TOWARD EARLY INTERVENTION: MODEL OF ACADEMIC PERFORMANCE IN A CDIO CURRICULUM

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ABSTRACT

After three years of implementation of the CDIO initiative in the electronics engineering program at the Pontificia Universidad Javeriana, the curriculum management has focused the operation of the program on monitoring students who, from the point of view of the assessment of learning, generate important information to the program evaluation. The performance of the students is an important marker that indicates the efficiency of the program and represents the level of success of the reform according to the CDIO methodology. The structure of the curriculum and the gradualness of the integrated competences, reflect a program transition behavior that is aligned with the student development model of the university. Three transitions were identified: first year, second and third year, and advanced students. These transitions show different behaviors and needs that, in the institutional context of risk prevention, involve the identification of realities that require early monitoring and intervention.

In order to implement, the student development model, the university generates a risk prevention program that takes into account individual, psychosocial, academic and financial factors. Based on this model, a system of early alerts is created. This system includes intervention and monitoring processes. The initiative is complemented by a student accompaniment program (PAE + N, by its initials in Spanish), which is being developed initially in the School of Engineering. Under this context, it is necessary to design and implement models to identify patterns associated with academic performance and transitions of undergraduate students. This project is developed with the aim of detecting problems which can be intervened by making use of the entire offer of accompaniment from the university (advisors, workshops, psychological counseling, etc.). These patterns are detected using variables available in the University's information ecosystem, using analytical techniques and artificial intelligence.

In this paper, the identification methodology for risk patterns is shown. Additionally, some of the alerts that are in development are described including the analysis of their incidence as efficiency indicators of the CDIO program. The results of this project will allow reforms to the courses, the program, the teaching methodologies, learning and assessment, as well as the programs of the accompaniment of students in all transitions.

KEYWORDS

Artificial Intelligence, supporting students, retention, Drop out, Standards 11, 12.

ANTECEDENTS

The School of Engineering of the Pontificia Universidad Javeriana (PUJ) has conceived, designed and implemented in four undergraduate programs (civil, electronics, industrial and systems) under the CDIO philosophy. This curricular process developed in a continuous improvement scheme allowed the assurance of the CDIO standards. In particular, standard 12 “Program Evaluation”, has been developed establishing a model to verify the effectiveness of the program (Brodeur, 2005). This model has the base of qualification of the assurance of learnings. In this sense, standard 11 (assessment) feeds the evaluation model of the program, positioning the measurement of student performance in each of the courses, as a marker of program success. From the point of view of the integrated curriculum, gradualness in the competences allows to identify different moments in the student's formation (Crawley, 2014). Each moment is associated to the level of advancement in its curricular route and all the variables included in the training process such as personal issues, socioeconomic context and behaviors associated with the transition of the secondary school, among others. A general research in PUJ, determined six continuous and separable student states. Each state is outlined by their own elements and this structure let PUJ propose a model of student development for the whole university (MSD) as shown in Figure 1.

This model locates students in transitions (Jaramillo, 2018). We can explain a transition as the state describing the student's progress profile. “High School Student” corresponds to high school students who can be candidates for engineering programs. The “Applicant” refers to a transit condition in which selected candidates for each program participate in a basic skills assessment activity. This process identified weaknesses and strengths for the subsequent intervention.

The transition of the “First Year” characterizes the adaptation time to the university system, the integration into an institutional culture, the reaffirmation to the disciplinary vocation and the approach of the project of life as professional projection. For MSD, this transition is critical because of the high levels of drop out and it is determinant for academic development (McKenzie, 2014), (McKenzie, 2016), (McKenzie, 2017), since it includes the basis for a good performance in the curricular lines.

The transition “2-3 Years”, coincides with the completion of the fundamental core of engineering, this stage determines the selection of the specialization line and the projection of the professional project. The transition “4-5 Years”, is considered as the period in which students have a variety of subjects associated with the specialization lines and includes the capstone project, which is the most significant design and construction experience in the programs (Crawley, 2011). Finally, the transition “Graduate”, in which the student becomes alumni of the program, it is a potential candidate for graduate programs and becomes a stakeholder for the evaluation of the program (Brodeur, 2005).

