Integrarea atributelor emoțional lingvistice în arhitecturile eLearning

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Integrating emotional linguistic attributes in eLearning designs

Recent advancements in big data exploration and affective computing open new avenues for the improvement of curriculum design. The paper places forward an argument for measuring emotional attributes within the construct of class forum discussions facilitated by educational platforms. The psycholinguistic features of the user can be translated into key performance indicators and be integrated into a learning analytics business model. Such a design can monitor the optimal threshold levels of academic achievement as well as signal the potential anomalies. The architecture can support the development of adaptive and personalized learning models based on the psycholinguistic profile of the student. Such a design could render competitive advantages both on the student retention level as well as on the student enrollment strategy.

Keywords: personalized learning, adaptive learning, educational data mining, curriculum design, learning analytics, educational performance prediction, key performance indicators

The rise of the big educational data: LMSs data processing with KPIs and visualized with LADs.

The procedure for investigating the corpus of educational data is not new and is positioned for an ascending trend. The specific task of inferring knowledge from emotional participation falls in the grand category of curriculum mining. Most if not all of the platformized educational models, either open source or for profit, are usually managed by a Learning Management System. The online design of academic interactions allows for an unprecedented level of access for academic data collection, processing and visualization. If the data posits value extraction potential than it becomes business intelligence information. The educational process has its own parameters of optimal functioning, and tracking important markers can reveal both strengths and weaknesses in the system. Monitoring and processing the performance of the student-tutor interactions, enables comprehensive visualizations of sectors that can benefit from immediate improvement. Such a psychometric mapping of the digital classroom can provide a quality control mechanism for optimal performance, benchmarking and anomalies.

The major advantage of such a design is that it accounts for both student and tutor performance, and delivers actionable data for rapid course redesign, mission alignment and regulatory compliance. The application of a business model to education can reveal unanticipated patterns at both the individual and at the group level behavior.[1] Such a design favors the development of a profitable economic model, specifically tailored for academic performance.

Learning Analytics Dashboards (LADs) offer a unique combination of business intelligence information and analytic instruments which are widely applied to measure performance, to identify patterns in the data, and to present the hidden information into actionable insights (Chiang et. al. 2012; Jones et al, 2016; Kessler, 2017). Business dashboards comprise a complete information management system, which track, analyze, and visualize metrics, key performance indicators (KPIs) and other key data values. By analyzing data in a timely manner and directly sending vital knowledge to a unified, highly interactive interface, BDs provide business professionals with the necessary guidance to improve their decision-making experience (Chiang et. al. 2012; Jones et al, 2016; Kessler, 2017; Konstantinidis & Grafton, 2013; Yassine et al, 2016;Yool et al, 2015).[2]

The data measured by KPI's can be created with each individual contribution in response to written assignments, forum discussion, quizzes, as well as student and tutor interactions. This information is generally managed by Learning Management Systems (LMS) which recently have received an additional function, which is that of a repository of information for the LMS. Becoming an infrastructure for content hosting as well, the new designs are recognized as Content Learning Management Systems (CLMS). The data repository advantage is that it offers instant access to an ecosystemic educational dataset which makes possible time sensitive decisions and interventions.

Such a KPI governed design, allows for mathematical curriculum evaluation and calibration based on the students' behavior. Curriculum assessment is one of the critical steps in ensuring that a program aligns with the university's mission as well as the education standards regulated by the government.[3] An additional immediate benefit of the LCMS-LAD-KPI-BD infrastructure, is that it provides real time visualisations of the curriculum performance and provides precise metrics for University's Course Redesign Program (CRP).[4] The sector responsible for extracting value from the interpersonal interactions is known as affective computing. These psycholinguistic instruments belonging are recognized as modules of a larger suite of industrial applications risk assessment tools. These instruments offer the capability of tracking independent markers of academic performance, and provide detailed visualisations of both the pedagogical infrastructure and of the individual academic achievements. Relevant to the behavioral aspect of education, the system can monitor variation in sentiment scores, levels of individual class engagement, group cohesion, tutor rapport, etc.

