A Topic Modeling Approach to Analyze Teaching Innovation Projects

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Abstract— Topic modeling is a data mining strategy that permit to automatically extract the topics discussed in a given corpus. The objective of this study is to discover the topics that are common in a set of educational innovation projects proposed by university teachers. The LDA algorithm, which is a generative probabilistic model, was used. To identify the correct number of topics the coherence and perplexity metrics were applied. Ten topics were obtained, which, among other aspects, reflect the careers and subjects that work the most in educational innovation projects, as well as the methodologies, strategies and resources that teachers use in their projects.

Keywords—Text mining, topic modeling, LDA, higher-educational institutions.

I. INTRODUCTION

Due to the large amount of information stored in most institutions, it is very common to seek techniques that automatically allow for the analysis and discovery of relevant knowledge for decision-making. Text mining, particularly topic modeling, plays a significant role in automatically identify topics and classify a set of documents. For each topic, a set of words or terms is obtained, these help to making sense of each topic and thus understanding what the analyzed corpus is about.

One of the topic models is Latent Dirichlet Allocation (LDA), a generative probabilistic approach that represents documents as a random mixture of latent topics. Each topic, in turn, is represented as a probability distribution of words [1].

In an academic context, topic modeling proves useful for discerning the main themes present in various types of texts. For example, LDA has been employed to analyze student evaluations of teaching [2, 3, 4], identify themes in texts from Facebook confession pages used by students in certain Philippine universities [5], and extract terms for sentiment analysis of students' feedback [6].

Additionally, LDA has found application in identifying themes in open-ended questions for teacher self-assessment surveys [7], analyzing pre-service teachers' perspectives on the nature of science (NOS) [8], and discovering themes in the teaching of ethics in artificial intelligence courses. This includes discerning trends in course delivery, instructors, and levels of cognitive complexity based on Bloom's taxonomy [9].

Other author used topic modelling to analyze curricula from academic programs offered by universities [10]. Also, LDA has been used to identify trends in research activities related to Computer Science and carried out by Indian researches [11]. Furthermore, The educational philosophies through the mottos of 1,535 universities in 61 countries were analyzed with different natural language processing (NLP) including LDA [12].

Given the utility of topic modeling in the realm of education, this study proposes the application of the LDA model to identify topics related to educational innovation projects originating from a university in Ecuador. Of particular interest are the projects proposed by teachers, as they serve as valuable sources of methodologies, strategies, and resources that contribute to enhancing the teaching-learning process. Through topic modeling, this study seeks to identify the interests and needs of teachers concerning these topics.

II. METODOLOGY

The Fig. 1 illustrates the steps followed to carry out the present study.

A. Data Collection

Annually, the university under investigation issues calls for professor to propose educational innovation projects. These projects consist of some fields, which the teachers input into a software platform in Spanish language. Table I shows some of the fields present in these projects. For the purpose of this study, data of 369 projects submitted between 2018 and 2022 were extracted from the software platform. Only projects with filled introduction and description fields were included in the data. Furthermore, the introduction, description, general objective, specific objectives, and results fields were combined into a single text to facilitate subsequent analysis steps.

B. Preprocessing

The development process was carried out using Google Collaboratory, which permits writing and executing Python code in the browser without necessitating any configuration. Within the preprocessing phase, several steps were undertaken, including symbol elimination, tokenization, normalization, removal of stop words, and the creation of bigrams and trigrams. Further details regarding these steps are presented in Table II and Fig. 2.

C. Documents Representation

Certain words, such as "estudiante," were found in more than 50% of the documents. To address this, tokens appearing in at least 5% of the documents and no more than 60% of the documents, considering the size of the collected projects, were retained. Subsequently, document representation was performed using Term Frequency-Inverse

