Personalized Smart Learning Recommendation System for Arabic Users in Smart Campus

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ABSTRACT

The advancement of technologies has modernized learning within smart campuses and has emerged new context through communication between mobile devices. Although there is a revolutionary way to deliver long-term education, a great diversity of learners may have different levels of expertise and cannot be treated in a consistent manner. Nevertheless, multimedia documents recommendation in Arabic language has represented a problem in natural language processing (NLP) due to their richness of features and analysis ambiguities. To tackle the sparsity problem, smart learning recommendation-based approach is proposed for inferring the format of the suitable Arabic document in a contextual situation. Indeed, the user-document interactions are modeled efficiently through deep neural networks architectures. Given the contextual sensor data, the suitable document with the best format is thereafter predicted. The findings suggest that the proposed approach might be effective in improving the learning quality and the collaboration notion in smart learning environment.

KEYWORDS

Arabic Natural Language Processing, Deep Learning, Internet of Things, Multimedia Documents, Personalized Recommendation System, Smart Campus, Smart Learning

1. INTRODUCTION

In the modern world, diffuse or ubiquitous computing enables the interconnection of all areas of life using new technologies to foster the creation of intelligent environments, such as smart campuses. It provides reliable Internet-of-Things (IoT) services to the users anytime and anywhere. Recently, the paradigm of smart learning has become popular because of its huge coverage of topics from around the world. It plays a vital role for learners to open the door to new opportunities on higher education. It introduces learning materials in a style that enhances learners' expectations and interactions with each other using different multimedia contents, such as graphics, audio, video, and text. However, a large number of resources is shared in an intelligent learning environment every day causing an overload of information exchanged. This can make it difficult to extract better content. Nevertheless, Arabic

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language is rich of morph-syntactic and semantic features that complicate its analysis (Mahmoud and Zrigui 2019a). It represents a fundamental problem in Natural Language Processing (NLP) due to the wide variety of applications associated with it (e.g., information retrieval, question-answer, temporal information retrieval, etc.) (Haffar et al., 2020a; Haffar et al., 2020b). Faced with these problems, Arabic documents recommendation-based approach is proposed. The main objective is to find the most suitable content that meets the needs of Arabic users. It facilitates the collaboration between users and improves their learning experiences in different situations. To tackle the sparsity and unbalanced ratings distribution problems, the main contributions of this work are the following:

- The use of users generated ratings and the title of Arabic documents as inputs.
- The enrich of latent features from items by using the advantages of deep neural networks.
- To the best of our knowledge, it is the first work focusing on Arabic resources recommendation within smart campus exploring the relative importance of heterogenous data sources (ratings and document title) for rating prediction task. Moreover, the complexities of Arabic language are processed using deep learning architectures and NLP techniques.

This paper is structured as follows: First, we present the general context of recommendation systems in smart campus. Then, a state of the art on mobile learning field reviews the existing personalized recommendation-based methods. Subsequently, the problems concluded are summarized. After that, we detail the motivation and the phases constituting our proposed approach. Finally, the last section describes a conclusion and our future works.

2. STATE-OF-THE-ART REVIEW

2.1. Smart Campus

The development of Information and Communication Technologies (ICT) facilitates the interconnection of all objects of everyday life into an exclusive identity through internet technology, called *Internet of Things (IoT).* It is the interconnection of physical devices, vehicles, buildings and other elements, integrating electronics, software, sensors, actuators, etc. (Tare et al. 2017). It can move data from many devices over a network without the need for human-to-human or computer-to-human interaction. Indeed, traditional campus is made up of well-equipped independent hardware and software equipment. However, a traditional equipment load is associated that does not meet the needs and leads to a waste of resources and information with a high-energy consumption. This is because of the unbalanced allocation of resources with misuse (Huang 2017). Hence, the need to build a smart campus comprising buildings, experimental classrooms, desktops or personal computers and peoples connected using IoT paradigm. A variety of services are provided to users with an intrinsic need. Their impact is not limited to academic aspects, but also to social, financial and environmental aspects on campus to reduce costs and provide high quality services.

Smart campus implementation depends on the campus needs and the surrounding citizens. It requires a digital infrastructure adapted from the smart city so that the campus information is accessible from a mobile phone or other gadgets (Ng et al. 2010):

- **Smart education:** Includes e-learning, personalized and collaborative learning and virtual classroom. It is a complete knowledge platform accessible anytime and anywhere. In smart campus, e-learning has a videoconferencing system that allows students to face teacher from different location or to help simulate and evaluate classes through virtual classroom.
- **Smart class:** Provides information about the room and the number of students present: the presence of students is recorded using RFID technology, the lights extend (light up) automatically if there is no human (if there are people in it) using PIR motion sensor.

- **Smart communication:** Includes social networks and communications, information sharing, workplace collaboration, social localization, model analysis, grouping of interests, etc.
- **Smart library:** Provides personalized digital and remote library services in real time.
- **Smart parking:** Provides information about its availability using a sensor.
- **Smart health:** Represents preventive, proactive and remote health care systems; mobile health; centralized online health records; intelligent bioinformatics, epidemic early warning platform, etc.
- **Smart security:** Centralized management and maintenance of buildings, automatic emergency system, automated monitoring, access and security control, etc.
- **Others:** Sustainability initiatives on campus operations can be organized in several key areas, such as energy, buildings, waste, water, transport, air and climate, as well as food.

