Driving Modern Day Education

with

my CourseVille

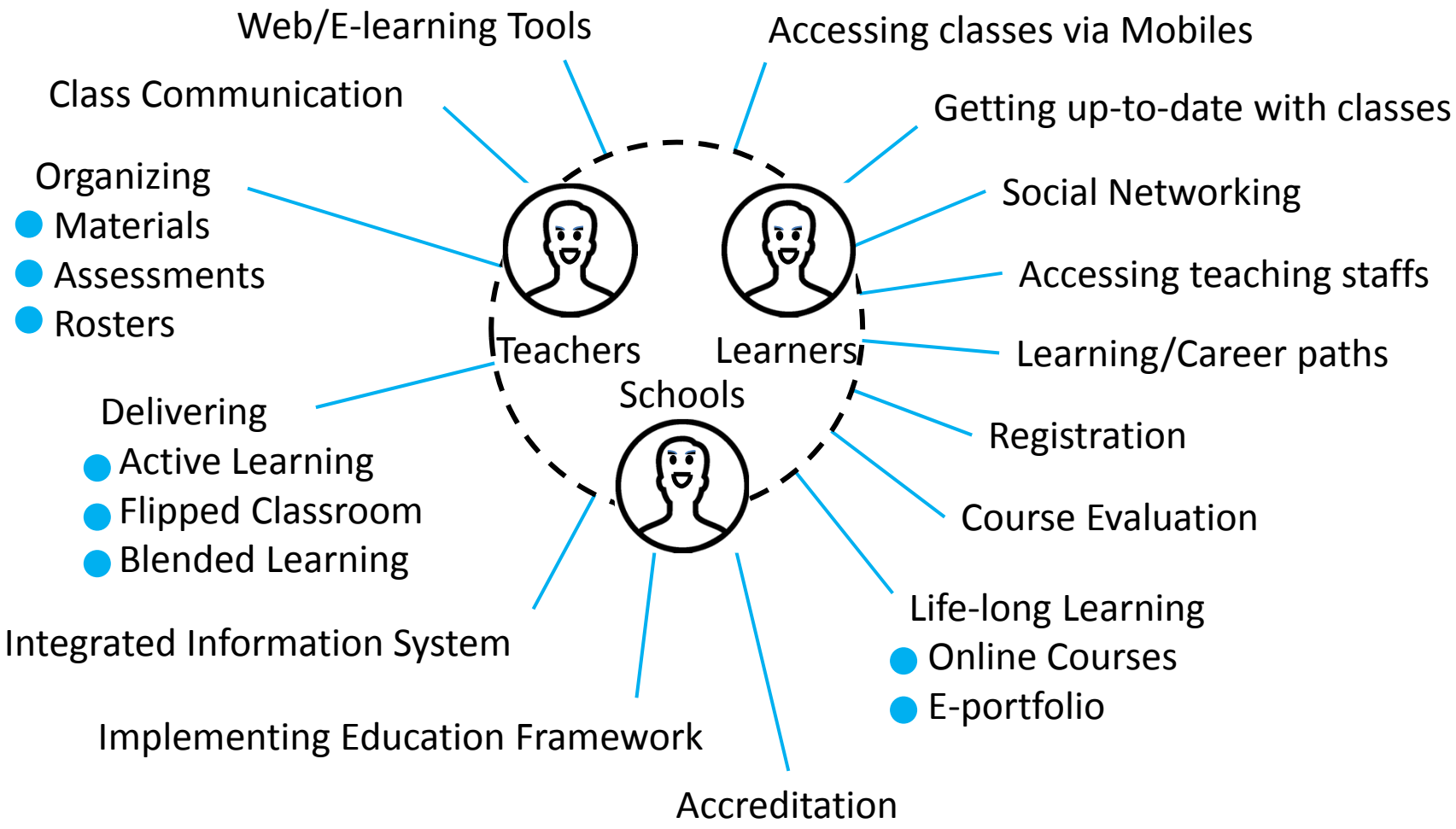
A case of

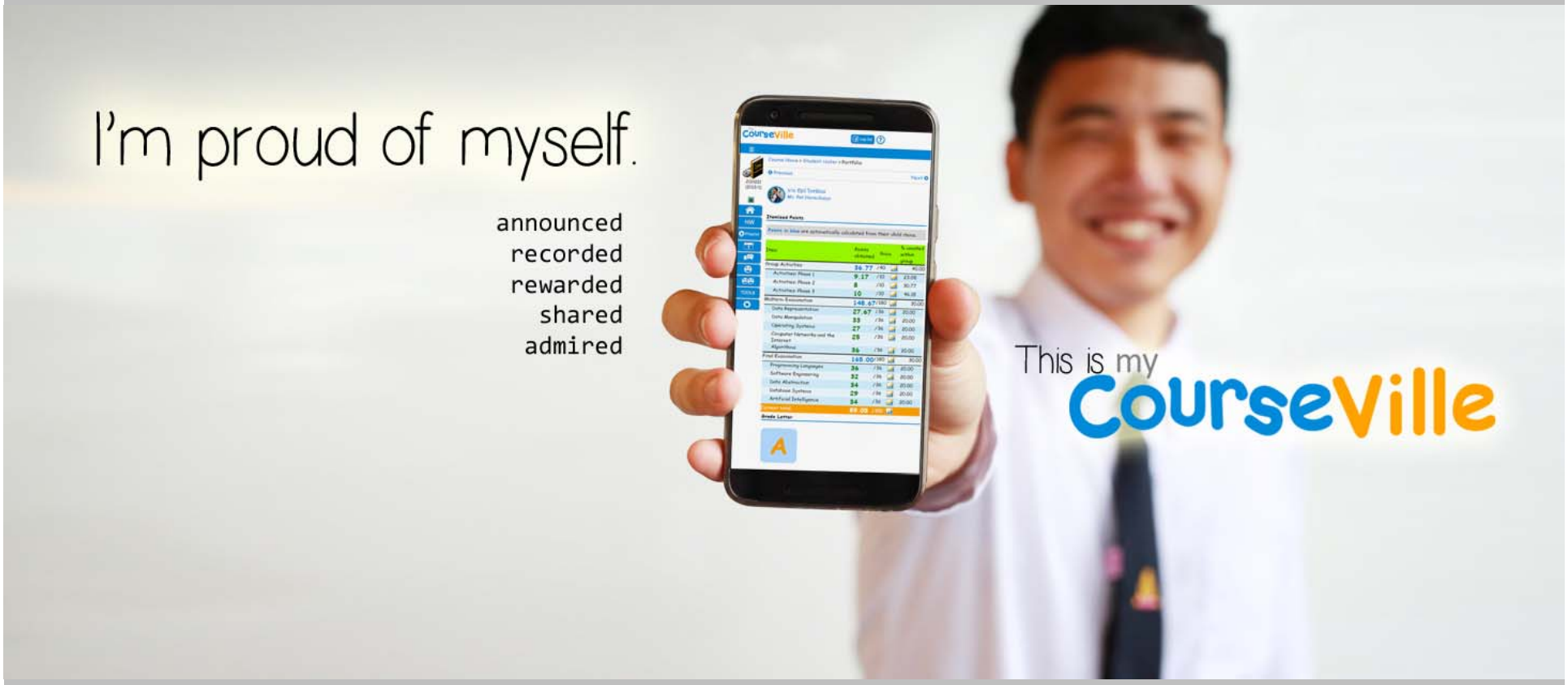
Chulalongkorn University

Agenda

- The “Many” Needs of Modern Day Education
- The story of a Home-grown Solution
- From “LMS” to “Education Platform”
- Learning Analytics
- Immediate Directions