However, among other reasons, the low acceptance of such a design may be related to two important dynamics. One, is the financial aspect, and relates to the availability of funding such systems. And the second, lays in the fact that it affects the traditional tutor-student power down structure. The factual reality is that none of the traditional academic models encourage such a design, and a written track record of student-tutor interactions is perceived by academics more often than not, as strange and uncomfortable. The lack of popularity of such an instrument is more prevalent in state run academic institutions, while premier educational entities however, build entire intelligence ecosystems around data modeling and value extraction. Commendable levels of academic competencies can only be achieved by incorporating performance traceability for both student and tutor as well. Such a design would target less obvious layers[5] located in the 'hidden curriculum' and would add new depths to the understanding of the educational architecture. Modern research argues the existence of both visible and invisible patterns in the pedagogical design and illustrates the diad through the iceberg concept:

[...] the visible park of the iceberg, which is above the water, consists of "objectives, subjects, time arrangements, methods, etc.," whereas the invisible part of the iceberg consists of "beliefs, attitudes and expectations of teachers, students, families and administrators." The underwater program is largely unknown, not discussed and often overlooked. In addition, there are beliefs and attitudes in the bottom layer of the curriculum (iceberg), individual styles, intelligence and abilities in the second layer, the learning process in the third layer, strategies in the fourth layer and qualifications in the fifth layer above water.[6]

Due to its extensive granularity, the depths of the information achievement complex can only be incrementally observed. The cadence of both the visible and invisible variables determine the pace at which a person/student/user is able to navigate the academic space. Arguing from the perspective of George Steiner, Radu Drăgulescu remarkably highlights the interdependence of logic and grammar in shaping the internal design of the "individual time"[7]

Since big data is arguably the new gold, the development of innovative and more precise instruments will be ever increasing.

The role of key performance indicators (KPI) in the acquisition of academic competencies (AC)

The key performance indicators allow for simultaneous traceability of each user's unique talents and interests, leading to the formation of comprehensive individual digital profiles. These vectors of academic interest represent each student's academic DNA, and if adequately processed, reveal individual and group paradigms that can be tested for statistical significance. These primary results constitute the foundation on which the edifice of personalized architecture can be built upon. For example, the training algorithms can be taught to classify and signal student's written contribution per event as low at 100 bytes, and as high at 500 bytes. The low thresholds can be associated with low topic correlation and classified as negative anomalies, while the high thresholds, can be identified as positive anomalies and a high level of correlation of aptitudes and interests with the topic. If both the positive and negative anomalies become recurrent, they can be subjected to sentiment analysis for consistency. This is how an anomaly, whether positive or negative, becomes a paradigm, and consequently a marker of performance. If for example, positive emotional polarity is found to be positively correlated with the topic over a longer period of time, such a level of correlation can function as a key performance indicator of positive correlation between interests and topics. Likewise with the low or negative correlation between interests and topics. Based on these classifications, the platform can automatically identify, select and recommend future reading assignments with the highest density of keywords matching the student's forum aptitudes and interests. While this is a highly reductionistic example, performance thresholds can be assigned to all critical attributes and expand the operating protocols to all areas of intended academic achievement. Rose and Bohne (2011) report accurate results in implementing automated keyword extraction from text based documents.[8]

Such a multidimensional design would gradually pave the way for personalized learning models that focus primarily on user's aptitudes, talents and interests. Delivering relevant content through a tailored curriculum design may set the stage for unprecedented levels of academic performance measurement. Educational technologies, therefore, have the potential to both ensure high levels of achievement for optimally functioning students as well as enhance student retention. The dual function is that of both enhancement and prevention, while the enhancement function may find positive traction in the student enrollment programs as well. The major advantage of Learning Analytics is that it offers real time tracking of critical learning processes and offer visualisations of personalized content performance and its impact on academic competencies achievement, bringing modeling prediction and calibration within immediate reach. The major advantage of LA is that it offers a scientific method for brokering student performance and prevention of student failure. The design provides a digital instrument to support high levels of academic achievement and low levels of academic failure, or high levels of academic engagement and low levels of academic disengagement. Probably one of the most overlooked metrics in measuring academic progress and indirectly learners' individual needs, is that of digital badge awarding. As symbols of learning, skills as well as individual competency achievements, digital badges, may enhance student motivation and engagement by providing a straightforward and intuitive path for the successful acquisition of course objectives.

