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# THE INTELLIGENT FORECASTING APPROACH OF LEARNING-CURVE IN FITS TRAINING OF STUDENT PILOT

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## Abstract

In this research, we were forecasting the Learning-curve of student pilot for instructors to recommend the training hours and furthermore the total cost of training. From the previously research, most of them are using the Qualitative Methods such as interview and observation. We are using the Quantitative Method, an intelligent approach – Machine Learning (ML). In flight academics, they recommend courses and training hours based on the regulation of civil aeronautics administration. In the real world, not each student could accomplish or satisfied the criteria by recommend hours. If an extend-training course occurred, and it has to be a more precisely recommended by hours. We build up an intelligent system by using linear regression method and collected data from the flight academics which training student for Recreational Pilot Licensee in Taiwan. And provide a learning-curve prediction by intelligent system. Traditionally, any training method that grading students by different scale. We need an objective grading method, in order to keep the precision in prediction. Compare to the traditional ways, the FITS training methodology is more objective in grading. The FITS program must include: Scenario Based Training, Single Pilot Resource Management, and Learner Centered Grading concepts. By the intelligent forecasting system that predict the learning-curve to estimate the training hours and cost. For further applications, it can be used on the airlines to evaluate the train-worthy of student pilots.

Keywords: Learning Curve, FAA-Industry Training Standards, Machine Learning, Linear Regression

## Introduction

As the pilot labor demands were growing from Asia in the past few years, especially in China. There are more and more airlines focus on recruit and train their own pilot locally. In order to take the challenges in pilot- supply tighten. In the next 20 years, the worldwide demand of new pilot will be 790,000, and the demands of Asia- Pacific will be 261,000. For airlines, how to control the training cost in new pilot is a key issue. The Learner Centered Grading from FAA-Industry Training Standards (FITS) program is a more objective way to evaluate a student pilot. The FITS concept has been emphasis as an efficiency approach in many academics and different level of flight licenses. From this point of view, FITS is a visible consideration when we talk about the evaluation of student pilot. Then we need an efficient approach to forecast the cost of pilot training, that's why we bring in an intelligent approach – Machine Learning. The bene fit of the prediction is not only for airlines and academics, but also for students.

The FAA-Industry Training Standards (FITS) program is a flight training program between Federal Aviation Administration, Industry, and Academia that are more convenient, more accessible, and less expensive. And redesign the flight training form the practical test to the real-world challenge.

Thus, the FITS acceptance the training curriculum and syllabus must include the following concepts: (a) Scenario Based Training (SBT), (b) Single Pilot Resource Management (SRM), and (c) Learner Centered Grading (LCG,). SBT should be deployed throughout the syllabus which based on the guidance of FAA Generic Master Syllabus. The scenarios should considerate to the aircraft, specific flight characteristics, and the similar flight environment. It should always require the pilot to make real-time decisions in a realistic setting. Once the student has performed the required skills, the scenarios should be planned and led by the student. SRM is clearly defined as Aeronautical Decision Making, Risk Management, Task Management, Information Management, Automation Management, Flight Management, Situational Awareness, and CFIT Awareness.

Thus, it has to be a part of every section of each scenario. SRM will be a graded item during pre-flight, pre-takeoff, takeoff, climb, cruise, descent, approach, and landing. It's different to manufacturer's curriculum. The learner centered grading is a way for the instructor and student to determine the student's level of knowledge and understanding. "Perform" is used to describe proficiency in a skill item such as an approach or landing. "Manage-Decide" is used to describe proficiency in the SRM area such as ADM. Explain and practice are used to describe student learning levels below proficiency in both. From the above concepts, the pilot in training will have the opportunity to practice, sort out the problems and tasks. The previous research reported the FITS also improve the efficiency in Commercial Pilot Training Course, and successfully reduced nearly 1/3 flight hours to meet Commercial Certificate.

What is the Learner Centered Grading? Since the training is learner centered, the success of the training is measured in the following desired student outcomes. The FITS divide LCG into the following sections:

*(a) Maneuver Grades*

Describe – at the completion of the scenario, the PT will be able to describe the physical characteristics and cognitive elements of the scenario activities. Instructor assistance is required to successfully execute the maneuver.

- Explain - at the completion of the scenario the learner will be able to describe the scenario activity and understand the underlying concepts, principles, and procedures that comprise the activity. Instructor assistance is required to successfully execute the maneuver.
- Practice - at the completion of the scenario the student will be able to plan and execute the scenario. Coaching, instruction, and/or assistance from the CFI will correct deviations and errors identified by the CFI.
- Perform - at the completion of the scenario, the PT will be able to perform the activity without assistance from the CFI. Errors and deviations will be identified and corrected by the PT in an expeditious manner. At no time will the successful completion of the activity be in doubt. ("Perform" will be used to signify that the PT is satisfactorily demonstrating proficiency in traditional piloting and systems operation skills)

- Not Observed - Any event not accomplished or required

*(b) Single Pilot Resource Management (SRM) Grades*

Explain - the student can verbally identify, describe, and understand the risks inherent in the flight scenario. The student will need to be prompted to identify risks and make decisions.