Modern Day Education




I'm proud of myself.
announced
recorded
rewarded
shared
admired
This is my
CourseVille

myCourseVille Timeline

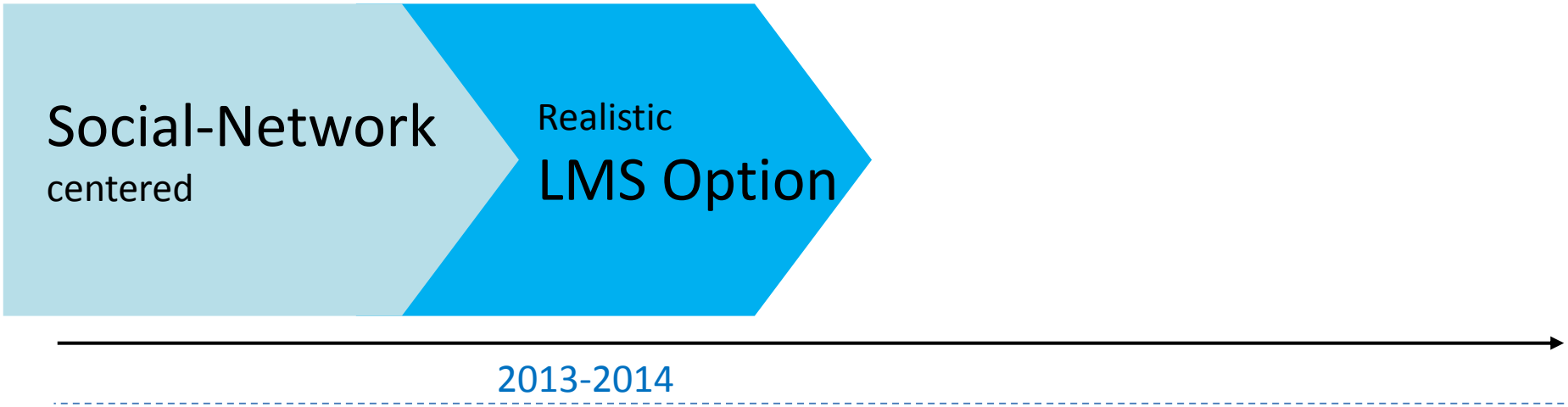
Social-Network
centered

2011-2013

- Always on with a Social Network Account
- Experimental Look & Feel
- Verbal Introduction to a group of colleagues
- Catching up with other mature LMS

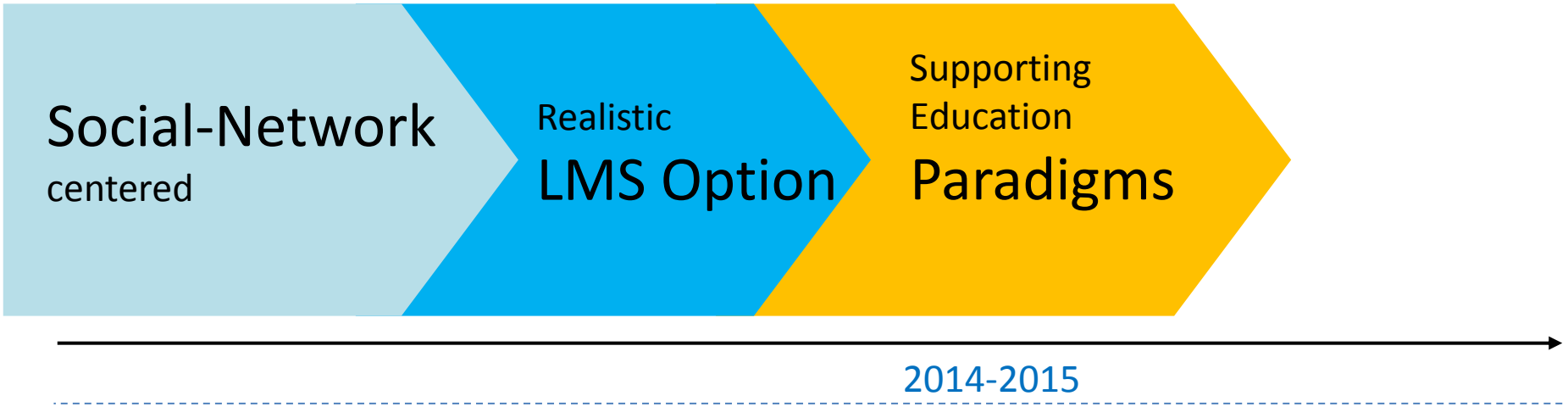
Student-centered

myCourseVille Timeline



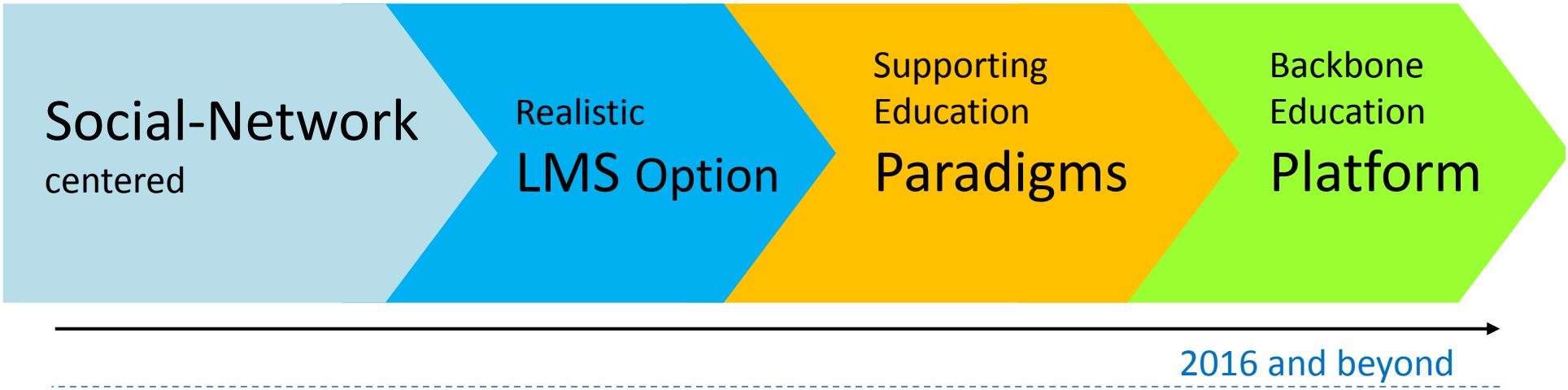
- Efficiency in Course Management
- Feedbacks from real (& decent amount of) users
- Campus-wide Roadshows & Workshops
- Customer Supports (Call Center / FB Page)