2.2. Personalized Smart Learning

E-Learning is a computer-based learning and teaching tool designed to provide learners with the opportunity to learn anywhere and at any time. It uses Learning Management Systems (LMS) to provide and manage educational contents and facilitate the delivery and organization of e-learning in large educational institutions (Fraihat et Shambour 2015). Different types of digital learning objects could be reused (text, audio, video, image, or website) and offered the same kind of course structure and learning objects. The integration of IoT technologies into traditional campuses has enhanced the effects of teaching and learning in the field of education based on three main visions (Kim et al. 2019):

Vision 1: The things-oriented vision for uniquely identify any object using sensors, such as RFID, NFC, etc.
Vision 2: The internet-based vision to create smart connected objects using the internet technology.
Vision 3: The semantic vision to solve interoperability problems related to data understanding in heterogeneous format.

In a smart campus, devices, applications, and peoples are interconnected through a common, shared technology infrastructure. This has greatly improved the academic experience (Sunnyrale 2018):

- Video and collaboration tools are used to open classes and lectures to more students without having to insert them all in one conference room.
- When students are sick or on bad weather can make campus access difficult, the class can still continue. Thus, students can connect to live lectures from their computer, participate in discussions, download course materials, and submit work without wasting time.
- For the universities themselves, distance learning offers even more opportunities: Strengthen the reputation (and enrollment) of the institution by opening online courses to all participants.
- Conference organization is easy with experts from the same field from all campuses or around the world.

Different from traditional face-to-face learning, distance learning is a revolutionary way to deliver long-term education. Although there is a great diversity of learners on the Internet, a unique set of resources is provided. However, learners may have different levels of expertise, and therefore, cannot be treated in a consistent manner. Hence, the need for a personalized referral system that can automatically adapt to the interests of learners, improve their satisfactions and the quality of learning.

2.3. Recommendation System Within Smart Campus

An intelligent campus allows for better coexistence between the university population and its surroundings, properly manages resources and provides places for learning. The rapid growth of broadband Internet access and the proliferation of modern mobile devices have made many data available on smart campuses. This phenomenon has raised the following challenges:

- A user looking for a service on a particular subject needs' guidance and assistance.
- The storage limitation of devices introduces a problem of mobile data overload.

In response to these problems, researchers have developed a variety of techniques to recommend services that best serve the user. They have provided the most relevant personalized information with less effort and in a satisfactory response time. In this section, the general process of recommendation system within smart campus is described.

2.3.1. Data Gathering Phase

The acquisition phase allows the collection of information from mobile devices in different ways (Kumar et Signh 2019). It consists of the following data:

- User profile (e.g., sex, gender, age, occupation, education level, etc.).
- Document metadata (e.g., title, keywords, topics, etc.).
- Physical context (e.g., temperature, light, speed, etc.) using the appropriate sensors for each type of data.
- User-item interactions identifying the user interests satisfied a particular need, distinguish:
    - **Explicit feedback:** Requires user-entered demographic information like user profile and their preferences (rating 1-5).
    - **Implicit feedback:** Use natural actions by the user to communicate with ubiquitous applications. They occur through gestures, facial expressions, body movements, sounds, manipulation of physical objects, and so on, access number (0,…, n), etc.

2.3.2. Preprocessing Phase

The preprocessing phase is fundamental in NLP systems. It aims to represent the data in a machine-readable form (Abdellaoui and Zrigui, 2018). The goal is to efficiently analyze and improve data quality by reducing the amount of trivial noise (Haffar et al. 2019). For example, an Arabic query is preprocessed as follows (Mahmoud and Zrigui 2021):

- Eliminate the least useful parts by removing diacritics, extra-white spaces, special characters, duplicate letters, and non-Arabic words.
- Normalize words (e.g., "أ, إ, ٱ, آ" to "ا" and "ة" to "ه") to reduce ambiguities.
- Detect the space between words to simplify their exploration.
- Annotate words with their grammatical classes (e.g., verb, noun, adjective, etc.).

2.3.3. Features Extraction Phase

A recommendation system only needs the relevant features to differentiate one object from another. For this, the choice of primitives is critical, and clearly influences the result. Several methods have been proposed:

- **Lexical techniques:** Take into account the words order of the request/document, such as Term Frequency-Inverse Document Frequency (TF-IDF), Bag Of Words (BOW), etc.
- **Semantic techniques:** Have overcame the limitations of lexical techniques. They compared linguistic units according to their meaning. Different methods have been developed (Sohail et al. 2017):

  - Corpus-based approach uses unstructured semantic data (Latent Dirichlet Analysis (LDA), Latent Semantic Analysis (LSA), etc.).
  - Knowledge-based approach uses structured semantic data such as ontologies.
  - Web-based approach collects statistics on co-occurrences based on search engine results and uses them to calculate the word relationship as Pointwise Mutual Information (PMI).
- **Deep learning techniques:** The traditional approaches mentioned above did not take into account the syntactic structure of the language. That is why; they could not capture the similarity effectively between words. As a result, competitive works have been learnt on distributed words representations using neural network models. They are useful for maintaining linear regularity between words, analyzing hidden contextual relationships between objects / words, mitigating scarcity and learning large sets of data. (Mahmoud and Zrigui, 2019b)