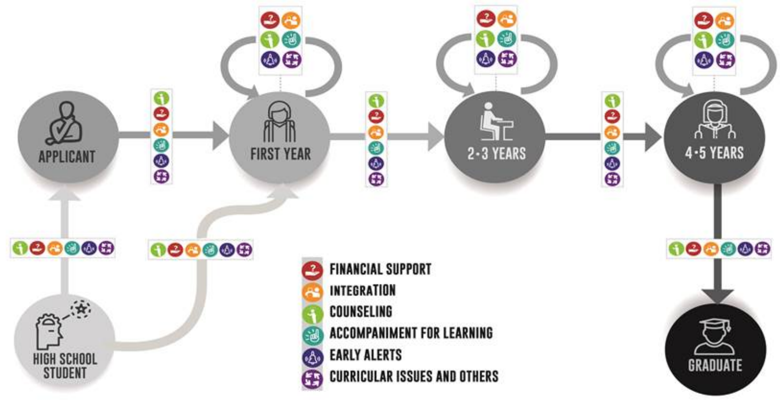

Figure 1. Student development model. (Jaramillo, 2018)

The conditions for a student to pass from one transition to another, are facilitated by institutional processes aimed to provide tools and strategies strengthening transit in the academic program (Torres, 2012). Tools and strategies are oriented to six dimensions of accompaniment (Jaramillo, 2018): “Financial Support”, as its name implies, are programs aimed at solving difficulties in the payment of tuition or maintenance, for example, scholarships and financing. “Integration” refers to all activities related to the adaptation to the institutional culture and to fostering a sense of belonging, including the induction week for new students and a Peer Mentoring Program (Moody, 2015). “Counseling”, is a program of support and follow-up directed by professors to guide the students in everyday situations of the university life. “Learning Accompaniment” includes strategies designed to strengthen skills needed in the development of curriculum competencies including personalized tutoring, study workspaces and a basic skill workshop (BSW) which is focused on ensuring success in areas related to mathematics and sciences (Lightbody, 2015), (Lightbody, 2016). Culture of “early warning”, is related to the culture of risk management oriented to prevention rather than treatment, the main component of this strategy is a system of early alerts, intervention and follow-up (SEAIF). Finally, the other strategies that link outreach units, psychological counseling, spiritual counseling, among others, complement the previous dimensions forming a large institutional program for risk prevention. In particular, the school of engineering materializes these strategies in a pilot program called PAE+ N (González, 2018). Since 2017, this program has been implementing and integrating all the aforementioned strategies, evaluating their effectiveness in the support of transitions and promoting a culture of prevention of student risk (Ministry of National Education, 2015), (Ministry of National Education, 2016).

Here it is important to highlight SEAIF as a project of early detection of risk. The system is designed to identify hazards associated with the individual, socioeconomic, academic and institutional issues. These four categories coincide with the types of risk proposed by the Ministry of National Education for priority attention in higher education institutions (Ministry of National Education, 2013). The alerts generated by SEAIF come from two sources, the academic community and the university information ecosystem. We can classify two types of alerts, the first ones that are generated by logical inference, that is, a combination of variables or by a direct declaration of a member of the community and the second ones are those of prediction of patterns of behavior. For example, teachers are key stakeholders in the generation of logical inference alerts as they inform about students with low academic performance, non-attendance, and even personal problems, among other risks. From this point, an intervention and follow-up protocol is activated, which attempts to mitigate the identified risks. For prediction alerts, a project has been generated in parallel to the development of the system. This project looks for prototypes for the recognition of patterns based on the information resident in the university information ecosystem. This project is led by the lab for student success, S2 Lab 4.0, where analytical and artificial intelligence techniques are used to detect these patterns. The following chapters show one of the prototypes of the laboratory, the methodology used and the intervention protocol of the generated alert.