myCourseVille Timeline



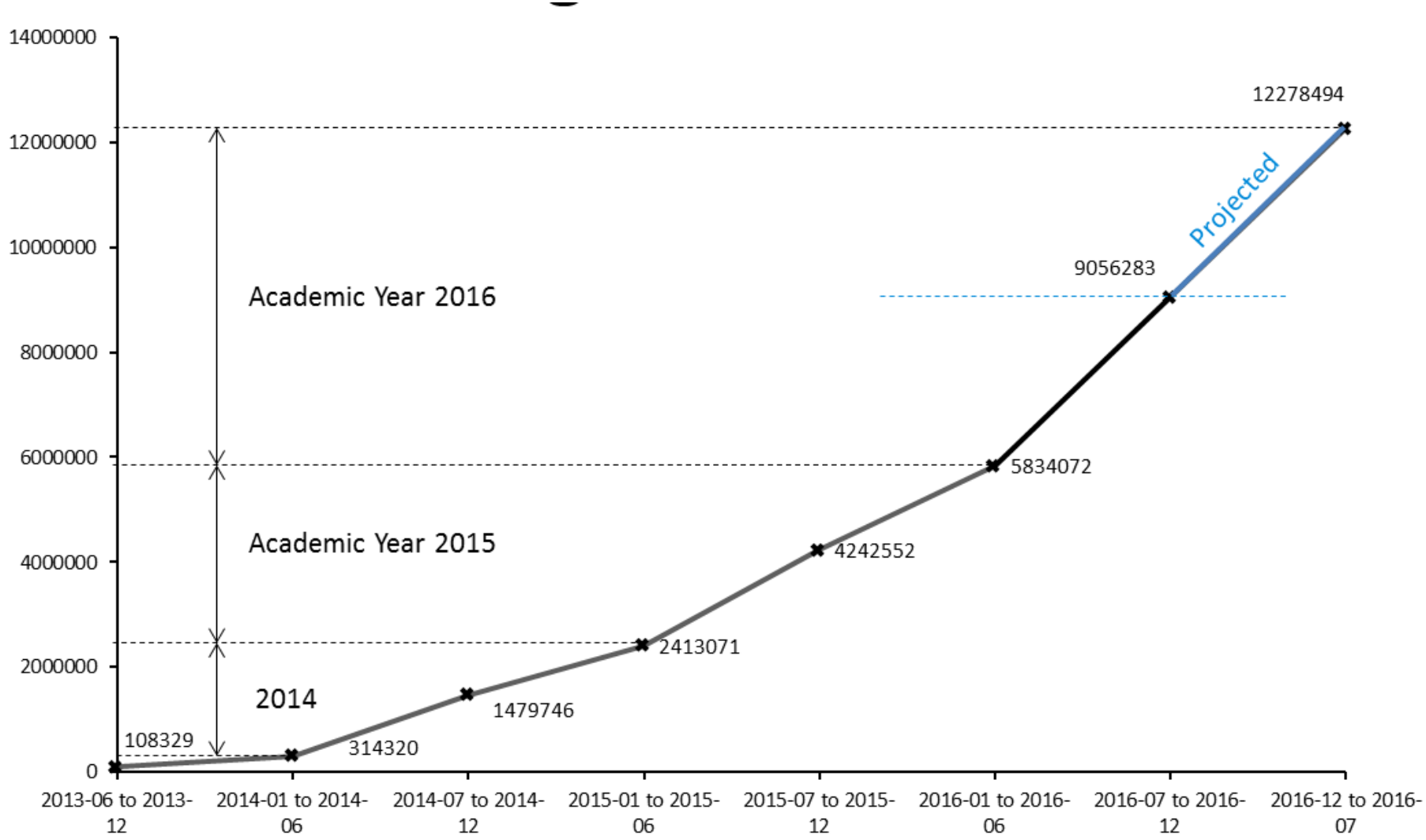
- Development in sync with Teaching/Learning techniques
- Platform for Classroom researches
- Larger variations of users

myCourseVille Timeline



- Expansion beyond LMS
- Inter-operation with other systems
- Challenges in Big-Data Analytics
  - Learning Analytics
  - Curriculum Analysis / Researches
  - Unsupervised Learning Recommendation
- Outcome-based
  - E-portfolio
  - Accreditation
- Blended Learning
  - Online Courses
  - Video Services
  - Active Learning

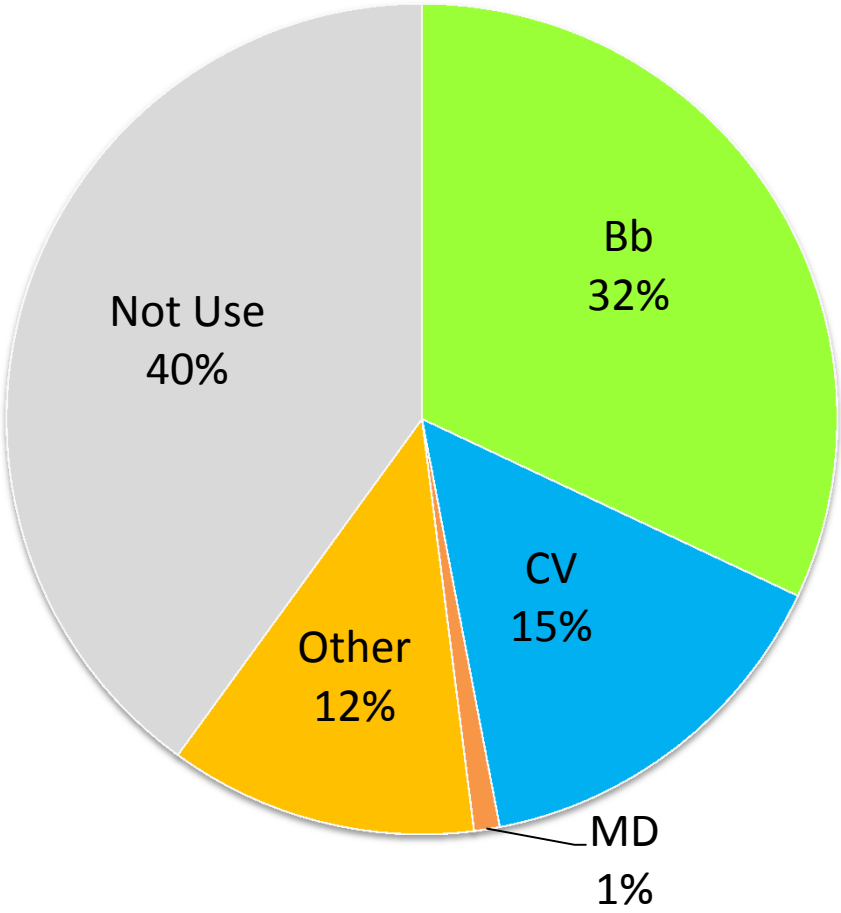
Current Status



Current Status

Chula 2016

Data from CU Learning Innovation Center



Current Status

myCourseVille in Chula Engineering

- Highly-encouraged
- ~70% of courses
- 100% of undergrad students

From “**Learning Management System**” to “**Education Platform**”

my CourseVille

as:

“Learning Management System”
“Knowledge Aggregator/Publishing”
“Teaching/Learning Tools”
“Online Course Platform”
“Distance Learning Channel”
“Learning Analytics”