Document Frequency (TF-IDF), one of the most widely used term weighting schemes in current information retrieval systems [13]. TF-IDF assesses word relevance by considering the frequency of occurrence within the document and across the entire set of documents. This approach ensures that the most common words are not automatically deemed the most relevant.
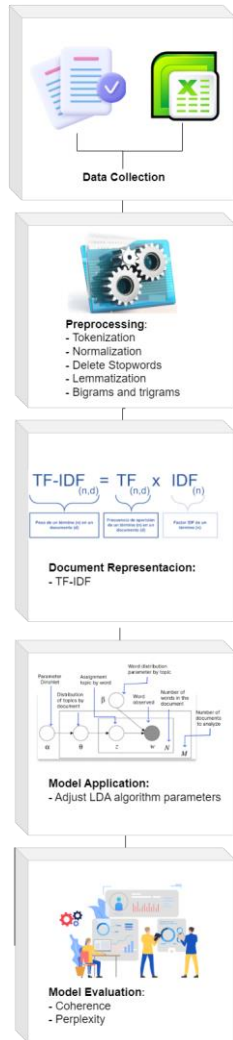

Fig. 1. Methodology

TABLE I. SOME FIELDS IN THE SOFTWARE PLATFORM FOR THE EDUCATIONAL INNOVATION PROJECTS.

Fields	Description
Id	Unique document identifier
Title	The project name
Introduction	Text related to the justification and state of the art of the project
Description	Text that describes what the project consists of and how it will be developed (detailing the selected pedagogical strategy). It should be related to the objectives and results to be achieved.
General Objective	Text that describes the general objective to be achieved with the project.
Specific Object	Text that describes the specific objectives to be achieved with the project
Results	Text related to the expected results by objectives. It describes the deliverables generated for each objective.
Date of register	Date on which the project was registered.

TABLE II. PREPROCESSING

Steps	Description
Symbols elimination	During the process of exporting information from a web platform, certain texts contained terms specific to the HTML language, such as " ." To address this, regular expressions were employed to identify and remove these occurrences.
Tokenization	All words were separated by a token identification process.
Normalization	All words were converted to lowercase
Delete stop words	The Natural Language Toolkit (NLTK) library's stop words list, tailored for the Spanish language, was utilized. Additionally, this stop words list was extended with some Spanish words to enhance its effectiveness.
Lemmatization	This step enabled the transformation of words into their base form, preventing issues arising from different verb conjugations, as well as singular and plural word forms. The selected word categories for this process included nouns, adjectives, verbs, and adverbs.
Creation of bigrams and trigrams	Compounded concepts comprising multiple words were identified. Based on this identification, bigrams were initially generated using the lemmatized documents. Subsequently, trigrams were formed, building upon the previously generated bigrams (refer to Fig 2 for a visual representation).

Fig. 2. Example of bigrams and trigrams

D. Model Application

LDA is a generative probabilistic model used for identifying topics in a collection of documents. In this model, documents are represented as a random combination of latent topics, and each topic is characterized by a probability distribution of words [1].

The graphical representation of the LDA model is depicted in Fig. 3, where the following components are illustrated:

α (alpha) and η (eta) represent the Dirichlet distribution. α is associated with the distribution of topics within a document, while η is associated to the distribution of words within a topic.

β (Beta) and θ (Theta) represent the multinomial distribution. β corresponds to the probability matrix, denoting the frequency of words in a particular topic, while θ represents the distribution of topics for a given document.
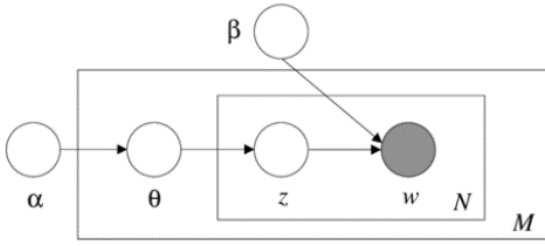
Fig. 3. LDA model proposed by [1]

z represents a set of topics.

w represents a set of words.

The outer box in Fig. 3 signifies the documents in the corpus, while the inner box represents the process of selecting words and topics during the generation of documents through the LDA model.

In this work, the LDA model is considered to identify topics. The basic idea of this algorithm is that documents are considered as random mixtures of hidden topics, where each topic is considered a mixture of different words [14]. The goal is to assign a topic to a set of documents, and documents can have multiple topics.