PERFORMANCE DIAGNOSIS

In the PUJ, the student regulation establishes an average minimum accumulated, in order to be consistent with the mission of educating comprehensive and academically excellent professionals. In this context, students are assessed from 0 to 5 and the curricula respond to an academic credit structure. In this sense, the accumulated average is weighted according to the amount of credits and the final note of the matter (GWA, graded weighted average).
The minimum GWA required to consider a student in a normal academic situation is 3.4 or when the average of the academic period is less than 2.5. PUJ is characterized by a culture of student accompaniment and risk management (Torres, 2012), (Jaramillo, 2018). At this point, we define a student at risk when he is very close to this minimum GWA or below. A student may be in 4 academic states as shown in Figure 2. The "normal" state represents a GWA greater than or equal to 3.4. The "First academic probation" state represents the first semester in which the student with a GWA less than 3.4 initiates the improvement plan to reach a GWA equal to or greater than 3.4. The "Second academic probation" State is presented when a student does not exceed the GWA condition less than 3.4 after having been in "first academic probation". Finally, the "excluded" state is reached when the student does not exceed the minimum GWA for two consecutive semesters. In the School of Engineering of the PUJ the prevalence of "First academic probation", during the periods 1630 to 1810 (second semester of 2016 until the first semester of 2018), can be differentiated in each one of the programs as shown in Figure 3.

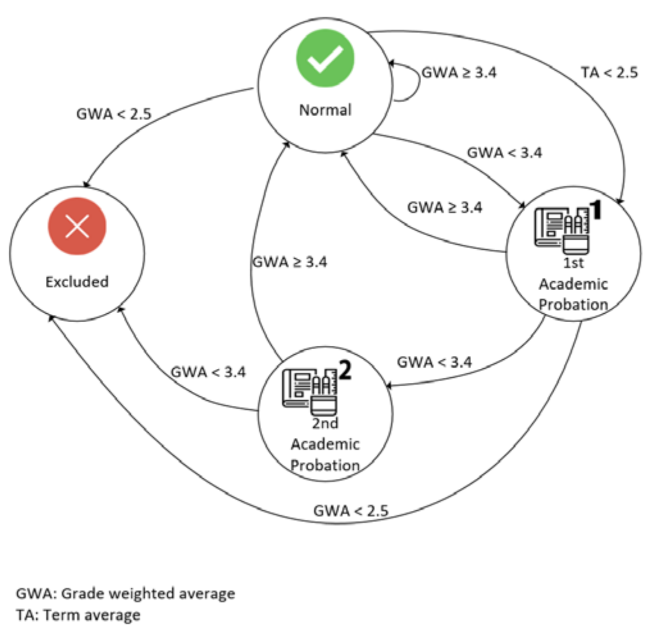

Figure 2. Academic probation model

Although the percentage of academic probation may not be considered significant for the university, the responsibility to train professionals for the country and to accompany the student in its life project makes this population more important for PUJ. A qualitative and quantitative analysis of the behavior of this population makes it possible to identify some patterns. For example, students who take the first 4 semesters of the program have a greater tendency to enter the state of academic probation, this explained by the conditions of adaptation (McKenzie, 2016), the paradigm shift between the levels of schooling (high school-university), deficient fundamentals in mathematics and critical reading (Ministry of National Education, 2006). Additionally, since the amount of credits taken has a direct effect on the GWA, in the first semesters we observe that poor performance in the academic term significantly affects the GWA. The opposite case occurs in the advanced semesters in which, due to the accumulation of credits, the performance in an academic term may not affect the GWA.

However, in the first semesters to overcome the academic probation, presents a minor challenge for the students, given the inertia of the GWA and depends directly on the decision of the courses to enroll. We can define the inertia of the GWA as the relationship between the academic credits accumulated and the variability of this average according to the performance of the academic term. In this sense, the performance of a student who is in the first semesters of the program will affect his GWA since the accumulated credits and the academic load of the semester are comparable. As the student advances, the proportion of credits taken is higher than the academic load of the semester and for this reason, inertia decreases.