Digital badges as representation of competencies may also contribute to students' self-reported confidence, which is positively related to their perceptions. Moreover, digital badges may serve as an indicator for students who need academic support. Thus, digital badges may serve as a platform for communication between staff and students about demands and adaptive support services in order to contribute to student retention.[9]

While the recommender engines are invisible to the user, there are also visible recognition paradigms that can operate as positive reinforcement mechanisms. These are the digital badges, available only in the platformized educational design. If the bibliography recommender engine makes the academic discourse seem more intuitive and native for the user, but the operating mechanics remain unacknowledged for, the digital badge, provides a public and tangible acknowledgment of a successful track record, creating a fair achievement hierarchy.

Such an elementary design can be enriched with additional protocols relating to gender, age, major, syllabus, grade, log session. Based on first year student classified preferences, the recommender system can suggest possible directions for the newly enrolled first year students, of the following year. Gradually, and enriched article recommender engine can gradually become the backbone of a course recommender architecture. For example, a high degree of correlation between commending grades and *traductology* of male students versus a high degree of correlation between commending grades and *english literature history* of female students in an English major of a 2019 class, can train the engine to deliver course recommendations for the first year English major 2020 class, in such a manner that it positively correlates with the previous year data. This would indicate male predisposition and aptitudes for traductology and possibly a major in LMA, while for females in literature history, with a major in the history on English literature. In all scenarios, the curriculum designer and the tutor have the authority of adjusting the response of the system to the various degrees of correlation. Such a case may occur in the situation of a high levels of correlation between failing grades in males studying traductology and mediocre grades associated with females studying english literature history. In both cases the system may signal negative anomalies and major change to match the aptitudes.

Accounting for emotional markers in digital forums extends the emotional impact of simple text specific to linguistics, into the deeper text-emoji expressivity covered by psycholinguistics.

When sentiment analysis can be organically integrated in learning analytics, the value extraction of the emotional expression, becomes systemic. A common architecture for improving academic competencies mirrors three different dimensions, the student's front end experience of the online materials, the back end managed by course designers and the accomplishment reward system usually administered by the tutors based on the global data performance of each student.

If the class assignments are posted on an emoji enabled discussion board, the collected data, may not only facilitate the easy aggregation of the general level of sentiment satisfaction, but it may also relay important data about the relationship between individual performance and the digital badge assignment, both for the front and back end actors. Such a quality control mechanism would mark the anomaly if the student receives a commending badge for exceptional completion of class requirements, but the forum sentiment analysis of the student's profile indicates a dominantly neutral or negative sentiment polarity.

Taking the investigation a step further, one may identify an array of completely invisible dynamics in the absence of emotional traceability.

Simulating a possible scenario, questions can be formulated to address all of the three areas of impact. Questions like: Given that student X's profile contains markers indicating high frequency in excessive sarcasm, asynchronicity with the group and repeated instances of curriculum disengagement, how did the student receive exceptional commendation badges and grades. What is this telling about the tutor? Is this an indicator of the instructor granting performance badges irrespective of accomplishments? Is the instructor an easy grader? Could it signal for lack of tutor supervisory involvement? Or, if the group's aggregated sentiment is neutral or negative, what does this say about the relevance of the class materials, and those who designed them? And even more, what needs to be changed in order to increase information appeal and the future levels of student engagement? This course of cascading quality control questions can extend directly proportionate with the number of generated variables. Depending on the desired depth of the data mining mechanisms, various levels of encoding can provide quality control data for both the student and the instructor performance. While this is an exaggeration modeling by design executed for the best of exemplification, the concept still holds solid relevance granting the fact that neural networks can easily pick up with high precision on such variances.