We use the gensim.models.LdaMulticore library in python to create the model, which requires the following parameters:

- corpus: A bag of words in dictionary, with the values of the word ID and the number of times that word appears in the document for each document.

- id2word: A dictionary that assigns an ID to the words in the document.

- chunksize: The number of documents that will be used for each training step.

- passes: The number of passes through the corpus.

- random_state: Helps ensure that the output of execution 1 is the same as the output of execution 2.

- num_topics: The number of topics to be extracted from the corpus.

- per_word_topics: If True, it calculates a list of topics ordered in descending order of the most probable topics for each word.

E. Model Evaluation

To evaluate the model, coherence and perplexity metrics were selected. Coherence allows validating how coherent a model is in terms of the distribution of topics. According to [15], topic coherence can be defined as the interpretation of a topic based on the degree of relevance between the words within the topic itself. Reference [16] mentions that the coherence of a set of words measures the unity and fit of individual words or subsets of them. There are some versions of this metric, for the present work the Cv version was considered. Also, in [16] mentions that Cv is a measure that combines the indirect cosine measure, normalized pointwise mutual information (NPMI), and the boolean sliding window.

According to [1], perplexity allows evaluating the performance of the model. A lower perplexity score indicates better generalization performance, i.e., the smaller the value of perplexity, the more accurate the model is. The perplexity formula is presented in (1).

$$perplexity\ (D_{test}) = \exp\left\{-\frac{\sum_{d=1}^{M}\log p\ (wd)}{\sum_{d=1}^{M}Nd}\right\} \quad (1)$$

Where:

M is the number of documents

N is the number of words (within the document)

p is the probability distribution of the model

w is the word in the nth position of the words in the document.

In the context of the LDA model, one of the critical parameters to determine is the number of topics. To identify a suitable number of topics for potential experiments, a coherence metric was employed. The results of this metric are presented in Fig. 4, which illustrates the coherence values corresponding to different numbers of topics ranging from 2 to 20

From the coherence plot, the following observations can be made:

1. From topic 8 onwards, the coherence value remains between 0.45 and 0.55.
2. A coherence value of 0.52 was obtained for 10 topics.

Based on these observations and in pursuit of further experiments, two LDA models were developed, the first with 15 and the second with 10 topics.

III. RESULTS

In this section a description of the results is presented.

Experiment with 15 topics

In this experiment, the LDA model resulted in a coherence score of 0.49 and a perplexity value of -16.09. The Fig. 5 shows terms that represent each topic, with the larger words having a greater weight in each topic. The terms in each topic are different, and as bigrams and trigrams are used, some topics also include these compound terms.

A. Experiment with 10 topics

In this experiment, the LDA model resulted in a coherence of 0.51 and a perplexity of -13.05. The Fig. 6 shows terms that represent each topic.

Comparing with the previous experiment, this experiment slightly improved the coherence and perplexity values, therefore, we will show more information about this result.

Table III shows the identified topics and the 15 terms that represent each topic, ordered according to the relevance of each term. Next, in Table IV, column 1 shows the lemmatized text of documents 0 and 2, while column 2 shows the terms from the most relevant topics for each document.

Fig. 4. Coherence from different number of topics.

The terms from the topics are present in the documents (highlighted terms), also exist some words in the documents that are similar to the terms (terms in bold).

In addition, in order to determine which topics are the most frequent in the documents the Fig. 7 was created. It should be noted that a document may have more than one topic, which is why topics 5 and 6 are the most frequent throughout the data collected.

IV. DISCUSSION

Due to our documents are related to the academic field, most of the topics present terms associated to careers, methodologies and resources used in the different projects proposed by the university professors. Next, an analysis of the topics is carried out, based on the terms of each topic.

Topic 0: In this topic exists terms that refer mainly to issues related to the fine arts and law careers.

Topic 1: Here we can find a variety of terms such as "videojuegos" (video games), "vocabulario" (vocabulary) and "repositorio virtual" (virtual repository) used for teaching, also, there are some terms related to subjects such as neuropsychology, basic education and human sexuality.

Topic 2: In this topic exists terms related to the health career.