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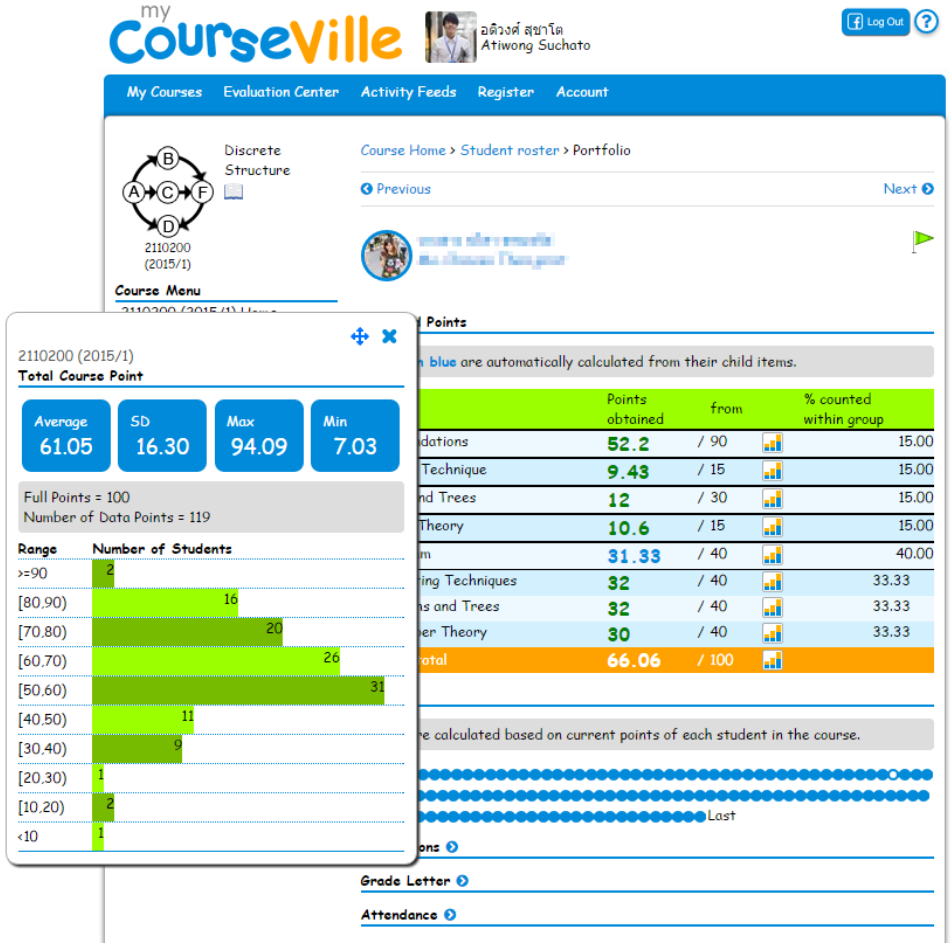
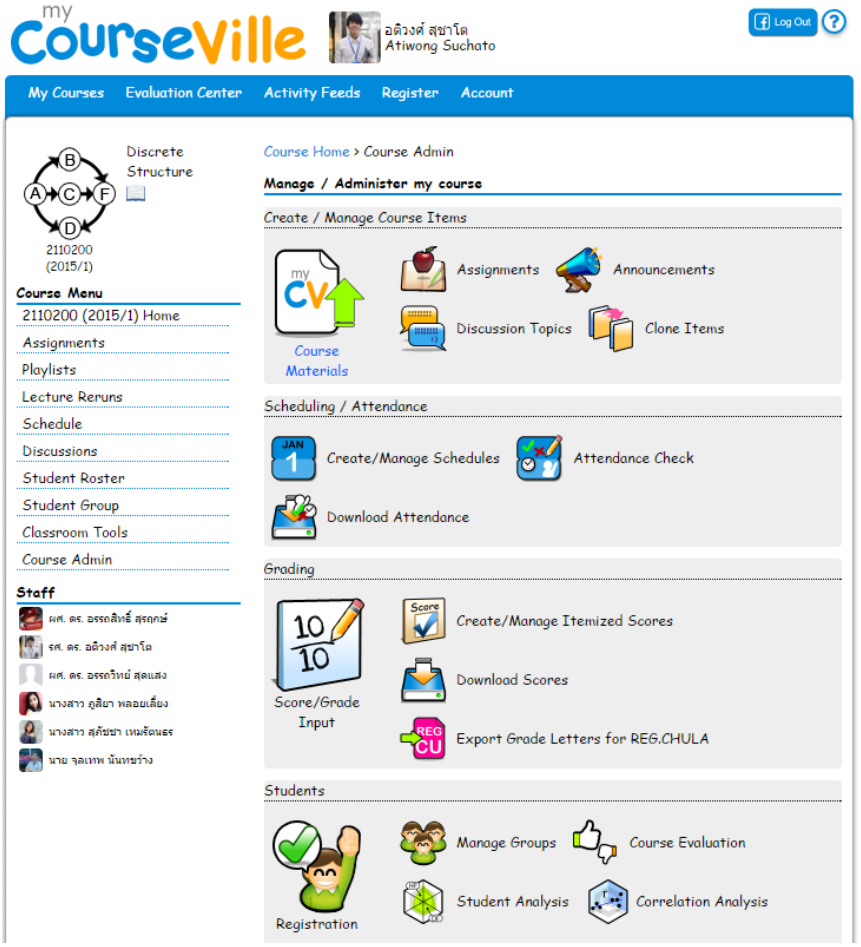
Learning Management System





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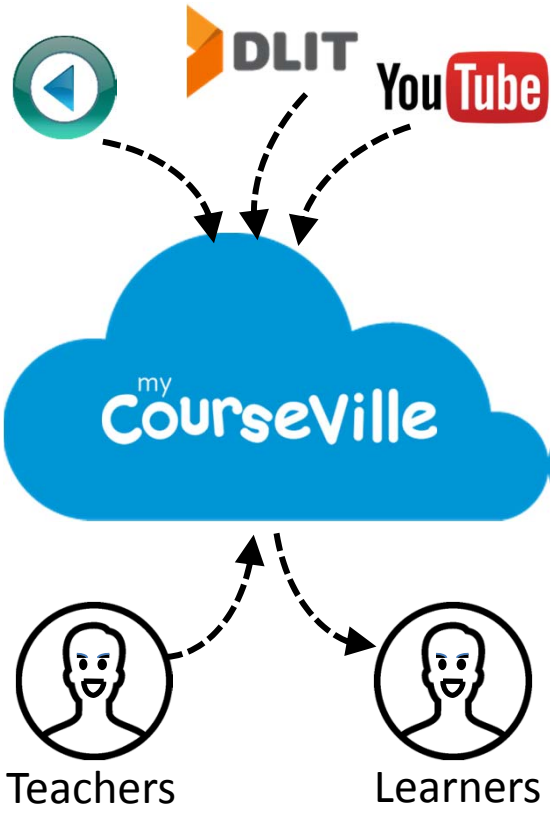
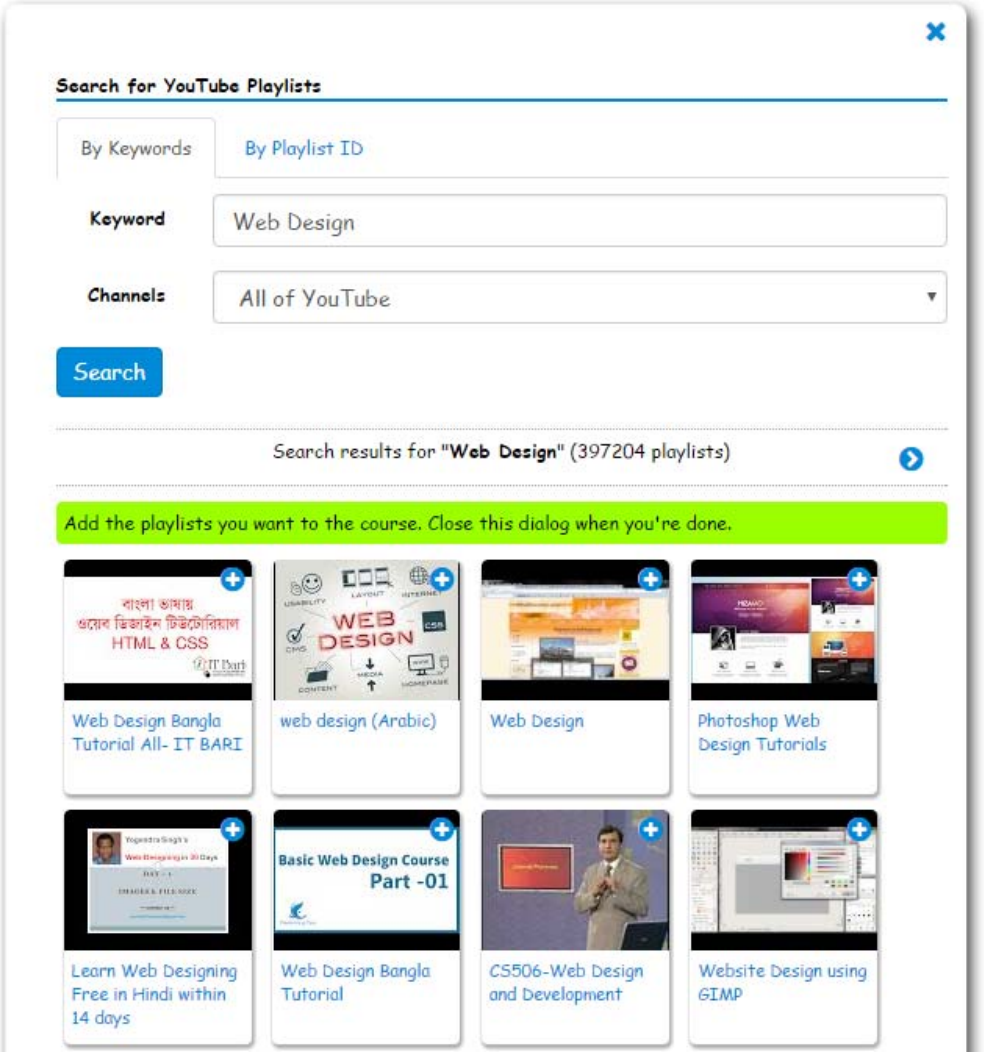
Learning Content Aggregator