2.3.4. Recommendation Phase

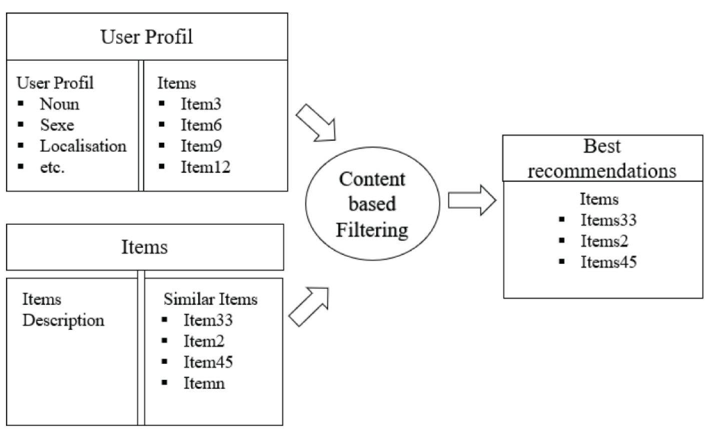
Several recommendation systems based on traditional filtering methods have been introduced to filter user-friendly contents from a potentially considerable number of choices, distinguish:

- **Content based filtering techniques:** Describe items rather than similarity between users to generate a list of products / items recommended as outputs, as shown in Figure 1.

A content filtering method requires the following operations (Suganeshwari et al. 2016): First, user profiles and their tastes are created at the beginning to avoid the cold start (new user) problem. Subsequently, an automatic learning algorithm is applied to induce a model of user preferences based on functionality factors. Depending on how the metadata is extracted, the content is secondly classified into simple categories. Then, different predictive models can be used to extract information from the content, mention:

- **Classification:** Predicts the output value of the distinct output variable (decision tree, Naïve Bayes, etc.).
- **Clustering:** Creates clusters in the data to find patterns (k-averages, hierarchical classification and density-based algorithms, etc.).
- **Attribute importance:** Is determined with respect to the prediction of the output attribute (minimum description length, pruning of the decision tree, etc.).

Figure 1. Content filtering principle



- **Association rules:** Search for interesting relationships in the data by examining co-occurring items (association rules, a priori algorithm).

Finally, predictions in content-based recommendation systems may be inaccurate for the following reasons:

- The extraction of the most discriminating primitives is a difficult task for multimedia documents.
- Identical elements can be referred with different titles. Hence, the need to have a filtering technique of similar items and different from each other.
- Lack of information about new users and items complicates the filtering process. It is difficult to recommend items when a new user enters in the system for which no previous information (such as browsing history, preferences, etc.) exist. In addition, no rating will be assigned to a new item entering in the system and it is likely that it will not be.
- Collaborative based filtering techniques: find users who share the same preferences as shown in Figure 2.

A user receives recommendations on items that have not yet been evaluated, but have already been positively evaluated by users in their neighborhood. They can be classified into memory and model-based techniques (Asanov 2011):

- **Model-based techniques:** Construct a model by applying different automatic learning methods such as matrix factorization, fuzzy systems, Bayesian classifiers and neural networks, etc. Although they have demonstrated their effectiveness in solving the problem of scarcity and scalability and improving predictive performance, they have presented the following limitations: expensive model construction, compromise between prediction performance and scalability, and information loss in the dimensionality reduction technique.
- **Memory-based techniques:** (1) find similar ones for the user in question; (2) apply an aggregation method, select the best recommendations, and (3) display the most relevant items. There are many functions for calculating similarities, such as Pearson correlation, Cosine, Jaccard and Manhattan distances, and so on.

The choice of filtering based on user or item depends on the application features, as summarized in Table 1.

Figure 2. Collaborative filtering principle

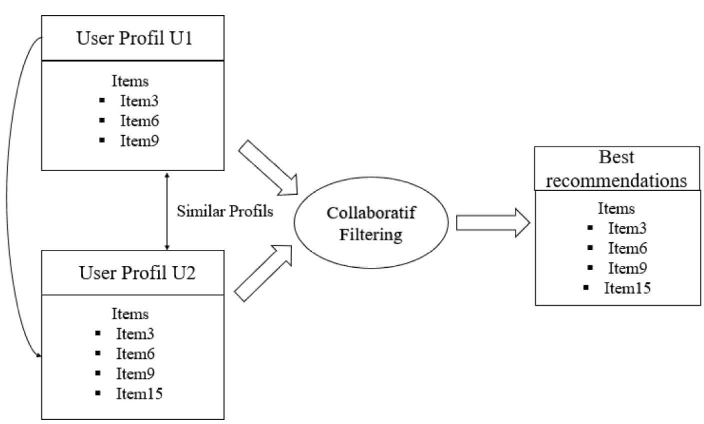


Table 1. Choosing Collaborative Filtering Techniques (Fraihat et Shambour 2015)

Application	Feature	Technique
Amazon	The list of items does not change much	Collaborative filtering based on the item
News	The list of items changes frequently	Collaborative filtering based on the user
Social Networks	The recommended item is a user	Collaborative filtering based on the user

Although collaborative memory-based filtering is easy to implement, adding new data is incremental without considering the content of the recommended objects, it has the following limitations: human assessments are required, cold start problem for the new user and item, rarity problem of the scoring matrix, and limited scalability for large datasets.