Topic 3: In this topic exists terms related to the law career.

Topic 4: In this topic exist terms that are very common in the academic programs such as "aula" (classroom), "titulación" (career), "académicos" (academics), "programas" (programs).

Topic 5: This topic contains words such as "recursos" (resources), "enseñanza" (teaching), "herramientas" (tools), "estrategias" (strategies) that are widely used in the educational field and especially in teaching innovation projects.

Topic 6: As in topic 5, in this topic there are words that are very common or general in teaching innovation projects. Some examples of the terms are: "contenidos" (content), "investigación" (research), "grupos" (groups), "bimestre" (bimester), "estudio" (study), "metodología" (methodology).

Topic 7: In this topic exists terms related to learning resources such as "microvídeos" (microvideos), "videoclases" (video classes), "materiales_didácticos" (didactic materials). There are also words that refer to architecture and law careers.

Topic 8: In this topic exists terms such as "laboratorios_virtuales" (virtual laboratories), "memes",

"juegos_didacticos" (didactic games) that refer to other type of learning resources. Also, there are some terms such as "candidatos" (candidates), "electoral" and "voto" (vote) because a project related to national or local elections was carried out.

Topic 9: In this topic the most relevant term is "economía_internacional" (international_economy) and others terms related to statistics. Also, there are terms that refer to strategies and resources used in the teaching-learning process such as "audiocuentos" (audio stories), "paneles_discusión" (discussion panels), "metodologías_ágiles" (agile methodologies), and "feria_virtual" (virtual fair).

V. CONCLUSIONS

By applying the LDA algorithm, it was possible to identify the main themes or topics that are present in the educational innovation projects. It was found that teachers address topics related to methodologies, strategies and resources applied in the teaching-learning process.

Another aspect that was identified is that few careers are mentioned in topics. Terms such as "derecho" (law), "ingles" (English), "clínicos" (clinics) are common in topics, this allows us to assume that law, foreign language and health are the careers the most projects present. This result allows us to suggest to encourage other academic fields to join these types of projects.

Topics 5 and 6 have general or common terms that are present in all educational innovation projects. Also, topic 4 contains other general terms present in academic programs, making it a popular topic after the aforementioned ones. The rest of the topics have unique characteristics that refer either to a specific academic field or to methodologies, strategies or resources.

For future work, it is proposed to continue experimenting with a strategy that allows for better selection of the vocabulary, perhaps assigning certain weights according to an ontology related to education. Also, it is necessary to work with an aggregation process for similarly words.

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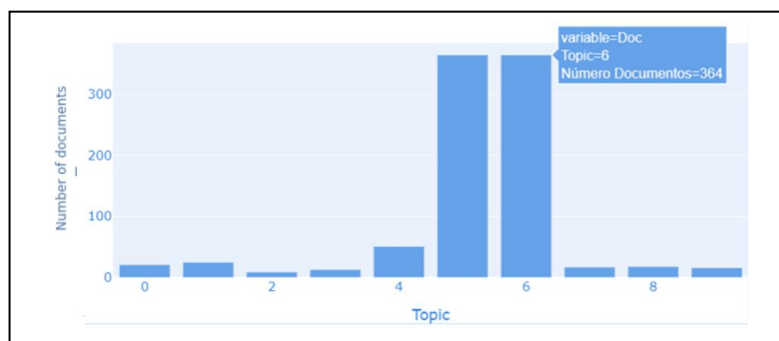Fig. 5. Word Cloud for the 15 topics.

Fig. 6. Word Cloud for 10 topics

Fig. 7. Number of documents per topic.