Monitoring design performance with emotional quality control mechanisms

Emojis are the modern vehicles of emotional messages in the digital space. The icons are compatible and can be easily integrated with both basic and advanced educational platforms. The latter, particularly those integrating artificial intelligence algorithms and learning analytics incorporate highly adaptive pedagogical mechanisms[10] to deliver a truly contemporary grade academic achievement. This ensures the rapid development of personalized learning models[11] and the delivery of a highly relevant and optimally performing workforce. Students are accustomed to receiving information in a native manner. The new normal for the digital user is to receive topical information reflecting the personal area of interest, information that fits the digital identity and reflects the personality narrative, information which allows the user to better integrate into knowledge groups, information that facilitates a fluid maintenance of relationships, information that enhances both self-representation and self-expression (Van House 2007).[12] Unless the student/user receives information preformatted in a native format, the information will likely end up in *spam* or will be *unfollowed*.

In order to prevent critical perception failures of academic design quality, efforts should be directed at emulating the already proven business models which identify the core needs and wants of the user:

Text-based affective computing drives decision support in a variety of application areas in which understanding the emotional state of individuals is crucial. […] Evidently, affective computing facilitates decision-making in all operational areas of businesses, such as management, marketing and finance. For instance, a firm can infer the perceived emotion of customers from online product reviews and base managerial implications on this data in order to support product development, as well as advertising. In a financial context, emotional media content has been identified as a driver in the decision-making of investors, which can thus serve as a decision rule for stock investments. Beyond that, it also provides public decision support with respect to politics and even education, as well as healthcare for individuals [...] In education, this methodology can be functional in eLearning, by improving the level of learning experience through classifying and regulating e-learners' emotions.[13] According to the social capital theory, well-connected students have better access to resources and to emotional and educational support, which can boost their sense of belongingness and motivation. [14]

Business models are not designed for value extraction only, but their primary objective is to bring competitive edge and profitability. Same could apply to platformized educational models to deliver advanced personalized learning formats. If elearning platforms deploy protocols that detect, classify and create a repository of socio-academic interactions, tit will very likely reduce the emotional distance and enhance student group cohesion. Besides knowledge, students will have an additional element rapidly available for group identification: emotional fingerprint. Feeling included equals to feeling accepted, therefore the sense of exclusion is reduced while the authentic sense of belongingness and motivation are positively stimulated. These emotional states can be assigned optimal performance thresholds and function as risk markers for academic dropout. Preparing high quality graduates is the key objective of all institutions involved in higher education,[15] and among the most relevant parameters for long term performance two critical protocols stand out. The first accounts for the 'continuous student assessment,' while the second relates to the 'psychological data investigation.' The 'Continuous Assessment' refers to the constant evaluation of dynamic student attributes such as class attendance, term scores, lab performance, course and lecturer assessment, forum participation and the effective use of resources. The 'Psychological Data' includes attributes such as personality and social activities.[16] The competitive advantage offered by platformed designs does not consist only in the ability to monitor the visible layer of the academic involvement, but also in its capability to classify the emotional data. Most importantly, however, its greatest strength may reside in its potential to offer field relevant prime data for aggregating with a high degree of confidence, both the cognitive and emotional states of the educational spectrum.

Emotions as markers of critical system failures

Probably some of the most subtle but prevalent patterns associated with academic abandonment are those associated with negative learning behaviors.[17] Identifying and limiting the prevalence of the negative emotional reinforcers at embryonary levels can be key to academic success. In digital forums, such emotions are visible in the negative sentiment patterns as well as in the low levels of positive correlation with the group. These instances gradually morph into alternating episodes of emotional withdrawal, excessive sarcasm, asynchronicity with the group and repeated instances of curriculum disengagement.An illustrative example of the negative emotional reinforcers has been tackled in a recent article by Radu Drăgulescu. The study presents the contextual variables which embody the umbrella of anxiety associated with academic achievement. The qualitative endeavor examines the types and levels of anxiety associated with academic achievement, particularly, the acquisition of Romanian as a foreign language in a Romanian university. Building on the Bailey-Brown argument of just enough anxiety, the author highlights both the prohibitive and competitive valences of anxiety.[18] While this makes reference to a particular type of acquisition, anxiety usually resides in all academic processes as they are associated with assimilating novel information. Learning management systems can be useful in moderating the anxiety levels by allowing students to exercise their natural choice of articles, ethnic group and gender affiliation as well as the foreign language aptitude background. Besides traditional class activity, the forum contribution may provide the written freedom of expression alternative not yet achieved in the speech proficiency. While providing a more comprehensive image of the student's profile, it also works as a positive stimulus in the direction of personal academic achievement.