- **Hybrid based filtering techniques:** To solve the problem of adding a new item or user (cold start), hybrid recommendation systems combine different collaborative-based and content-based filtering techniques in a unified way and join at the end the result (Kumar et Singh 2019). Although they are able to overcome the low density of collaborative filtering and improve forecasting performance, the complexity and implementation costs are increased. Therefore, recommendation based on modern filtering methods combine the filtering techniques used in ubiquitous systems with conventional recommendation systems (Sohail et al. 2017). They incorporate the following features as shown in Table 2.
- **Context-based filtering techniques:** Include sensitive user preferences and exploit their requirement complications. They pay attention to the following information (Garg et al. 2012):
    - Primary or spatial context information (identity, time and place) to index and identify entities.
    - Secondary context information (the current state, its activity, etc.) to cover aspects of the entity.
- **Knowledge-based filtering techniques:** Gather knowledge about users (needs, preferences) and available items and then identify matches to generate recommendations, distinguish (Kumar et Singh 2019):
    - **Case-based recommendation:** Evaluates the resemblance of an item to the user's preferences. To reduce the complexity of acquiring explicit knowledge from the user, McSherry (2003) applied decision trees to identify an item as a recommendation object and store it in a single case library.
    - **Constraint-based recommendation:** Find items that are not frequently recommended. If there is no recommendation, the system automatically proposes solution options explaining the items features (Sohail et al. 2017).

Table 2. Features of modern recommendation systems

Feature	Description
Awareness of the context	Operate in a three-dimensional space (user, service, context) and offer services according to the context of the user.
Proactivity	Provide personalized services in fewer time and minimize explicit interactions with the intelligent environment.
Anticipation	Anticipate future contexts and user preferences in new situations.
Scalability	Evolve over time to support any changes such as user preferences.

2.4. Mobile Learning Recommendation Systems

Mobile-learning recommendation systems include analyzing user data and extracting the most discriminant primitives for future predictions. Several works have been proposed for recommending learning objects, learning courses, learning pathways / activities, etc.

2.4.1. Content-Based Recommendation Systems

By accurately disclosing and understanding the features of reader's interest and preference, the digital library can become smart to recommend proper items to the reader and enhance reader's experience to save the time for searching books, journals or magazines that they need. To solve the problems of redundancy, lack of innovation and inconvenience, Li and Cai (2016) developed a mobile library application for smart phones. Similarly, Zhao (2021) proposed a smart library recommendation method. First, the topics with high user preference score were estimated and recommended using LDA technique. To help students understand course content, Nakayama et al. (2019) developed an e-learning recommendation system. They extracted keywords from each page of an electronic manual to retrieve the related websites. Xie et al. (2019) proposed a model composed of the following operations: (1) the learner entered the previous knowledge levels for the selected words provided by the system. (2) By integrating external data sources, the learner profile was established using explicit and implicit data. (3) Once the learning task completed by the learner, the system examined whether the entire learning process was completed. By cons, Nafea et al. (2019) proposed an approach based on the Felder and Silverman learning style model. K-means classification algorithm, Cosine similarity, and Pearson correlation were effective for implementing learning-object recommendation. In the same idea, Sunil and Doja (2019) presented a personalized adaptive online learning approach based on the learning style and level of learner knowledge. In addition, Cerna (2019) developed a recommendation system for online courses based on topics. Also, Perumal et al. (2019) generated frequent item templates by analyzing the changes in the user's interests. Then, fuzzy rules adapted the constraints of their exploration to all types of learners. For the same purpose, Asadi et al. (2019) grouped students with similar interests and skills. Once similar students were found, dependencies between course selections were examined using fuzzy association rules exploration.

2.4.2. Collaborative Recommendation Systems

Dong et al. (2016) developed an OnCampus mobile platform. They adopted the XMPP protocol and used the two-tier server structure to implement the system and save energy. They then developed three functional modules to provide services related to learning, quality of life and entertainment, namely: Group, Buy-Sell and Forum modules. Similarly, Umam et al. (2017) used an Interactive Internet Mail Group (IIMG) to improve learner-speaker interactions, engagement, and smart campus behavior. To better cover the complexity of the domain and serve the user, traditional collaborative filtering methods were proposed: Pearson's coefficient, cosine, mean squared difference and their combinations. However, they couldn't capture the similarity between scattered objects and new users. Therefore, Liu et al. (2014) calculated three sub-similarities in user-rating matrix including proximity, impact, and popularity. Each one was contributed with different weights to calculate the similarity between users. Then, a refined neighborhood was assembled for collaborative filtering. Similarly, Diaz et al. (2019) examined the cold-start problems of users and networks for which little prior information was available to make good real-time recommendations on the CHUNK website. In recent decades, deep learning-based filtering methods were achieved promising results in computer vision and NLP (Bsir and Zrigui, 2019; Mahmoud and Zrigui 2019c). However, they were not applied deeply in recommender systems. Several studies were proposed for overcoming the complex interactions between users and items and extracting auxiliary information to create recommendations. For example, Chen et al. (2019) joined Multi-Layer Perceptron (MLP) and matrix factorization to model user and item latent vectors. In contrast, Convolutional Neural network (CNN) was widely used for computer vision and speech recognition. For books recommendations, Kim et al. (2016) integrated Convolutional Matrix Factorization (ConvMF) into probabilistic matrix factorization (PMF) for enhancing the rating prediction. In the same idea, Wadikar et el. (2020) demonstrated that CNN model was efficient than cosine similarity to identify similar book covers from Amazon and Flipkart. In addition, Recurrent Neural Networks (RNN) addressed efficiently the temporal dynamics of ratings and sequential features of users and items as demonstrated by Chambua et al. (2019).