คลังสื่อการสอน (DLIT Resources)

เลือกกลุ่มสาระฯ ระดับชั้น พบ DLIT วิดีโอที่ผลิตใหม่ (สั้นๆ เข้าใจง่าย ตรงหลักสูตรฯ) และสื่อประเภทต่างๆ ที่รวบรวมมาไว้ที่นี่ ได้แก่ วิดีโอ, แผนการจัดการเรียนรู้ , สื่อ Learning Object และอื่นๆ คุณครูสามารถเปิดฉาย และ/หรือ ดาวน์โหลดไว้ใช้ประกอบการสอนได้ หาสื่อการสอนที่ต้องการได้ง่ายๆ กดเลือกกลุ่มสาระฯและชั้น เพื่อกรองข้อมูลคลังสื่อการสอนที่ต้องการ

เลือกกลุ่มสาระฯการเรียนรู้
ภาษาไทย	คณิตศาสตร์	วิทยาศาสตร์	สังคมศึกษาฯ	ภาษาอังกฤษ

DLIT Resources คลังสื่อการสอน DLIT (177)

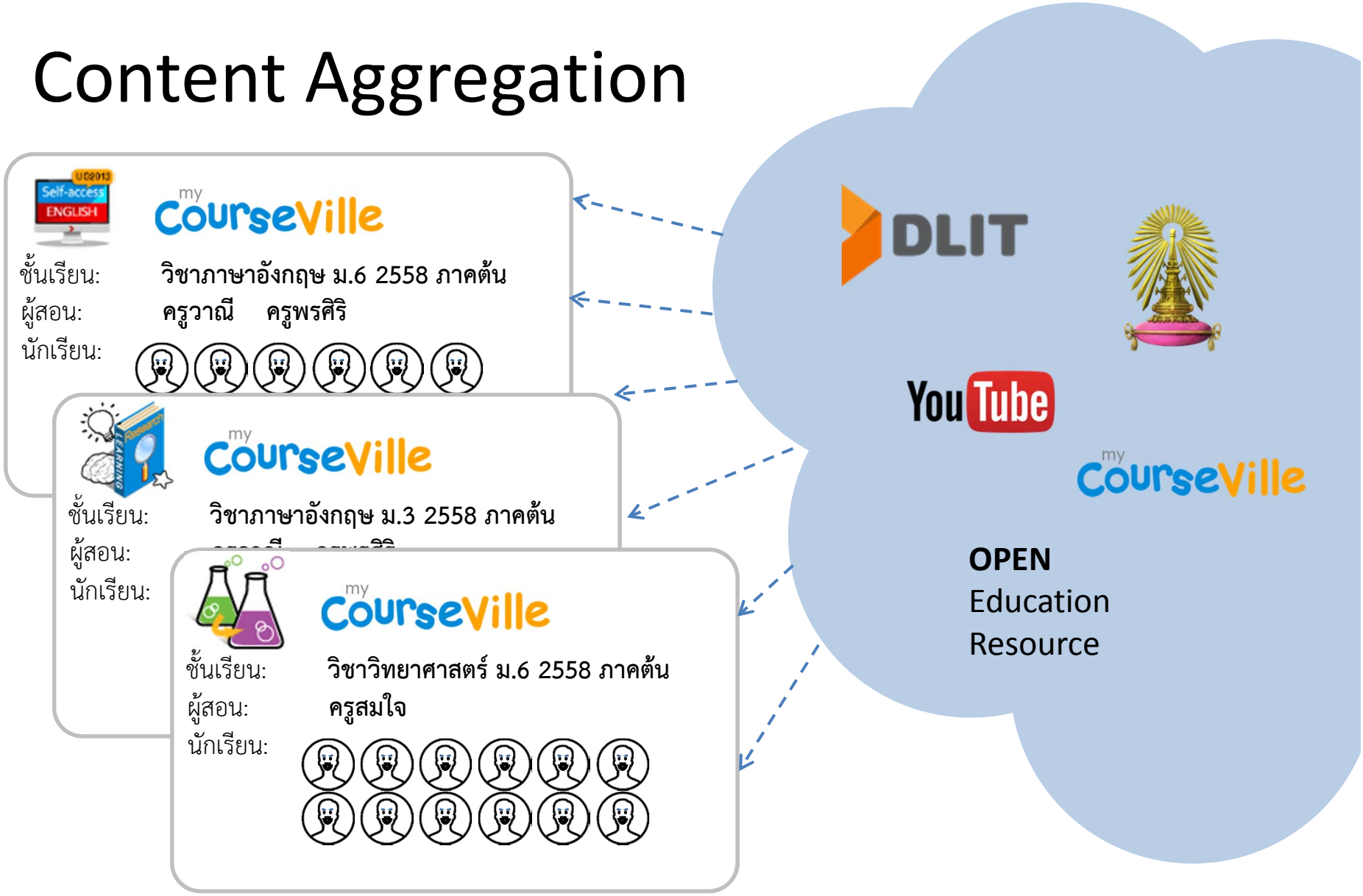
Brain Break ตอน 20 : Take Five

Brain Break ตอน 19 : Dum Dum Dah Dah

Brain Break ตอน 18 : Medley Brain Gym

Brain Break ตอน 17 : ชาลาปัว

Content Aggregation

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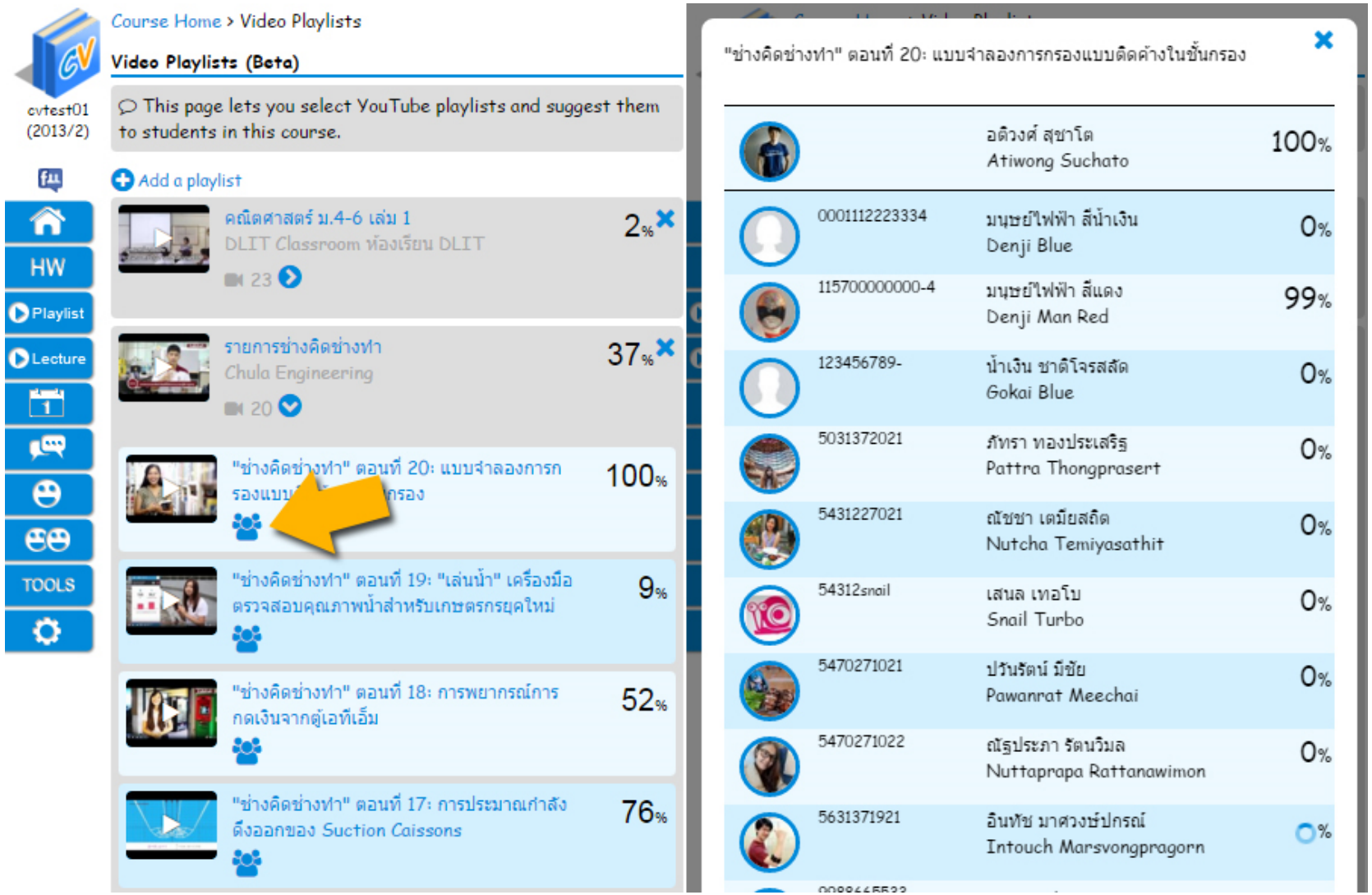
Learning Analytics

Analysis Tools & Visualization

YouTube Playlist



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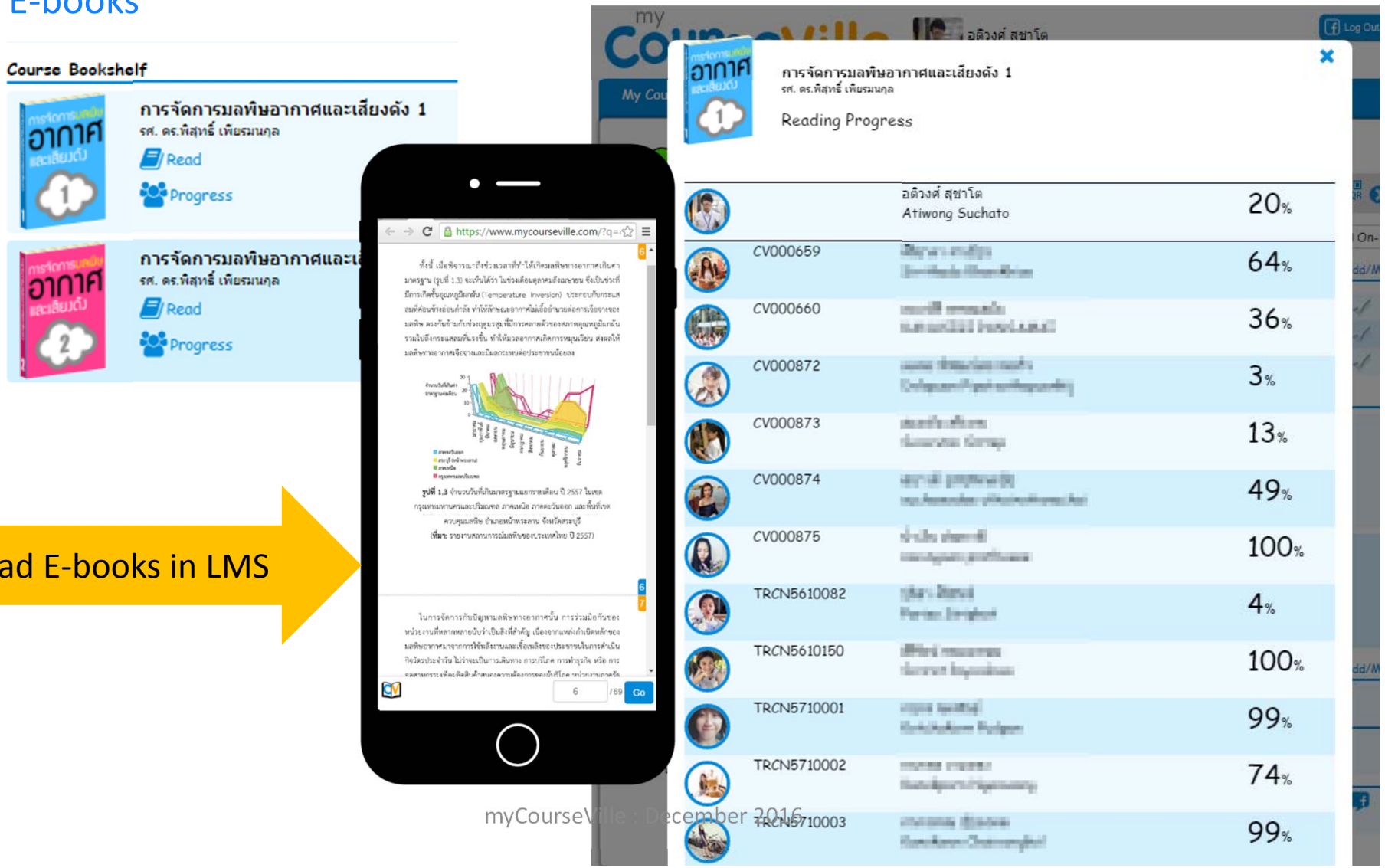
E-books