As the only source to date for platform modeling exists only in social media, what becomes critical therefore, is understanding how the knowledge base associated with groups in social platforms is transferable to groups in educational platforms. Since not much data exists on the latter, but granting the fact that an educational group also shares social attributes, it becomes relevant exploring the relationships between the emotional layers in the online platform interactions. The potential benefit of the knowledge transfer is immense. If such a transfer can be successfully implemented, than, the learning analytics will dispose of a growing educational database that incorporates an increasing number of variables associated with the digital persona of the user. Enriching the database, increases the potential for relevant instructional design resources, and creates ample space for curriculum calibration and redesign.

So far, little attention has been devoted to characterize the type of social links according to sociological dimensions, and recent work on the accommodation of linguistic styles to power differentials provides an example of the intellectual opportunities now available at the intersection of social theory and conversational data (Dănescu-Niculescu-Mizil et al. 2012) […] Due to its open nature, Flickr has been one of the most studied platforms to this respect. Early work relied on interviews and user studies to identify the different usage of Flickr groups (Van House 2007), finding five main motivations for users to join groups (memory, identity and narrative, relationships maintenance, self-representation, and self-expression).[19]

In Romania, the type of educational platform that models onto the social links and sociological dimensions paradigm, is EDMODO. Since students in Romania are technologically native by a wide margin, adopting the western models of social media interactions in class, becomes higly intuitive and natural.[20]

Besides enhancing personal identity and promoting group cohesion, one critical aspect that can be imported in the digital academic design is "the accommodation of linguistic styles to power differentials" (Dănescu-Niculescu-Mizil et al. 2012). This represents a unique opportunity to build a digital record of the psycholinguistic variations relative to power differentials. Such a library can deliver the information for the testing and visualisation of different course events and account for at least the student group gender format, topics, curriculum design and tutor gender. Thresholds on the power differential marker can track and illustrate anomalies and consistencies related to the type of the power differential. Repetitive anomalies become patterns and have the ability to indicate the health of the interactions. Such data might reveal for example, tutor power down structures, flat power structures, or student group power down structures. These dynamics reflect how easily the information is disseminated, processed and fed back into the system. The benefit of a power differential marker is that it mirrors the way the social dimensions influence the social links.

Modeling deeper on the power differentials relative to event, topic, course type and gender, one may identify specific patterns. If for example, the students post the homework assignment on a blended class discussion board, the students' behavior will very likely be patronized by the condescending power differential model of the legacy education.

It is anticipated that students in a blended class will act differently than students in an exclusive online class. The students in the first group will be more inclined to simulate perfect emotional engagement by employing almost exclusively positive emotional expressions, leading to low diversity in emotional polarities. Given the lack of a condescending power differential in platformized interactions, the second, may indicate more ample sentiment diversity.

Probably one of the greatest strengths of the digital educational model is that it impacts positively the power differential by reducing the perceived interractional distance between student and tutor. Since the interactions of the first group still include the direct classroom contact between the student and the tutor, the student will very likely engage in a 'safe' behavior, especially if the online assignments amount for an equal of 50% towards the final grade. The situation can change dramatically in the second scenario, where exclusive virtual communication is the only way to transfer information. Since all grading is based on online behavior, it is anticipated that students in the elearning class will make use of a more colored emotional expressivity.

Moderating the power differential requires anchoring the performance thresholds into the larger ecosystem of relevant parameters. This can be usually accomplished by:

[...] selecting didactic methods, procedures, and specialized content according to the learners' needs and the dynamics of their knowledge can be accomplished in a few ways. One way to facilitate this is by organizing professional situations/contexts in which the interaction of learning prevails, to place the learner at the center of the learning process, stimulating receptivity, productivity and creativity […] Another avenue may focus on stimulating, maintaining and capitalizing on motivational tensions in activities which target text and the context of specialization. Important as well is the adjustment of the syllabi to meet the needs of learners and to introduce the digital pedagogy elements. And on the logistical level, it remains important to invest in modernizing the study conditions (specialized content manuals, multimedia laboratories, etc.) that facilitate the activities and operations for the amplification of general and communicative skills […].[21]

Among other agents that can operate bot as constraints and enforcers of emotional engagement one may identify age, gender, technological literacy, device availability and the financials associated with the class. Engaging in emotional expressivity may diffuse as well as enact emotional tensions. However, the greater benefit of such an approach is that the asymmetries will create the final and unique emotional fingerprint of the group. In turn, group's fingerprint can grow into a larger knowledge base, gradually acquiring the statistical relevance of both control and experimental groups. This type of engagement can generally stimulate the desire for self discovery and receptivity, increasing the student's degree of identification with the group and with the academic process itself.

