Performance evaluation of some clustering algorithms and validity indices", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 12, pp. 1650–1654, 2002.

[8] N. Settouti, M. Bechar, and M. Chikh, "Statistical Comparisons of the Top 10 Algorithms in Data Mining for Classification Task", *International Journal Of Interactive Multimedia And Artificial Intelligence*, vol. 4, no. 1, pp. 46–51, 2016.

[9] A. M. Jalil, I. Hafidi and L. Alami, "Comparative Study of Clustering Algorithms in Text Mining Context", *International Journal Of Interactive Multimedia And Artificial Intelligence*, vol. 3, no. 7, pp. 42–45, 2016.

[10] K. Swan, "Learning Analytics and the Shape of Things To Come", *The Quarterly Review of Distance Education*, vol. 17, no. 3, pp. 5–12, 2016.

[11] Q. Nguyen, D. T. Tempelaar, B. Rienties, and G. Bas, "What learning analytics-based prediction models tell us about feedback preferences of students", *The Quarterly Review of Distance Education*, vol. 17, no. 3, pp. 13–33, 2016.

[12] S. De Freitas *et al.*, "Foundations of dynamic learning analytics: Using university student data to increase retention", *British Journal of Educational Technology*, vol. 46, no. 6, pp. 1175–1188, 2015.

[13] O. J. Oyelade, O. O. Oladipupo, and I. C. Obagbuwa, "Application of k Means Clustering algorithm for prediction of Students' Academic Performance", *International Journal of Computer Science and Information Security*, vol. 7, no. 1, pp. 292–295, 2010.

[14] J. A. Reyes, "The Skinny on Big Data in Education: Learning analytics simplified", *TechTrends*, vol. 59, no. 2, pp. 75–80, 2015.

[15] R. Klamma, "Community Learning Analytics – Challenges and Opportunities", *Advances in Web-Based Learning – ICWL 2013. Lecture*

Bibliografía

El nivel de actualización del artículo científico se determina atendiendo a la bibliografía consultada y que se encuentra en los últimos 3-5 años de publicación

Editores de textos científicos

Bienvenidos a LaTeX

¿Por qué LaTex?

- Simplifica la gestión de referencias
  - BibTeX para formatear la bibliografía.
- Potente leguaje de expresiones matemáticas
- Plantillas disponibles en la inmensa mayoría de revistas y congresos.