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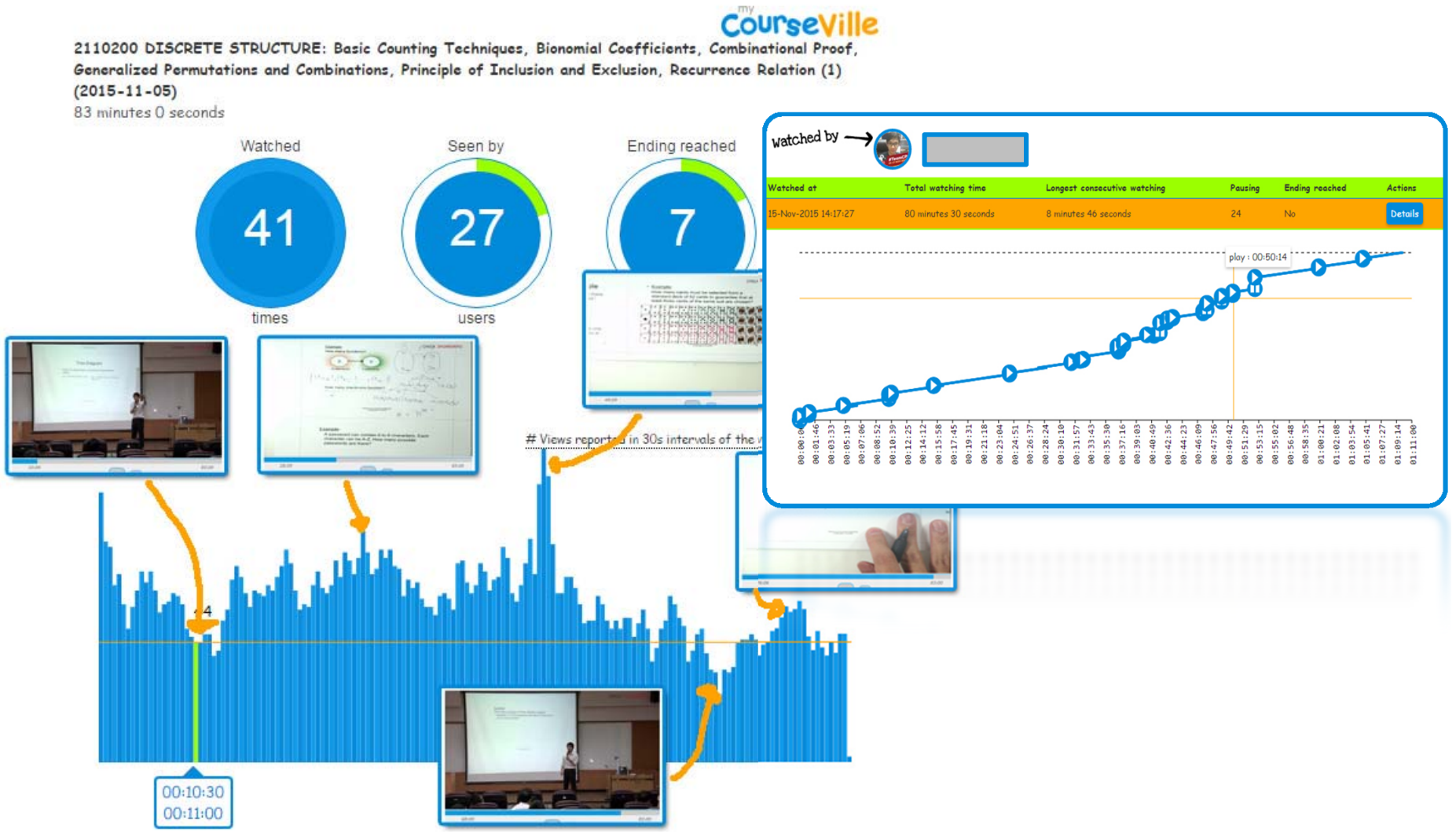
Analysis Tools & Visualization

Lecture Re-runs



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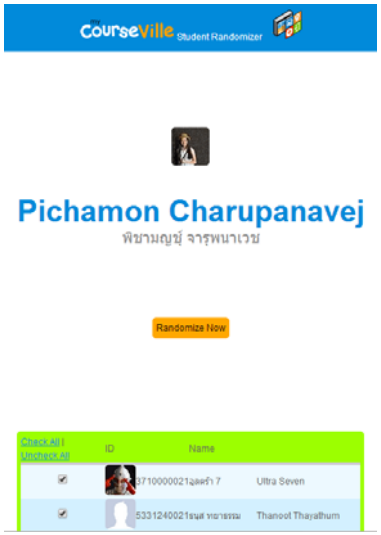
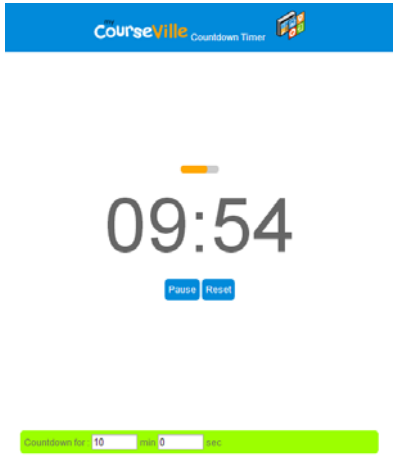
Active Learning Tools

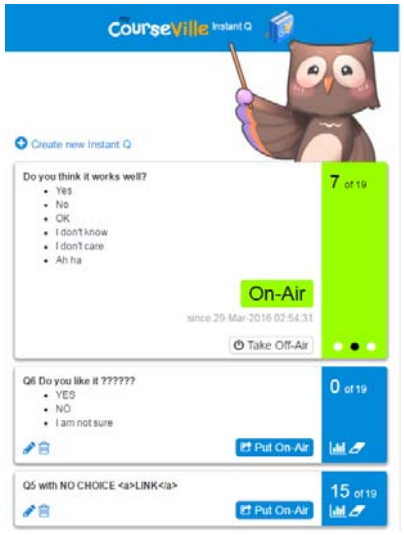
Student Randomizer

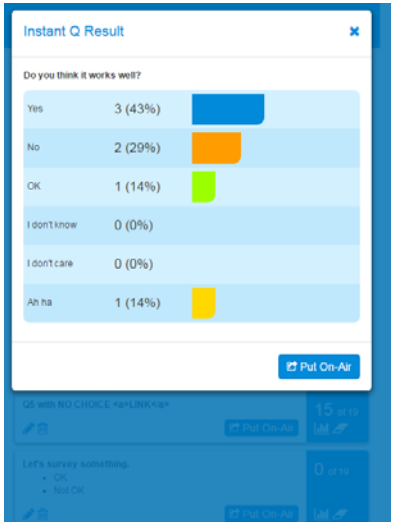
Countdown Timer

Instant Q









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Online-Course Platform

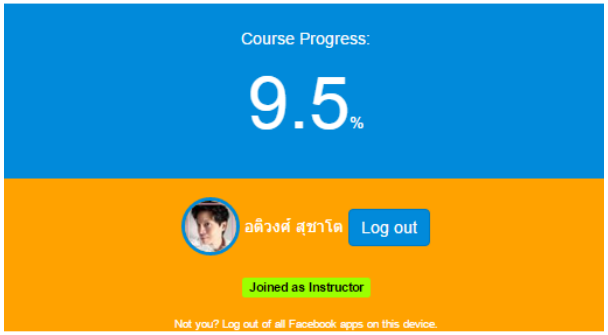
CU.MOOC.0001 (2016/2)

Survival Thai

This **Survival Thai** course aims at teaching the Thai language and culture at a basic level to students and those who are interested. It consists of 14 lessons classified into 4 groups, with a focus on the spoken language used in everyday life.

CU.MOOC.0001 (2016/2)

Survival Thai



This **Survival Thai** course aims at teaching the Thai language and culture at a basic level to students and those who are interested. It consists of 14 lessons classified into 4 groups, with a focus on the spoken language used in everyday life.

Each lesson presents vocabulary, a role-play conversation and an explanation by the instructor. A simplified phonetic