2.4.3. Hybrid Recommendation Systems

Sun and Li (2016) developed an intelligent campus architecture at the China University of Science and Technology. They provided services to students in their daily lives and helped university administrators to produce positive social effects. They built a personal lifestyle reporting system (e-campus card data, school e-mail interaction data, university hospital-provided health reports, cell phone sensor data, chronology data of Weibo and Renrens, and Jiepangs recording data). The profiles (place of birth, place of residence, class, supervisor, laboratory) were used to recommend roommates and colleagues to Renren students. They used them with other contextual information (department, class, selected courses, and student's semester) to make book recommendations. Ansari et al. (2016) proposed a hybrid (content-based and collaborative filtering) and context-specific recommendation system for interactive programming online learning for Persian-speaking users. The main goal was to advance learners' level of learning and performance by providing personalized and user-specific recommendations as well as educational resources. Li et al. (2019) proposed a course recommendation system based on a hybrid-filtering algorithm: First, similar learners were classified into several groups according to their online learning style. Then, collaborative recommendation algorithms were applied to each group of learners. Subsequently, a personalized recommendation list was generated based on user history and similarity data.

2.4.4. Context Recommendation Systems

Context is considered any information that can be used to characterize the entity situation that is considered relevant to the interaction between a user and an application. For example, Li et al. (2014) defined the context using five factors (who (user), what (object), how (activity), where (place) and when (time)) and from different perspectives (context focused on human, knowledge-based context and technology-based context). Similarly, Dias et al. (2019) made a set of choices for making decisions (what to learn, how to teach, whom to learn, etc.). Merging these contexts was effective in finding similar users to the active one, and then generating recommendations. On the other hand, Tarus et al. (2018) generated sequential learning models using an ontology to incorporate contextual information about the learner (such as learning objectives and level of knowledge) and solve data scarcity and cold start problems.

2.4.5. Knowledge Based Recommendation Systems

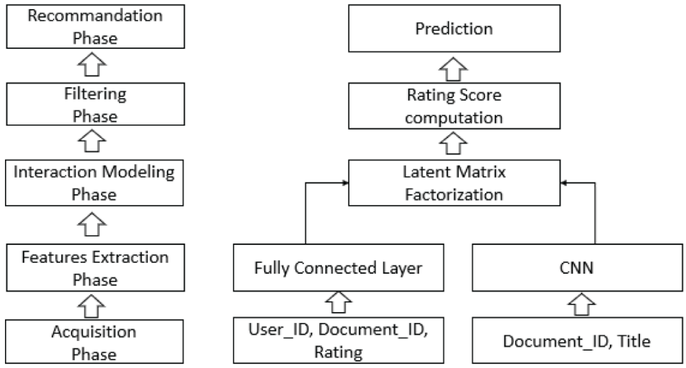
Neves et al. (2013) demonstrated that ontology was useful for defining the domain knowledge model, while the propagation activation algorithm was necessary to learn the users' interests. They used them to develop an agent-based architecture for recommending custom and contextual events. Similarly, Fraihat and Shambour (2015) used intra and extra semantic relationships between project managers and learner needs to provide personalized recommendations. The semantic recommendation algorithm was based on the extension of query keywords using the semantic relations, concepts and means of reasoning of the domain ontology. However, Somsuphaprungyos et al. (2016) developed an ontology to derive student activity using an integrated inference engine based on RFID sensors located in front of each room door and basic data from universities. In the presence of multiple activities and users in the campus, the following activity prediction process seldom produced a single candidate for the next activity. Therefore, Kim et al. (2017) generated several candidates for the next activity using word incorporation algorithm (word2vec). Subsequently, Long-Short Term Memory (LSTM) model found semantically significant relationships between subsequent activity incorporations from a previous group of activities. Shampa et al. (2019) developed a personalized recommendation system, which linked classroom notes with outdoor experiences captured with a camera to suggest websites that broaden learners' knowledge.