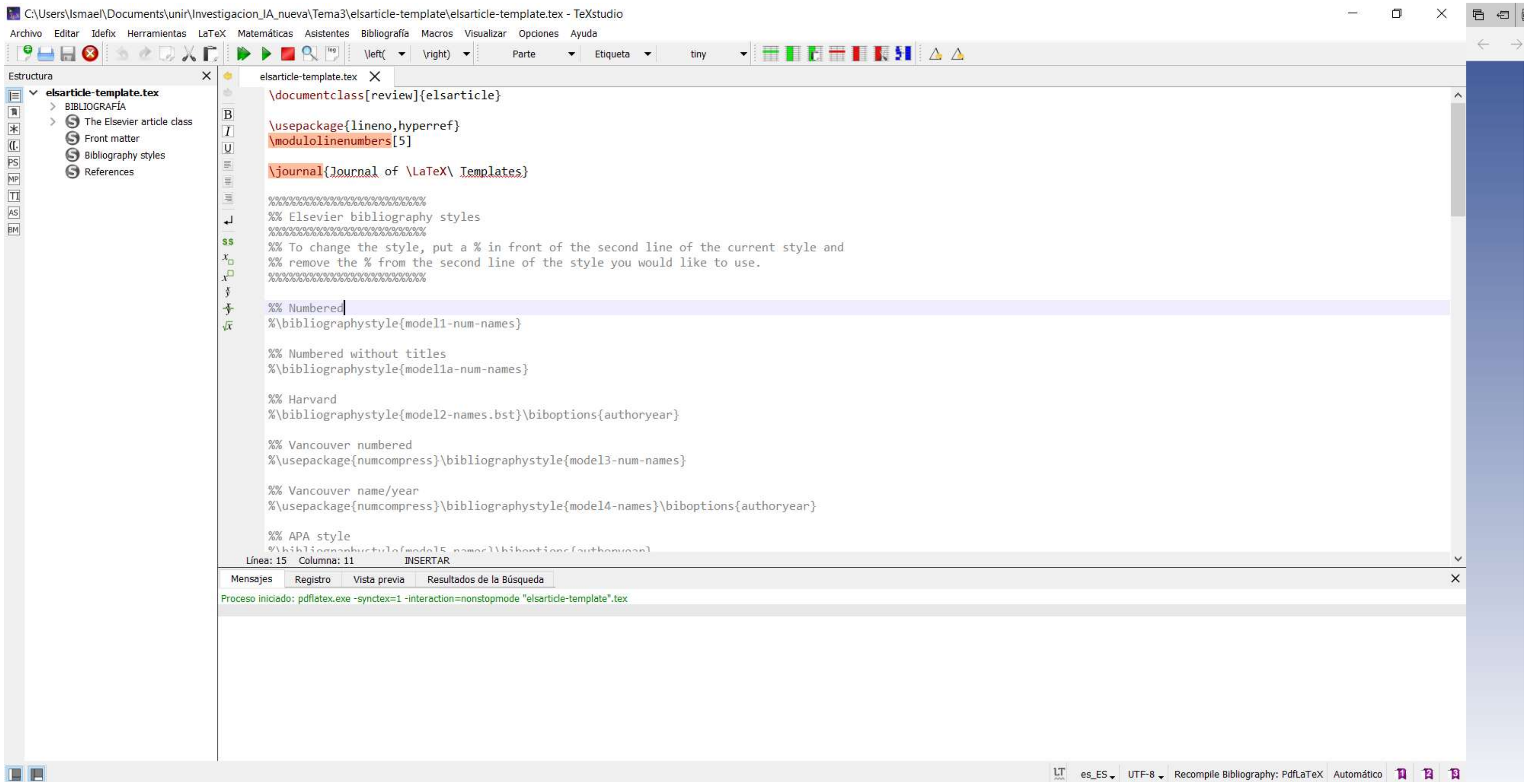
Instalando LaTex

- Descargar LaTex
  - https://www.latex-project.org/get/
    - Windows MikTex
    - Mac MacTex
    - Linux Ubuntu/debian apt.
- Recomendable editor