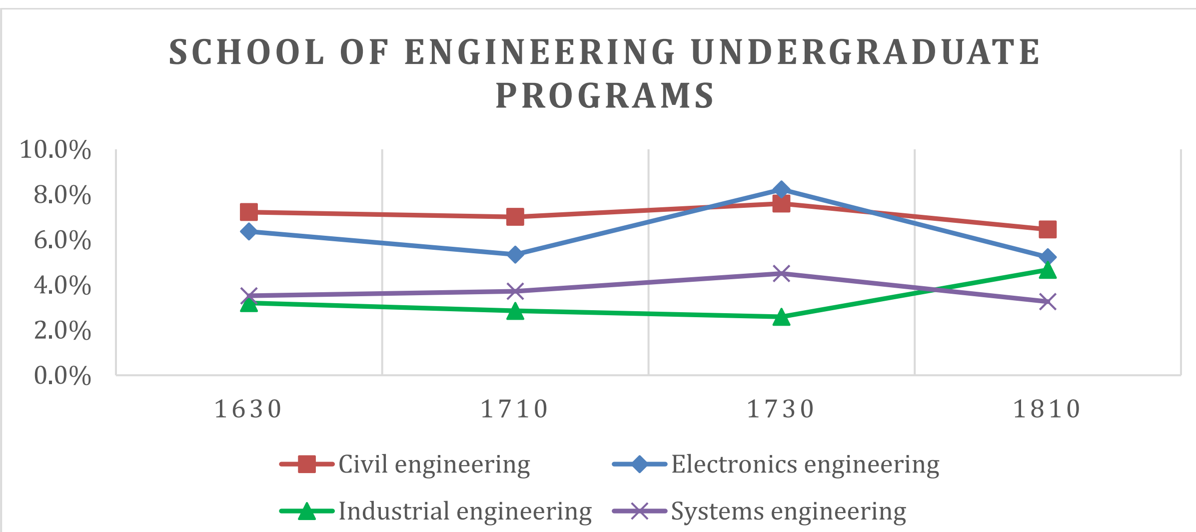

Figure 3. Prevalence in School of Engineering undergraduate programs

A low performance in the academic term occurs when students who have difficulties in the basic sciences and in the curricular core, face an academic term in which the majority of credits corresponds to the aforementioned areas. However, students with these same characteristics have a better result, if the load of credits of the semester is balanced between the curricular core and free choice courses (elective courses focused on the integral education).

At this point, we have noticed that a balance between the curricular core courses and the free choice courses have an impact on the weighted average of the semester. Timely intervention will advise the student to make the best decision of which courses to join up. For this reason, we have designed strategies that include academic behavior predictions to be able to make accompaniment, intervention and opportune follow-up to students.

The understanding of the phenomenon of academic performance includes a directly related to the problem variable categorization. Although there are many determinant factors in the performance of a student (Wilson, 2017), the prediction proposed in this paper, is limited to purely academic variables without including individual elements related to physical and mental health, motivation, social and economic conditions, among others.

In this context, we can intuitively identify as possible academic variables, related to the phenomenon of performance: the average of the semester, GWA, load in academic credits, accumulated credits, performance in curricular areas, morbidity in particular courses, history of notes by courses, difficulty of the semester associated to the type of course, and perishable variables like the classification of the high school according to elements of quality and performance in state quality tests. The purpose of this work is a primary exploration of variables, which allows us to achieve the intervention and monitoring of the population. We established a methodology from the identification of the hypothesis to the approach of strategies of diversified accompaniment, including a review of resources (counselors, information systems, support material, among others).

METHODOLOGY

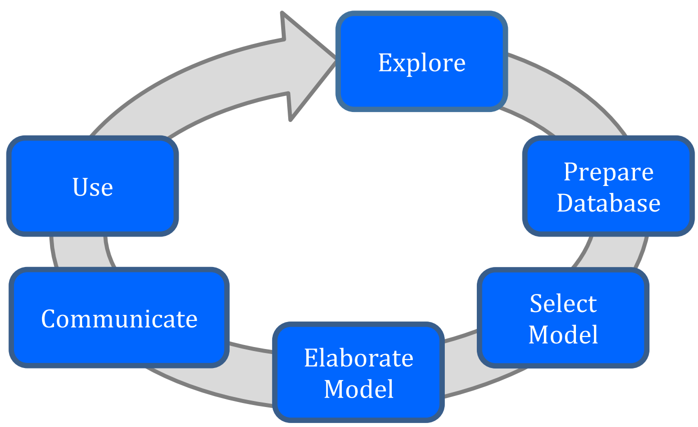

Figure 4. Methodology cycle

The proposed methodology follows the cycle of Figure 4, which describes a process of data analysis focused on the defense of a hypothesis to later use the conclusions and return them to the context to produce an improvement. In this way, the research question that motivates this work arises in the stage of exploration of the cycle. That question is focused on investigating the possibility of predicting first academic probation even before the student course the academic term. The prediction is based on academic history, advance and the intention to enroll in particular courses. This is how the following question is raised: is it possible to predict first academic probation using academic variables? With this question we can generate several scenarios:

> For students who are predicted to enter in the first academic probation, a balance in the type of courses (core - free choice) will reduce the risk of entering in this state in the academic term.
>
> The understanding of a student's performance can be measured on the basis of the relationship between approved credits and taken credits. This relationship allows us to characterize the student according to its potential for approval.