TABLE III. TERMS WITH 10 TOPICS

Topics	Terms in topics
0	artistas, costos_producción, artista, administración_justicia, judiciales, artística, tinta, carrera_derecho, audiencias, acabó, anual, ideate, leyendas, inspiración, idea_emprendimiento
1	Vocabulario, videojuego, vocabulario_inglés, emisiones, carbono, practicantes, aprendizaje_psicofisiología_neuropsicología, educación_básica_media, histología, logístico, repositorio_virtual, sexualidad_humana, videojuego_denominado_bingo, series_temporales, mejores_mecanismos
2	casos_clínicos, externado, desarrollo_razonamiento_clínico, clínicas, contribuyentes, asistencial, niif, flipgrid, banco_preguntas, expandida, tributarias, fiscal, médicas, mozilla, hubs
3	diseño_legal_inteligente, twitter, novela, hilos, sonoros, corrupción, comunicativos, verificación, sonoro, equipo_tutores_institucionales, ciudadano, leer, lectura_escritura, obras_infraestructura_básica, legal_inteligente
4	aula, motivación, titulación, productos, derecho, fundamentos, realidad_aumentada, académicos, biología, grupo, juego, modalidad_presencial, programas, facilitar, movilidad
5	recursos, fase, herramientas, enseñanza, educación, alumnos, prácticas, clases, asignaturas, información, estrategias, docentes, nivel, necesidades, recursos_educativos
6	contenidos, comunicación, investigación, digitales, grupos, cultura, bimestre, prototipos, trabajo_colaborativo, plataforma, estudio, violencia, metodología, arte, solución
7	sistemas_arquitectónicos_energéticamente_eficientes, investigación_científica, club, tema_inclusivo, dictados, microvídeos, constructivo, videoclases, prototipado, constitucional, materiales_didácticos, construirán, mancomunidad_bosque_seco, producción_artística, derecho_procesal_constitucional, garantías, planificarán, inherentes, levantamiento
8	laboratorios_virtuales, candidatos, memes, electoral, electorales, calificadas, instrumentos_evaluación, políticos, voto, histología, riesgo_biológico, calificada, discursos, constructos, juegos_didácticos
9	economía_internacional, componente_estática, ensayos_académicos, testear_teorías, fuentes_hídricas, comercio, audiocuentos, tdah, períodos, paneles_discusión, metodologías_ágiles, sprint, assemblr, lucidchart, feria_virtual