  - TexStudio: https://www.texstudio.org/
- Edición online y colaborativa:
  - https://www.overleaf.com/

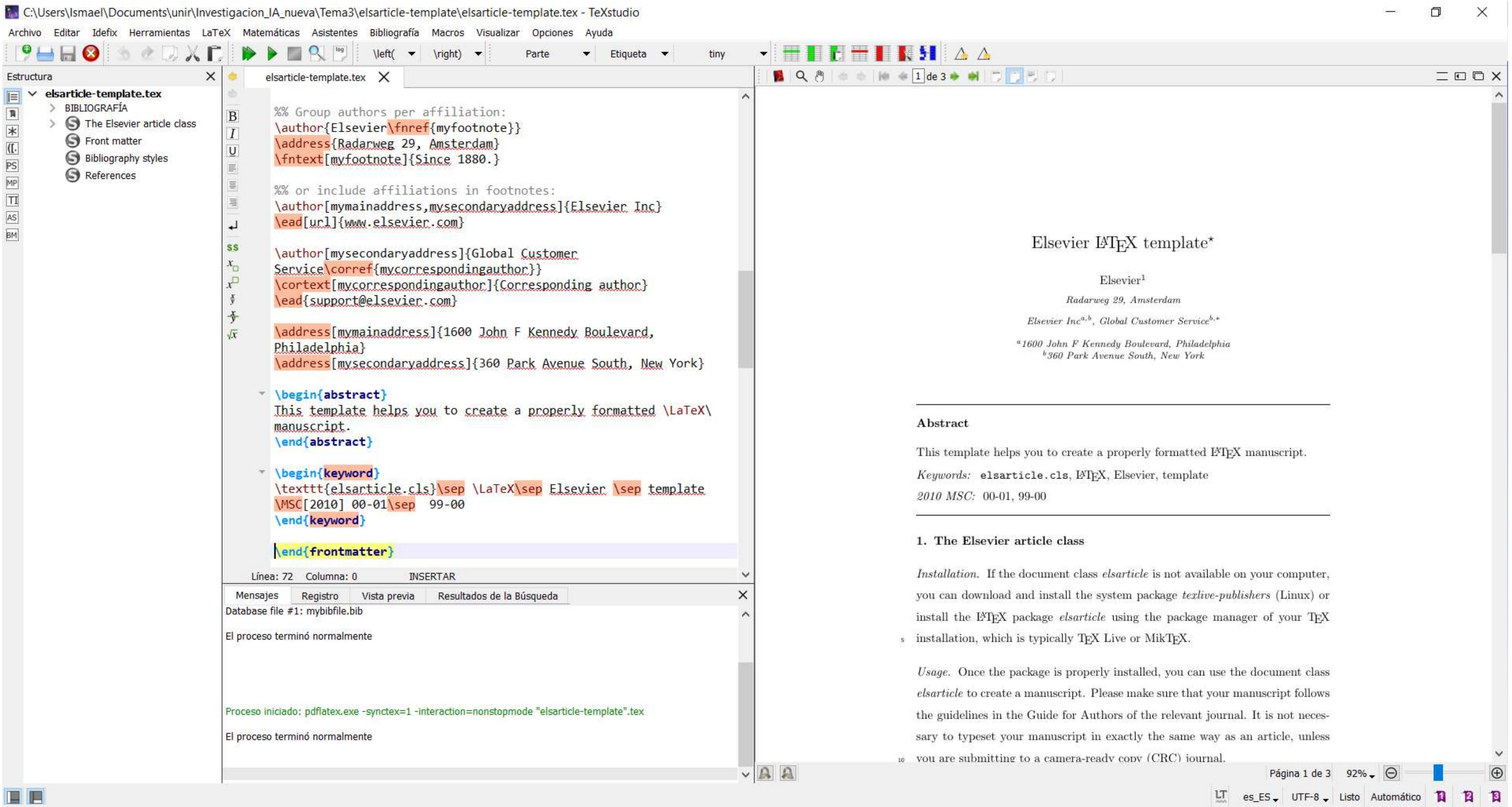
Ejemplo de artículo en LaTeX (plantilla):