The effect of the inertia of the GWA can be controlled using the balance between the load in credits and the balance between the types of courses enrolled in the academic term.

In the stage of preparation of the cycle, the data necessary for the validation of the hypotheses are collected. The necessary data are in the PUJ ecosystem, specifically in the university information bases. The system includes monitoring the advancement of students and integrates enrollment modules, grade book, counseling and socio-demographic databases. However, the consistency, coherence, and completeness of all information should be reviewed.

The databases contain a great amount of information that includes GWA, average of all academic terms, notes of each course, professors, evaluation of professors, geolocation of the student´s home, among others. These bases describe the evolution of student performance over time and are it is determined by an environment under controlled conditions, in the context of a curriculum and its characteristics (approval threshold in the grade, contents, competencies, among others). Given the large number of variables, in the planning stage of the model, we decided to revise which variables are sufficient for a first exercise of prediction and test hypothesis. For this work, we use a simplification heuristic in which we choose three variables that are considered important and with a high potential to be a predictor: GWA, load in credits and approval rate.

The GWA is an indispensable marker in the prediction of the academic risk and its weighted nature allows to extract indirect relations on descriptors of the phenomenon. In addition, according to our hypothesis, the load to be taken and the potential for approval are predictors of the student's performance during the semester. The three variables selected, can be intuitively related as risk descriptors of the phenomenon. A first academic probation prediction using these variables requires combination, approximation and training techniques. A technique that attempts to define the relationship between variables, in different ways and with different weights, is the Artificial Neural networks (ANN). An ANN uses phenomena modeling. These phenomena evolve over time and under this condition, ANN uses a technique of learning based on labeled data to weigh about the characteristics and obtain an exit that approaches the true behavior of each phenomenon. For this reason, the model selected for the test of the hypothesis in the first approximation is the ANN. For the implementation, ANN was developed in MATLAB and some parameters of the technique were varied, to find the best structure and combination of them, using a verification protocol. The network has as output a list of students that the technique predicts will enter academic probation.

The above procedure was carried out for the four programs of the School of Engineering. We used the classifiers for the prediction of the academic term of the second semester of 2018. The results were delivered to the respective heads of the program. The program heads validated the results delivered from an expert assessment by reviewing each of the cases and assigning a potential risk to each one. With this validation were identified four levels of risk: critical, priority, moderate and mild. Students at the critical level are whose GWA is at the limit of the minimum demanded and those who have a poor performance in the current academic term will change the state to first academic probation imminently.

A characteristic pattern of this population is a non-satisfactory performance in the core courses, which results in a delay in the advance route that will block the possibility of enrolling courses of the same. In addition, such performance will lead to a low charge for limited options in core courses. Finally, we have found that some of these students have iterated between the normal state and first academic probation. Students who have poor performance in core courses but their GWA is far from the required limit, are considered at priority risk, in. They are students who in advancing the core courses face greater complexity of the subjects. This reality can mean poor performance and hence a decrease in GWA. On the other hand, students who have many accumulated credits (low inertia of the GWA), present a performance in the average population of the program and have downward trend in the core courses are classified as moderate risk. Finally, people who are not going to be in academic probation but have a tendency to decrease their performance are at a slight risk.

The intervention with the students is designed to mitigate the level of risk, in this sense we identify that the behavior of the population depends on the average grade necessary to obtain the minimum GWA required, the performance in the core courses and the student transition. As previously mentioned, for the School of Engineering, transitions correspond to first year, second and third year, and fourth and fifth year. For this process, the temperature map strategy is used. The map describes the relationship between the probability of occurrence of an event and its impact. Figure 5 shows a two-dimensional temperature map, in which the y-axis corresponds to the impact and is expressed in terms of the balance between the tuple amount of credits in the core and the load of the semester. In the ' x ' axis are the mentioned tuples to describe the behavior of the population.