2.5. Issues Within Smart Campuses

The shift from static to dynamic learning based on knowledge remains a challenge. It allows constructing semantic representations from which complex inferences could be made about the concepts presented in the content exchanged by different mobile devices. Throughout the state of the art, IoT technology-based distance learning recommendation systems face more complex challenges than traditional ones:

- **Scalability:** Increasing the number of users and items requires multiple resources to process information and make recommendations. However, there is an ambiguity in the services description and the need to integrate contextual information (time, place, etc.) that is difficult to specify. As a result, imprecise recommendations because of the inability to analyze heterogeneous relationships between users and items.
- **Cold start:** For new users, it is difficult to make recommendations since their tastes are unknown. On the other hand, a document can be recommended if a large number of users has evaluated it. This problem is particularly detrimental to users. Different learners have different knowledge and preferences, which makes similarity unreliable and causes parsimony and cold start problems.
- **Clarity and confidence:** There are always users who have evaluated only few resources. Using collaborative and other approaches, referral systems typically create user districts using their profiles. If a user has evaluated only few resources, it is quite difficult to determine their priorities and it could be related to the bad neighborhood.
- **Linguistic complexities of Arabic language:** A recommendation request can be expressed in several ways, what is needed from a process of detecting the semantic similarity between identical requests and resources of the same topic. Often, few works have been developed for Arabic documents recommendation in smart environment. Arabic is a language of the Koran and the sacred book of Muslims. It is a Semitic and official language of the Arab world (Zrigui et al. 2016). It has more than 445 million speakers and ranks eighth among the number of pages on the Internet (Mahmoud and Zrigui 2020; Terbeh et al. 2019). Its automatic processing is difficult and requires a lot of time because of its great variability of specificities (Meddeb et al. 2016):
  - Arabic is a morphological complex language because of the existence of diacritics, ligatures, and superimposed letters above or below the baseline of words (Meddeb et al. 2017; Meddeb and Maraoui 2017).
  - Arabic is an agglutinative language. A word can have several possible divisions (proclitic, flexive and enclitic forms). They increase the ambiguity of its segmentation, including poor quality of evaluation and time complexity. (Hkiri et al. 2017; Sghaier and Zrigui 2020).
  - Arabic language is characterized by the absence of concatenation in which a word can have different meanings depending on its grammatical category (e.g., noun, verb, adjective, etc.). (Mansouri et al. 2018)
  - Arabic is a derivational complex language in which Arabic words corresponds to names, active / passive particles, and other derivations based on model changes. (Batita and Zrigui 2018)

Figure 3. Proposed architecture of Arabic documents recommendation in smart campus



3. PRPOSED ARCHITECTURE OF THE ARABIC DOCUMENTS RECOMMENDATION IN SMART CAMPUS

The integration of IoT technologies has adapted traditional learning to produce high-quality educational resources. It facilitates the collaboration between users and improves their learning experiences in different situations. This is by selecting relevant documents according to the user profile. The main objective is to set up a recommendation system based on new forms of representation. It allows to process and deliver resources in a smart learning environment. To tackle the sparsity and unbalanced ratings distribution problems, Arabic documents recommendation-based approach is proposed as shown in Figure 3. It is focused on Arabic documents recommendation within smart campus exploring the relative importance of heterogenous data sources (ratings and document title) for rating prediction task. Indeed, the complexities of Arabic documents are processed using deep learning architectures and NLP techniques.

3.1. Acquisition Phase

A classic recommendation system works in two-dimensional space (user, item). In a smart campus, the huge amount of multimedia content for e-learning paradigm is available as open education resources for learners and depends on their contexts. Therefore, intelligent algorithms for the acquisition and processing of multimedia content are needed to create new forms of representation.

3.1.1. User Profile Acquisition

User profile consists of the following components:

- **Personal information:** Such as the user identifier ID .
- **Preferences:** Each user has preferred documents regarding to the ratings meted. According to his preferences, the proposed filtering model displays the suitable top N-recommendations.

3.1.2. Document Profile Acquisition

Each document contains a profile composed by an identifier doc_ID and a title doc_Title, in which documents that do not have it are removed from the dataset. After collecting Arabic documents, several NLP operations of preprocessing are applied. They represent documents in a machine-readable form to improve data quality and reduce the amount of trivial noise. In this study, documents are cleaned by following these steps:

Step 1: Un-useful data elimination by removing diacritics, extra-white spaces, special characters, duplicate letters and non-Arabic words.
Step 2: Ambiguities reduction by normalizing words such as "أ, إ, ٱ, آ" to "ا" and "ة" to "ه".
Step 3: Exploration simplification by detecting the space between words and extracting tokens.

3.1.3. Ratings Acquisition

With n users $U = \{u_1, u_2, \ldots, u_n\}$ and m documents $D = \{d_1, d_2, \ldots, d_m\}$, the user rating behaviors to documents is a matrix R of size $N \times M$. Each value can be seen as a 3-uplet in the form of $R = (u, d, r)$, where u is the user, d is the document, and r represents user u as rating r in d. The user/rating dimension is extracted in order to personalize recommendations. The users and the documents that have less than rating from 1 to 5 are also removed.