- Descargar la plantilla desde:
  - https://www.elsevier.com/__data/assets/file/0007/56842/elsarticle-template.zip
  - Importarla en TextStudio.
  - mybibfile.bib: referencias bibliográficas.
  - Secciones (\subsection{nombre})
  - Compilamos (F6) Tools > Compile.
  - Citas (\cite{identificadorRecursosBibliográfico})

Ejemplo de artículo en LaTeX (sin compilar):



Ejemplo de artículo en Latex (Compilado):

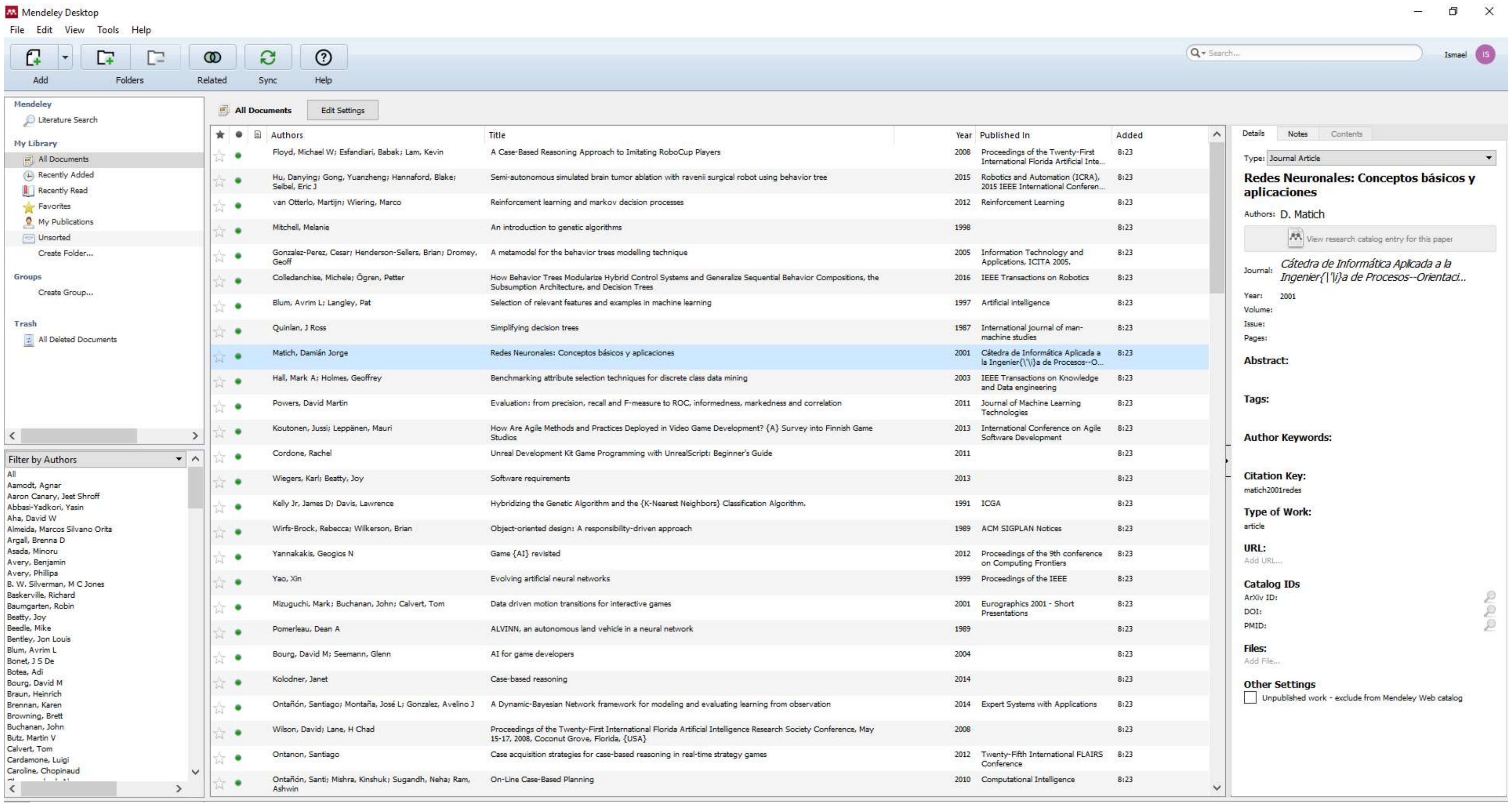


Citas y bibliografía

Gestores bibliográficos

- ¿Qué son?
  - Permiten gestionar las referencias de vuestro trabajo.
- Mendeley
  - https://www.mendeley.com/
- RefWorks
  - https://www.refworks.com/es

Mendeley


Mendeley Desktop
File Edit View Tools Help
Add
Folders
Related
Sync
Help
All Documents
Edit Settings
Authors
Title
Year
Published In
Added
Redes Neuronales: Conceptos básicos y aplicaciones
Authors: D. Match

Citas

- Cómo obtener citas en Google Scholar:

A fast and elitist multiobjective **genetic algorithm**: NSGA-II
K Deb, A Pratap, S Agarwal… - IEEE transactions on …, 2002 - ieeexplore.ieee.org
Multi-objective evolutionary algorithms (MOEAs) that use non-dominated sorting and sharing have been criticized mainly for:(1) their O (MN/sup 3/) computational complexity (where M is the number of objectives and N is the population size);(2) their non-elitism …
☆ 99 Citado por 26301 Artículos relacionados Las 20 versiones

Citar

APA Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation*, *6*(2), 182-197.

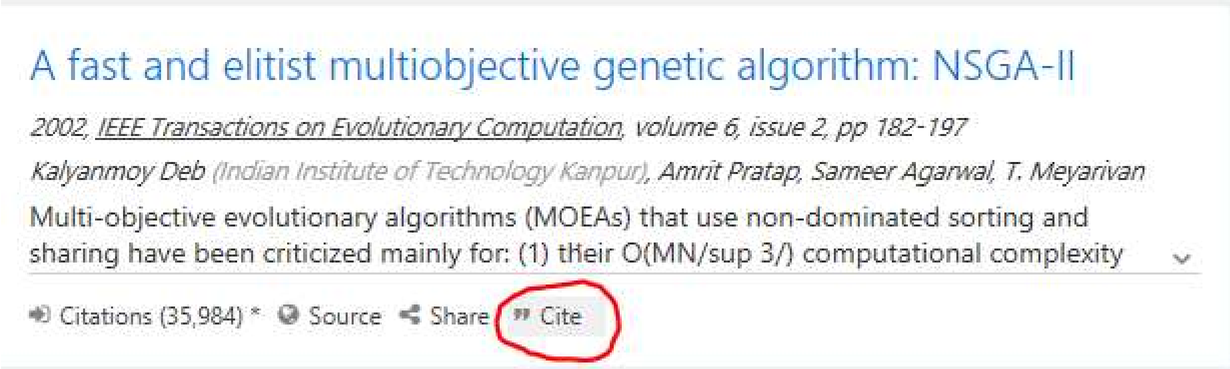
ISO 690 DEB, Kalyanmoy, et al. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation*, 2002, vol. 6, no 2, p. 182-197.