- Practice - the student is able to identify, understand, and apply SRM principles to the actual flight situation. Coaching, instruction, and/or assistance from the CFI will quickly correct minor deviations and errors identified by the CFI. The student will be an active decision maker.
- Manage / decide - the student can correctly gather the most important data available both within and outside the cockpit, identify possible courses of action, evaluate the risk inherent in each course of action, and make the appropriate decision. Instructor intervention is not required for the safe completion of the flight.

In the LCG concept, the student should achieve a new level of learning through each flight. It also means the grading should be progressive. In 2011, Shaobo Huang proposed the prediction of student academic performance helps instructors develop a good understanding of how well or how poorly the students will perform. And instructors can take proactive measures to improve student learning. One of models was developed using multivariate linear regression (MLR).

## Materials and Methods

In this research, we collected data from an aeronautical academic in Taiwan. These students were trained for Recreation Pilot License Program. We performed a pre-test on 24 students, 16 data of collected been used on building the module, 8 of them used to exam the module. There are 12 courses in the training program, and 30 hours total times were suggested by academic (shown in Table 1). We applied a pre-test and got scores based on LCG method which is the sum of Maneuver and SRM Grades (shown in Table 2).

Table 1. The Course Component and Suggested Training Hours

| Course Component | Suggested Training Hours |
|---|---|
| Operation and Effect of Controls | 2 |
| Straight and Level | 2 |
| Climbing and Descending | 2 |
| Turning | 2 |
| Stalling | 2 |
| Revision | 2 |
| Circuits | 2 |
| Cross-Wind Training | 4 |
| Circuit Emergency | 2 |
| Solo Circuit | 2 |
| Forced Landing | 4 |
| Precautionary and Searching Landing | 4 |
| TOTAL | 30 |

Table 2. The score points between Maneuvers Grades and SRM Grades

| Maneuvers Grades | Scores | SRM Grades | Scores |
|---|---|---|---|
| Describe | 1 | Explain | 2 |
| Explain | 2 | Practice | 4 |
| Perform | 3 | Manage/Decide | 6 |
| Not Observed | 0 | | |

From previous research studies as described above, we addressed twelve variations from the dimensions of course component as the indicators of course component in Learner Centered Grading, namely (a) CCS1: Operation and Effect of Controls; (b) CCS2: Straight and Level; (c) CCS3: Climbing and Descending; (d) CCS4: Turning; (e) CCS5: Stalling; (f) CCS6: Revision; (g) CCS7: Circuits; (h) CCS8: Cross-Wind Training; (i) CCS9: Circuit Emergency; (j) CCS10: Solo Circuit; (k) CCS11: Forced Landing; and (l) CCS12: Precautionary and Searching Landing .

The flowchart of model evaluate using machine learning is shown as Figure 1. The steps are as following:

*Step 1. Select columns in Dataset. Samples of machine learning*

The data source is provided by the same flight instructor, and saved in CSV format.

*Step 2. Split Data. Select the splitting mode*

Divide the data into training group and test group, which determined by the total percentage value of amount data.

*Step 3. Train model*

In the train model, each output value AT1~AT12 is affected by the input variables CCS1~CCS12.

*Step 4. Linear Regression*

The machine learning model is based on the methodology of Linear Regression. Given a data set [{[AT]_i,[CCS]_(i1,)……,[CCS}_ip}] _(i=1)^(n) of n statistical units, a linear regression model assumes that the relationship between the dependent variable AT and the p-vector of regressors CCS is linear. This relationship is modeled through a disturbance term or error variable ε - an unobserved random variable that adds "noise" to the linear relationship between the dependent variable and regressors. Thus the model takes the form:

[AT] _i=β_0 1+ [β_1 CCS] _ (i1,)

+⋯…, [β_p CCS] _ip+ε_i= [β_p CCS]

_ip

where T denotes the transpose, so that CCSiTβ is the inner product between vectors CCSi and β. β is a (p+1)- dimensional parameter vector, where β_0 is the intercept term (if one is included in the model-otherwise β is p- dimensional). Its elements are known as effects or regression coefficients (although the latter term is sometimes reserved for the estimated effects). Statistical estimation and inference in linear regression focuses on β. The elements of this parameter vector are interpreted as the partial derivatives of the dependent variable with respect to the various independent variables. ε_ is a vector of values ε_i. This part of the model is called the error term, disturbance term, or sometimes noise (in contrast with the "signal" provided by the rest of the model). This variable captures all other factors which influence the dependent variable AT other than the repressors CCS.