3.2. User and Document Modeling Phase

3.2.1. User Latent Features Representation

Rating modelling component capture pair dependent latent representations using user-item rating pairs. Given the identities embeddings of users $ID_1, ID_2, \ldots, ID_n$, the sparse representations are projected to a dense vector P via a lookup function ∅. It is defined as follows in Equation (1):

$$P = \left[\varnothing\left(ID_1\right), \varnothing\left(ID_2\right), \ldots, \varnothing\left(ID_n\right)\right] \tag{1}$$

Then, a fully connected layer is introduced to capture a latent vector for user z_u in the context of numerical ratings, as denoted in Equation (2):

$$z_u = ReLU\left(W.P + b\right) \tag{2}$$

3.2.2. Document Latent Features Representation

For document modeling, deep neural networks have achieved promising results in different NLP applications. They were useful for latent features extraction among embedding dimensions. Based on the advantages of these models, document latent features are represented through the following operations:

3.2.2.1. Word Embedding

Each Arabic document is characterized by a title $T = \{w_1, w_2, \ldots, w_k\}$ of K words. It is transformed into a dense numeric matrix through an embedding layer. Although traditional bag-of-words model based on one-hot representation were effective in transforming a word into a vector, it suffered from the curse of dimensionality and ignored semantics and grammatical structures of words. In this study, we employ word vectors representation (word2vec) algorithm based on Skip-gram model (Mahmoud and Zrigui, 2018). It is advantageous in predicting the context of Arabic words and training systems quickly. More formally, each word w_j in the document is represented by its corresponding row vector v_j of dimension l in a matrix $V = \{v_1, v_2, \ldots, v_k\}$ of size $l \times K$. Consequently, we obtain m documents vectors representations as shown in Equation (3):

$$X = \{V_1, V_2, \ldots, V_m\} \tag{3}$$

3.2.2.2. Convolutional Neural Network (CNN)

CNN is a kind of deep learning architectures. It achieved high performance especially for sentence modeling. Its main advantage is the ability to learn different sentence structures automatically (Mahmoud and Zrigui, 2020). Indeed, the proposed CNN model consists of the following layers:

- **Convolution layer:** Extracts the context features from the document vectors. They are extracted by applying a convolutional filter to produce feature maps, a window size w_s determining the number of surrounding factors, a weight vector W decreasing the complexity of training, a bias term b for polarization, and a non-linear activation function creating sparse representation (i.e., Rectified Linear Units ReLU). The convolution layer is defined as follows in Equation4):

$$c_j = f\left(W.V_{j:j+w_s-1} + b\right) \tag{4}$$

The contextual feature vector of a document is constructed as below in Equation (5):

$$C = \left\{c_1, c_2, \ldots, c_{k-w_s+1}\right\} \tag{5}$$

- **Pooling layer:** Extracts the most representative features from the convolution layer. In this study, max-pooling operation is used to produce a reduced feature maps of a document into a fixed length vector as denoted in Equation (6):

$$M_j = Max_{1 \leq j \leq k-w_s+1} C_j \tag{6}$$

- **Fully connected layer:** Combines all the feature maps from the previous layers and uses them as features to enhance the generalization ability of the model. These are fed thereafter into the interaction modeling and prediction phases. It captures a latent vector for document defined as follows in Equation (7):

$$d_t = ReLU\left(W.M_j + b\right) \tag{7}$$

The same process in section (3.2.1) is adopted by the document network with corresponding layers, and we can acquire the latent vector for document d_r in the context of numerical ratings. Each document is characterized by a latent vector concatenating $d_r \text{ and } d_t$ as defined in Equation (8):

$$z_d = \left[d_r, d_t\right] \tag{8}$$

Table 3. Data used

Data	Size
Number of users	3,000
Number of Arabic books	2,500
Number of ratings	10,000

3.3. User-Document Interaction Modeling Phase

For modeling user-document interactions, Latent Factor Model (LFM) is applied which has been widely used for collaborative filtering with efficient scalability. It predicts a user's preference for a document with a linear kernel (i.e., a dot product of their latent factors). It is defined as follows in Equation (9):

$$a_{u,d} = z_u \odot z_d \tag{9}$$

3.4. Recommendation Phase

The high-level features obtained from the previous layer are projected into the output layer to produce the estimated score of the user-document interaction by using a non-linear Sigmoid function, as defined in Equation (10):

$$\widehat{y_{u,d}} = Sigmoid\left(h^t a_{u,d}\right) \tag{10}$$

where h controls the weight of each dimension $a_{u,d}$.

Then, prior information such as sparsity is encoded. Given the predicted value $\widehat{y_{u,d}}$ and the ground-truth value $y_{u,d}$ of user u on item d, a point-wise loss function is adopted defined for rating prediction as follows in Equation (11):

$$L = \sum_{u\in U, d\in D} \left(\widehat{y_{u,d}} - y_{u,d}\right)^2 \tag{11}$$

where U and D denotes a set of users and items instances for training.

4. EXPERIMENTS AND DISCUSSION

4.1. Datasets

The lack of public and structured resources represented a challenge for evaluating Arabic documents recommendation in smart campuses. Therefore, experiments are conducted on Arabic books which are extracted from Books Reviews in Arabic Dataset BRAD1.0. The details of the created dataset are summarized in the following Table 3. For experiment, it is splitted randomly into a training set (80%) and a test set (20%).

Table 4. Parameters of word2vec and CNN

Model	Parameter	Values
Word2vec	Vector dimension	300
	Window size	3
	Epochs	25
CNN	Window size	3
	Activation function	ReLU
	Filters numbers	128
	Pooling function	Max
	Fully connected layer	ReLU
	Prediction function	Sigmoid

4.2. Parameters Settings

Table 4 details the configurations of word2vec and CNN models that performed our approach.