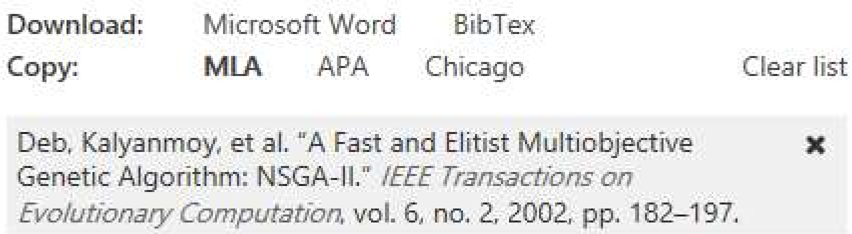
MLA Deb, Kalyanmoy, et al. "A fast and elitist multiobjective genetic algorithm: NSGA-II." *IEEE transactions on evolutionary computation* 6.2 (2002): 182-197.

BibTeX EndNote RefMan RefWorks

Citas

- Cómo obtener citas en Microsoft Academic:



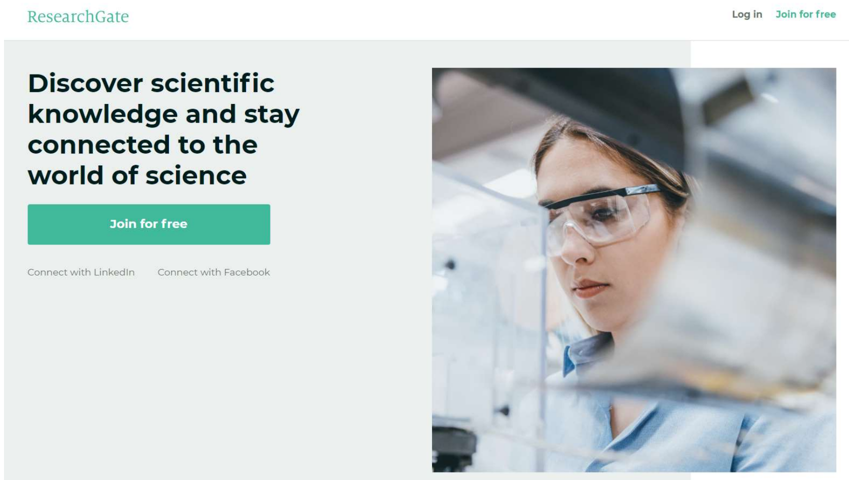


Redes sociales científicas

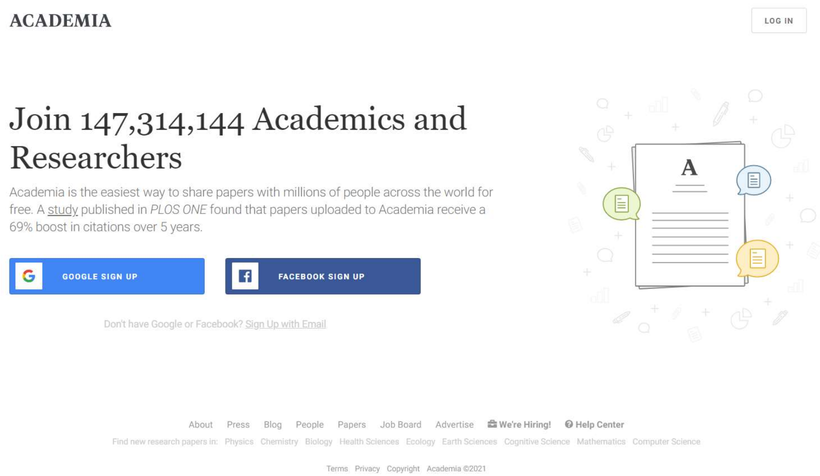
Mantener contacto con comunidad investigadora

Redes sociales científicas

- ResearchGate
  - https://www.researchgate.net/



- Academia
  - https://www.academia.edu



Cerrando

Resumen

- Hoy nos hemos centrado en el estilo y la estructura de un artículo científico…
- … y en algunas de las herramientas que nos ayudan en su redacción

Para la próxima semana

- Soluciones empresariales de IA
  - La IA en la empresa
  - Soluciones comerciales para IA

¿Dudas?

unir

LA UNIVERSIDAD EN INTERNET

www.unir.net