The larger umbrella where emotional engagement belongs to is that of user experience or the 'UX.'

According to ISO 9241-110:2010, the term "user experience" refers to "a person's perceptions and responses that result from the use and/or anticipated use of a product, system or services." Simply put, the user experience describes how a person feels about using a product in particular conditions, including the experiential, affective, meaningful, and valuable aspects of product use. Recent research suggests that user experience focuses on individual perceptions (e.g., subjective usability, user-perceived quality). Several studies have identified a variety of aspects - such as values, emotions, expectations, and prior experiences - that influence the experience evoked by user - product interaction. UX generally describes the internal and emotional state of a person during and after an interaction with a product.[22]

Adaptive and personalized learning designs have a lasting impact on the user. A long lasting positive impact reinforces academic performance, while a long lasting negative impact reinforces the risk of abandonment. The first concept may support a profitable economic model, while the second may be subject to loss of opportunity and resources.

Conclusion

Personalized curriculums and behavior tracking can serve as both enhancer and deterrent mechanisms.

The enhancement function will be based on the unique academic fingerprint of the user and will facilitate the development of a bespoke academic achievement architecture. Regarding the deterrence factor, universities will have at their disposal a complex instrument which can offer solid defensive arguments against potential damages to the institutional image, false claims, scams, online harassment and trolling. Even if evaluated for the deterring factor only, the design can provide sufficient insurance value against false claim scenarios. At the same time however, the architecture can provide reliable evidence to prove that the claims are not false, but true. If such is the case, the architecture may be able to point in the data, anomalies associated with the academic malpraxis event or events both in terms of recurrence and intensity. For example, one may be able to reconstruct the context and determine the score of academic disengagement per event, group's engagement score for reading assignments, average grade scores and power differential scores. Such investigations can provide sufficient objective evidence to verify if the claims are true or false.

The unique advantage of a digital corpus is that it will provide a detailed academic record database, which can be verified against claims of neglect, power abuse, injustice, etc., occurring within the confines of the academic space. Such a design would deliver an efficient quality control and prevention mechanism. At the same time, by incorporating learning analytics and visualisation tools, the concept will encapsulate a competitive academic achievement architecture.

The main objective is promoting a climate of sustainable curriculum design that is both natively relevant to its users in terms of content and mode of delivery, and strategically competitive at the institutional level:

Universities must adapt to the information relevant in the society, so they are able to continue spearheading some of the quality information that is produced in these institutions. And even more than ever before, universities are to participate and collaborate in training the million of new professionals whom will be required in the information technology sector by 2020, according to data from Eurostat.[23]

The emotional evaluation will most likely become an integral part of adaptive and personalized learning designs. It is well known that AI algorithms can execute with precision automated tasks such as classification, intermediate interval training, sentiment analysis and critical marker monitoring. The classification-recommender architecture is already present and evolving in the shape of a virtual teaching assistant. Since 2016, the chatbot is operational at the Georgia Institute of Technology. Here, students enjoyed communicating with the new teacher's virtual assistant, Jill Watson, who quickly and accurately answered their different questions. But the students were unaware that Ms. Watson's true identity was actually an IBM-AI-system-equipped algorithm with the same name. With the help of Dr. Ashok Goel, a professor of computer science, the teacher's assistant Watson accurately responded to more than 40,000 posts on the discussion forum with a minimum of 97% confidence interval.[24]

Probably one of the most impressive applications to date, is the development of an economic model which combines a predictive enrollment architecture with a genetic algorithm to successfully optimize merit-based financial aid allocation and maximize student enrollment.[25]

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