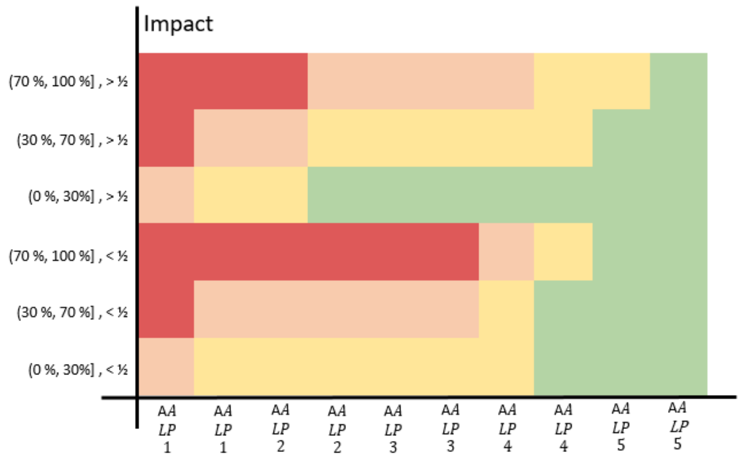

Figure 5. Temperature map

For example, a student who has a GWA close to the required minimum (AA), a low performance in the core (LP), which is in the first year, and whose intention of enrollment is to take between 70% to 100% of the core, with more than half load is at a critical risk. For this reason, the intervention is focused on making a variation in the location of the student in the temperature map in the elements of the tuples with variability, i.e. the axis of impact. The construction of the temperature map is the result of the expert validation of the program heads who assigned a risk value to each of the student profile-impact combinations.

The intervention strategies include the counseling in which they suggest changes in the intent of enrollment: load, subjects and balance. On the other hand, students are referred to various types of accompaniment depending on the level of risk: personalized tutorials, classrooms of study guided by teachers, psychologic counseling and follow-up to the process by counselors.

CONCLUSIONS

In this first simplified test, we can conclude that it is possible to make a prediction of academic performance before the student is in the academic period, based on their history, academic advancement, and on an intention to enroll in courses. Although the first approximation was simplified, it allowed early intervention to students who were classified at risk, giving them tools to make the right decisions and mitigate the risk in which they were. Evaluation models based on the assessment of student learning, not only allow to regulate the curriculum by identifying improvements in course programs, CDIO competencies, curricular integration and the structure of the program (Crawley, 2007), (Al-Atabi, 2013), but also, these models allow to monitor the performance of the students from the individual point of view and the possible generalized behavior of the population. From the understanding of the phenomenon of academic performance, it can be made an intervention to each one of the factors (curriculum-individual), responding to fulfilled facts. From the point of view of the student, said facts correspond to courses enrolled and taken, the result in the performance of them, overload of credits in the semester, imbalance between the complexity of the courses, among others.

From the perspective of the curriculum, these factors correspond to learning outcomes (Crawley, 2014), resources, assigned teachers (Brodeur, 2005), the relationship between the allocation of credits and contents of the courses. This intervention will have a direct impact on the future population of the program without having a direct effect on the population studied, i.e. in a treatment scheme and not prevention. By including prediction alerts, performing the non-fulfilled intervention allows a direct impact on the population by anticipating behaviors and preventing incorrect decision making. On the other hand, the prediction of patterns of behavior, allows to quantify resources in advance in such a way that the institution can anticipate a number of advisers, mentors, tutors, classrooms and to initiate the processes of accompaniment even since the inscription of courses. The anticipated understanding of the population that initiates an academic term allows an institution to make changes in the curriculum from the point of view of the methodology, activities and evaluation strategies, and gives to the professors, elements of judgement allowing a classroom-focused accompaniment. For the particular case of the alert chosen answering the question, “is it possible to predict first academic probation using the academic variables?”, we concluded that it is possible because one of the factors that affect the academic performance is the individual, and this element is mapped directly from the selected variables. In addition, this first exploration allows establishing a clear path of study for future works. For example, S2 Lab 4.0 proposes to add for the case of the prediction of first academic proofing, several variables that explain with greater detail the phenomenon. The new variables proposed include curricular factors such as professors, complexity of the courses, morbidity of the courses, complexity of the academic term, among others. S2 Lab 4.0 also proposes to include other alerts associated with the prediction of loss of courses, tuition fees, prediction during the semester, delays in progress IB and learning difficulties.

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BIOGRAPHICAL INFORMATION

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