4.3. Performance Measure

As the evaluation measure, we use the Root Mean Squared Error (RMSE). It is the square root of Mean Squared Error (MSE) function related to an objective function of conventional rating prediction model. Also, it measures the error of a model in predicting quantitative data as defined in Equation (12):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{k}\left(\hat{y}_i - y_i\right)^2}{k}} \tag{12}$$

where $\hat{y}_i$ are the predicted values; y_i are the observed values, and k is the number of ratings.

4.4. Discussion

Collaborative filtering-based method is proposed predicting the user preference based on their past interactions. Experiments and comparisons with the state-of-the-art methods are conducted on our created dataset.

Salakhutdina and Mnih (2007) proposed the first Probabilistic Matrix Factorization (PMF) method. It was the standard MF model based only on ratings to learn user preferences. The model often exploited Gaussian distributions to model the latent factors of users and items. However, the use only of rating reflected the overall satisfaction of a user towards a document. It made hard for PMF to explicitly and accurately model user and item features and achieved the worst result of 0.905 RMSE. To address this problem, Chen et al. (2019) proposed a joint neural collaborative filtering method based only on ratings, called J-NCF. This method was efficient for modeling complex nonlinear user-item interaction through Multilayer Perceptron Neural Network (MLP). It obtained 0.856 RMSE. However, these methods didn’t take into consideration the textual information of documents. They had an important impact for extracting relevant features from documents that had few ratings and tackling subsequently the sparsity problem and the unbalanced distribution problem. In this context, experiments demonstrated the superiority of our proposed approach. Indeed, the use of document title reflected an overall profile of an Arabic document. It increased the results with 0.815 RMSE. Thus, CNN learned efficiently the contextual features through convolution and pooling layers. They were

Table 5. Overall experimental results for Arabic documents recommendation methods

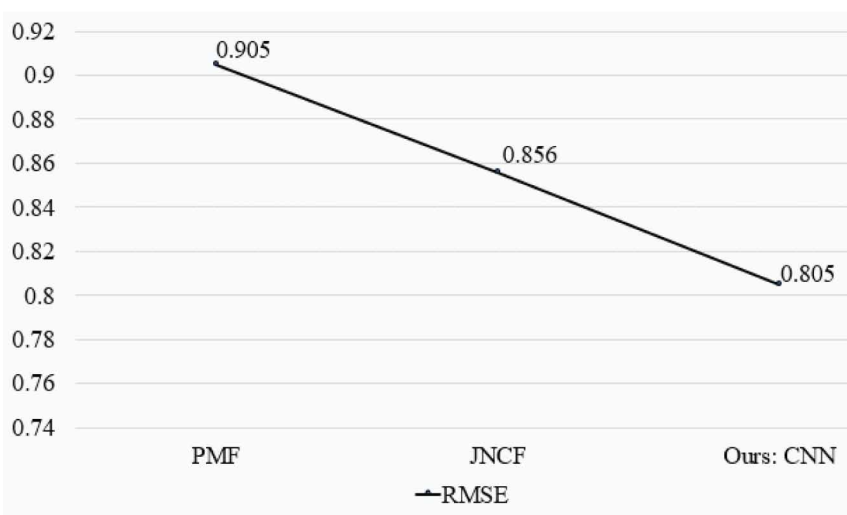
Author	Approach	RMSE
Salakhutdina and Mnih (2007)	PMF	0.905
Chen et al. (2019)	JNCF	0.856
Ours	CNN	0.815

useful for extracting local features and most relevant representation of Arabic titles. This approach was useful to bridge the semantic gap between text information and the vectors of latent factors. Then, the LMF based method enabled efficiently the latent features of users and documents to interact with each other. Overall results demonstrated that our proposed approach was advantageous and could cover efficiently the semantic and syntactic specificities of Arabic documents compensating for shortage ratings. Moreover, the context analysis improved the prediction results. Table 5 and Figure 4 summarizes the efficiency of our proposed approach.

5. CONCLUSON AND FUTURE WORK

The use of new technologies has modernized e-learning within smart campuses and have emerged new context through communication between different mobile devices. In this paper, we have tried to offer a user the possibility of receiving only the interested data without being quickly overwhelmed by the endless flow of data using a recommendation system. In this work, a neural network-based filtering approach is proposed for personalized mobile learning in smart campus. Indeed, CNN architecture was beneficial to model latent features of documents and users. This model was introduced as a decision support tool for mobile learning in order to: spontaneously provide personalized resources to the user who evolved over time, take into account his contextual information and his level of satisfaction, and improve the quality of learning and the notion of collaboration in a smart learning environment. Although the superiority of our model compared to the state-of-the-art methods in terms of RMSE, we will try to estimate complex user-item interactions in a low-dimensional latent space by the use

Figure 4. Comparison with state-of-the-art methods



of a large number of latent factors through deep neural networks architectures. Moreover, many improvements will be done in the future: we will implement our proposed model by attempting to use other NLP and machine learning techniques to improve relevance of the resulting recommendations, study the effectiveness of other deep learning architectures and filtering techniques for mobile learning recommendation in smart campus.

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