TABLE IV.   ANALYSIS OF TERMS PRESENT IN 2 DOCUMENTS

Example of documents	Terms
Document 0: topic 5 has de highest probability with a value of 0.66. 'característica', **'estudiante'**, 'exitoso', 'aprendizaje', 'literatura', 'mencionar', 'efecto', 'positivo', 'tecnología', 'herramienta', 'soporte', 'mejorar', 'eficacia', 'aprendizaje', 'targamadze', 'petrauskienir', 'medida', 'tecnología', 'desarrollar', 'ofrecer', 'oportunidad', 'aprendizaje', 'alumno', 'bozkurt', 'tecnología', 'capturar', 'atención', **'estudiant'**, 'familiarizar', 'fácilmente', 'herramienta', 'bravo', 'herramienta', 'ayudar', 'crear', 'ambiente', 'emprendizaje', 'rico', 'potente', 'actualidad', 'definido', 'concepto', 'denominado', 'vídeo', **'educativo,'** 'costo', 'vídeo', 'corto', 'demostración', 'objetivo', 'específico', 'creado', 'período', 'tiempo', 'corto', 'recurso', 'combinar', 'incrustar', 'material', 'curso', 'simo', 'contexto', 'pretender', 'generar', 'aprovechar', 'potencial', 'comunicativo', 'imagen', 'sonido', 'palabra', 'transmitir', 'experiencia', 'práctico', **'estudiant'**, 'carrera', 'biologío', 'estimular', 'aumentar', 'interés', 'motivar', 'aprendizaje', **'estudiante'**, 'bachillerato', 'educación_superior', **'estudiante'**, 'mostrar', 'comunidad', 'proyecto', 'investigación', 'desarrollar', 'elaborar', 'guión', **'estudiante'**, 'asignatura', 'estudiant', 'guión', 'revisado', 'docente', 'equipo', 'calidad', 'carrera', 'biologío', 'mejorar', 'estructura', 'calidad', 'presentación', 'información', 'laboratorio', 'docente', 'realizar', 'grabación', 'edición', 'video', 'generar', 'recurso', 'difusión', 'actividad', 'prototipo', 'difusión', 'global', 'carrera', 'biología', 'difundir', 'trabajo', 'investigación', 'realizar', 'carrera', 'comunidad', 'motivar', **'estudiante'**, 'vincular', 'carrera', 'biología', 'video', 'proyecto', 'investigación', 'periodo', 'redes_social', 'estudiante', 'desarrollar', 'competencia', 'análisis', 'presentación', 'información', 'motivar', **'estudiante'**, 'ingreso', 'bachillerato', 'formar', 'carrera'	Topic 5: 'recursos', 'fase', 'herramientas', 'enseñanza', 'educación', 'alumnos', 'prácticas', 'clases', 'asignaturas', 'información', 'estrategias', 'docentes', 'nivel', 'necesidades', 'recursos_educativos'
Document 2: Topic 6 has the highest probability with a value of 0.88. 'proyecto', 'práctica', 'docente', 'proponer', 'modelo', 'aprendizaje', 'basado_problema', 'design_thinking', 'metodología', 'estímulo', 'interesante', 'alumno', 'aportar', 'concepto', 'desarrollo', 'proyecto', 'gráfico', 'aplicar', 'enfoque', 'completamente', 'práctico', 'cooperativo', 'propuesta', 'proporcionar', 'problemático', 'visual', 'obtenido', 'situaciones_reales', 'presentado', 'compañero', 'escuelo', 'estudiante', 'revisar', 'material', 'prototipo', 'muestra', 'entregado', 'docente', 'respectivo', 'análisis', 'fortalecer', 'participación', 'compromiso', 'activo', 'estudiante', 'proceso', 'aprendizaje', 'convertir él', 'alumno', 'protagonista', 'formación', 'fortalecer', 'docente', 'convertir', 'guía', 'orientar', 'andamiaje', 'estudiant', 'convirtiendo él', 'autónomo', 'modelo', 'basado', 'situaciones_reales', 'metodología', 'utilidad', 'fortalecer', 'conocimiento', 'estudiant', 'necesitar', 'despertar', 'habilidad', 'desarrollo', 'proyecto', 'gráfico', 'estudiante', 'componente', 'diseño', 'prensa', 'alumno', 'materiar', 'reproducción', 'analógico', 'digital', **'trabajar,'** **'conjunto'**, 'proporcionar', 'información', 'documentado', 'usar él', 'contenido', 'materia', 'consistir', 'solución', 'visual', 'problemática', 'presentado', 'estudiante', 'escuela', **'artes_visual'**, 'dar', 'inicio', 'socialización', 'información', 'aplicar', 'paso', 'establecido', 'estrategia', 'clase', 'estudiant', 'atender', 'tema', 'explicado', 'docente', 'formar', 'grupo', 'permitir', 'revisar', **'solucionar'**, 'problemática', 'existente', 'seguido', 'alumno', **'trabajar,'** 'solución', 'diseño', 'proyecto', 'gráfico', 'clase', 'terminar', 'presentación', 'avance', 'discusión', 'solución', 'propuesto', 'aplicar', 'aprendizaje', 'basado_problema', 'estrategia', 'enseñanza', 'crear', 'innovación', 'visual', 'soporte', 'evidenciar', 'propuesta', 'estudiante', 'fomentar', 'participación', 'estudiante', 'dinamizar', 'clase', 'atreverse', 'proceso', 'experimental', 'manual', 'digital', 'determinar', 'propuesta', 'visual', 'publicitario', 'evidenciar', 'resultado', 'alcanzado', 'documento', 'impreso', 'digital', 'promedio', 'académico', 'infografía', 'proceso', 'aplicado', 'clase', 'portafolio', 'digital', 'elaborado', 'estudiante', 'docente', 'realizado', 'estudiante', 'involucrado', 'proceso', 'proyecto', 'práctica', 'docente', 'contraste', 'diagnóstico'	Topic 6 'contenidos', 'comunicación', 'investigación', 'digitales', 'grupos', 'cultura', 'bimestre', prototipos, 'trabajo_colaborativo', 'plataforma', 'estudio', violencia, 'metodología', arte, solución