*Step 5. Score Model*

Score label is the predicted value of the actual output variable AT which trained by the methodology of machine learning.

*Step 6. Evaluate Model*

Examinee the accuracy of prediction by the data of the test group. If the Accuracy of the training group is poor, it means that the model under fitting. If the accuracy of test group is poor than the training group, it means that the model is over fitting.

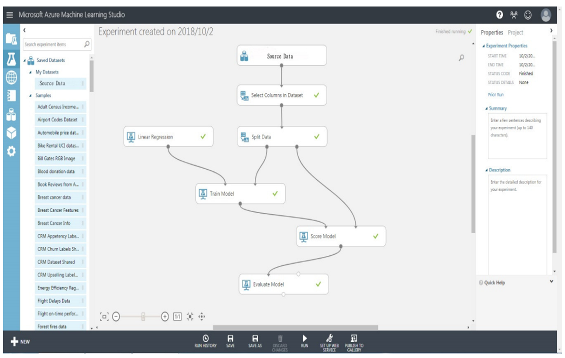

Figure 1. The flowchart of machine learning.

Results

In the research using intelligent and linear regression methods, calculated by Microsoft Azure Machine Learning Studio. We collected 24 sets of data, we put into 14 sets of data to build the module, then exam it by another 8 sets of data. It turned out the time prediction of 12 courses by 8 datasets. The results are shown as the following:

1. There are a few significantly deviations in course 3 from the dataset 3, 4, and 6 (shown as Table 3. and Figure 2.).

Table 3. The comparison between the Prediction and the Actual Training Hours in Course Component 1 to 3.

| AT1 | Scored Labels | AT2 | Scored Labels | AT3 | Scored Labels |
|---|---|---|---|---|---|
| 4 | 4.136173 | 6 | 7.066776 | 4 | 4.617222 |
| 1 | 0.000297 | 4 | 2.679812 | 1 | 0.317451 |
| 1 | 0.853766 | 2 | 2.095043 | 1 | 2.221879 |
| 1 | 1.554664 | 4 | 5.436241 | 2 | 5.016433 |
| 4 | 3.840526 | 5 | 7.189334 | 4 | 6.66864 |
| 1 | 2.299032 | 2 | 2.305989 | 1 | 2.6546 |
| 5 | 4.042448 | 5 | 6.886819 | 4 | 6.035461 |
| 1 | 0.64868 | 2 | 2.369538 | 2 | 2.227872 |
| 1 | 1.346715 | 3 | 3.354251 | 2 | 3.735802 |

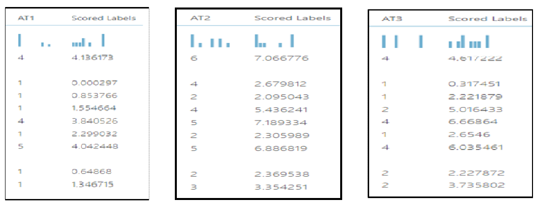

Figure 2. The deviation of course component 1 to 3

2. There are a few significantly deviations in course 4 and 6 from dataset 4 and 6(shown as Table 4. and Figure 3.).

Table 4. The comparison between the Prediction and the Actual Training Hours in Course Component 4 to 6.

| AT4 | Scored Labels | AT5 | Scored Labels | AT6 | Scored Labels |
|---|---|---|---|---|---|
| 5 | 6.970357 | 5 | 3.980942 | 6 | 8.025716 |
| 2 | 0.95785 | 1 | 1.118687 | 4 | 2.332649 |
| 1 | 2.17034 | 1 | 1.616046 | 1 | 1.668282 |
| 3 | 5.658694 | 2 | 3.744007 | 4 | 3.687329 |
| 3 | 8.320159 | 4 | 5.112111 | 4 | 7.753072 |
| 2 | 2.708437 | 1 | 1.775794 | 2 | 3.523884 |
| 3 | 6.986317 | 4 | 3.689564 | 5 | 8.092261 |
| 2 | 1.352732 | 2 | 1.950621 | 2 | 1.348559 |
| 2 | 1.770758 | 2 | 2.056778 | 2 | 2.50712 |

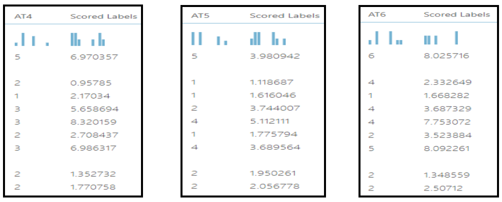


Figure 3. The deviation of course component 4 to 6

3. There are a few significantly deviations in course 8 from dataset No.4 and 6(shown as Table 4. and Figure 3.).

Table 5. The comparison between the Prediction and the Actual Training Hours in Course Component 7 to 9.

| AT7 | Scored Labels | AT8 | Scored Labels | AT9 | Scored Labels |
|---|---|---|---|---|---|
| 5 | 8.042743 | 10 | 13.45088 | 5 | 7.499647 |
| 4 | 2.306342 | 8 | 8.533491 | 3 | 2.046989 |
| 2 | 2.766634 | 3 | 3.501854 | 2 | 3.088774 |
| 4 | 6.528452 | 6 | 9.458074 | 2 | 5.508706 |
| 5 | 9.005932 | 9 | 17.375679 | 4 | 7.959505 |
| 3 | 3.904489 | 7 | 9.847394 | 4 | 6.079527 |
| 5 | 7.889983 | 9 | 17.810778 | 4 | 6.367999 |
| 2 | 2.540801 | 4 | 4.494379 | 2 | 1.937397 |
| 1 | 3.706782 | 4 | 6.441241 | 2 | 5.670901 |

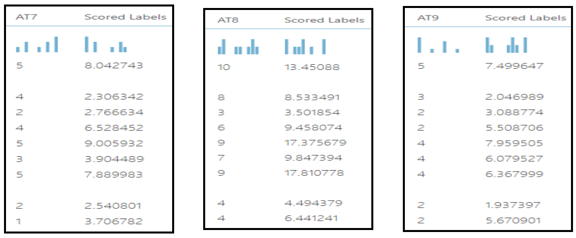


Figure 4. The deviation of course component 7 to 9

4. There are a few significantly deviations in course10, course 11, course 12. From dataset No.3, 4 and 6 (shown as Table 6. and Figure 5.).

Table 6. The comparison between the Prediction and the Actual Training Hours in Course Component 10 to 12.

| AT10 | Scored Labels | AT11 | Scored Labels | AT12 | Scored Labels |
|---|---|---|---|---|---|
| 5 | 4.90852 | 11 | 9.710579 | 18 | 19.400684 |
| 8 | 6.366101 | 5 | 3.163514 | 12 | 6.912695 |
| 1 | 2.675245 | 3 | 4.561034 | 3 | 3.351992 |
| 5 | 8.785689 | 6 | 10.054214 | 8 | 13.402338 |
| 5 | 14.006054 | 10 | 14.380285 | 18 | 23.519074 |
| 7 | 8.533263 | 6 | 7.013764 | 8 | 9.767505 |
| 6 | 13.862405 | 11 | 13.038406 | 18 | 24.534003 |
| 2 | 4.969271 | 5 | 6.522535 | 5 | 6.673843 |
| 2 | 6.684836 | 5 | 5.300059 | 4 | 4.892263 |

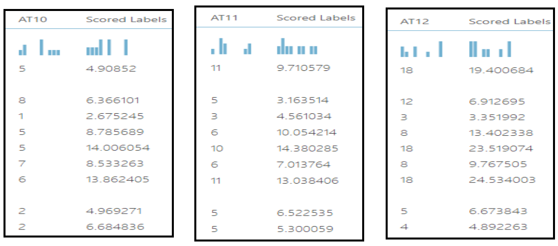


Figure 5. The deviation of course component 10 to 12

## Discussion

From the results above, we had proved the model can be used on forecasting. The characteristics and trend of the forecasting system are of valuable reference. There is one thing need to do that is improving the accuracy. The dataset 4 and 6 shown a significantly deviations in 7 of 12 courses that the actual training hours is far below the prediction. We also have the same finding from dataset 3 in course 3, 11 and 12.

The deviation probably caused by two reasons. Firstly, we may have independent cases from the datasets. Especially in dataset 4 and 6, they have a different learning curve than others. They have a better performance in learning, even if they got a poor score in pre-test. Secondly, it might be due to the limited number of samples. The lack of samples may influence the precision of the model. If we could collect more datasets as input to build up the module, the accuracy of results can be improved.

## Conclusions

In the research using intelligent and linear regression methods, the pre-test score of 12 courses as inputs to the intelligent prediction system, and the actual training hours as outputs to predict the results of the student pilot assessment. From the results obtained, it can be understood that the linear regression-based training hour prediction system is an efficient method to forecast the learning curve of student pilots. Regardless the lack of samples, we have proposed a new way to forecast the training hours of student pilot. Thus, these findings help airline managers to predict their cost in pilot training. Making decision more efficiently and easily to pilot training policy to meet the economy levels of costs.

Furthermore, the forecasting system can be adjusted to any level of pilot license. The indicators of course component in Learner Centered Grading can be adjusted to achieve the desired pilot-training results by using a decision support system with an intelligent prediction system. This also indicates that if managers pre-set a cost level of a student pilot, machine learning model could help them to deploy resources to achieve goals. It can be used to adjust the strategies of airlines and instructors to achieve the desired quality in pilot training and improve customer satisfaction in practice.

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