Course Outline

#	Topic	Materials	Progress
0	Introduction to the sound system of Thai language		45%

Course Outline

#	Topic	Materials	Progress
0	Introduction to the sound system of Thai language		45%
1	Lesson 1: Introducing oneself		98%
2	Lesson 2: Pronouns		0%
3	Lesson 3: Saying goodbye and thank you		0%
4	Lesson 4: Ordering food		0%
5	Lesson 5: Making apologies, Making requests, Asking permission and Forbidding		0%
6	Lesson 6: Time and date		0%
7	Lesson 7: Making appointment		0%
8	Lesson 8: Directions and traveling		0%
9	Lesson 9: Question words and Yes-No questions		0%
10	Lesson 10: Seasons and weather		0%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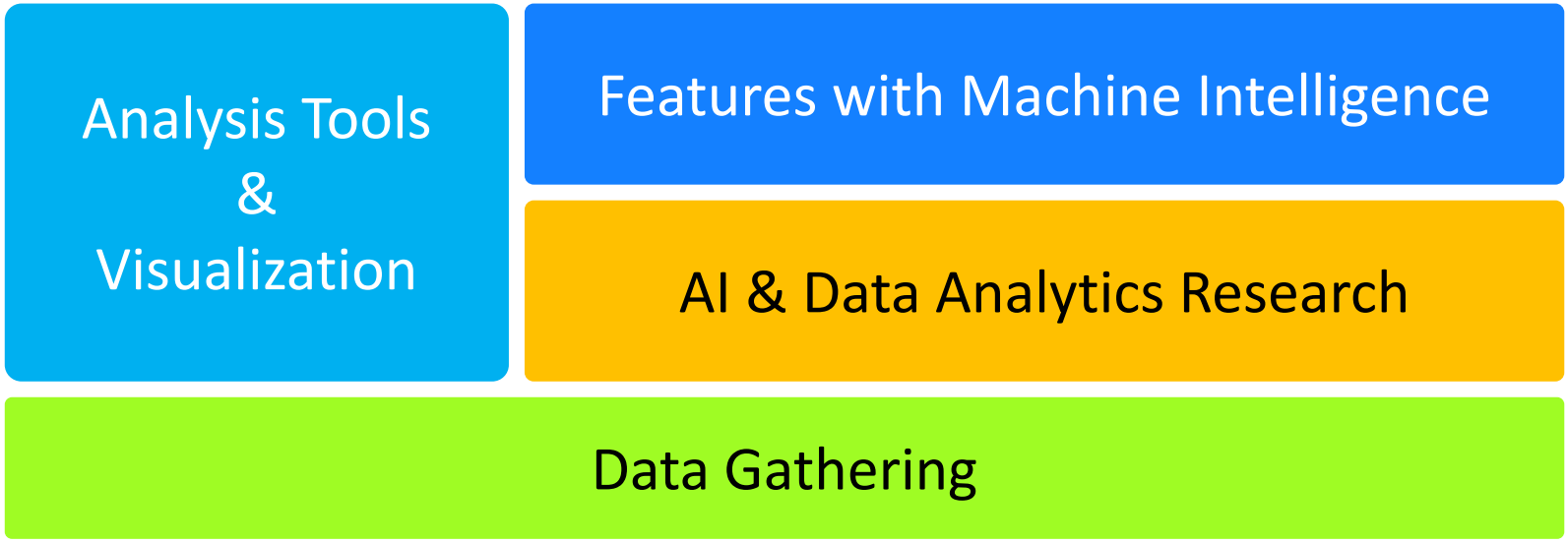

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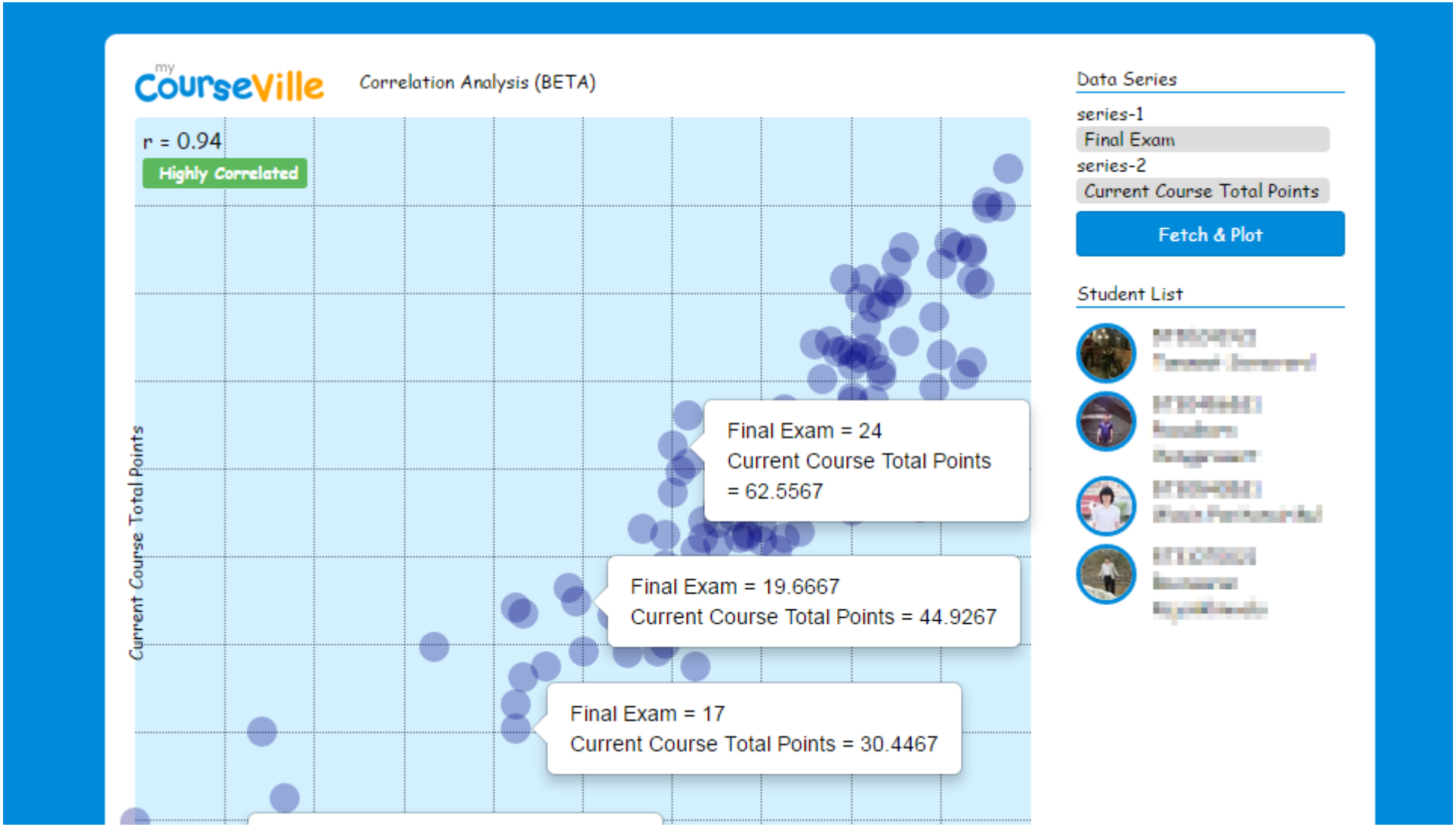
Analysis Tools & Visualization

Correlation Analysis



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Analysis Tools & Visualization

Student Traits

Abbr	Attribute	Rating
AC	Academic Performance	84%
DP	Discipline	86%
EG	Course Engagement	65%
LMS	LMS Usage	67%

Abbr	Attribute	Rating
AC	Academic Performance	64%
DP	Discipline	90%
EG	Course Engagement	24%
LMS	LMS Usage	61%

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Toward Machine Intelligence in Education

Published and Ongoing Research Works with myCourseVille

Learner's Performance		Learner's Performance vs. Activities in LMS
Academic Patterns		Course Periodic Behavior Modelling
Real Curriculum Coverage		Inferring Coverage of Knowledge Units from LMS Course Materials

ICSESS 2016, Beijing, China
August 26-28, 2016

Prediction of Student Achievement From Learning Management System Behaviors Using Supervised Learning

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Abstract— **To improve the quality of teaching, teachers must understand how students learn. Such objective can be best achieved through the analysis of students' behavior, using learning analytics tools. These tools employ data mining or machine learning algorithms to reveal patterns from a given set of data, usually big data, and can further serve as a predictor as documented in many researches in the past. In this paper, we describe the development of a predictor that can predict students' performance using their behavior from a Learning Management System (LMS). We utilized supervised learning technique, Support Vector Machine (SVM) in particular, to uncover the meaning of the data collected through Chulalongkorn University's LMS, called Courseville. We analyzed its log files to extract the features that reflect students'**

to have some new features such as open, social, personal, flexible and learning analytics [5].

Learning analytics is defined as collecting traces that learners leave behind and using those traces to improve learning [6]. It is one of the most interesting areas in education. There are many researches that develop advanced learning analytic tools in order to improve learning environment in various points of view. Examples include the development of tools that can analyze weekly behavior of the system and predict the activities occurring in LMS. This predictor not only assists teacher with an insight into student's nature but also lets system maintainer know when the LMS will likely to receive high traffic [7]. Another example is the development of an

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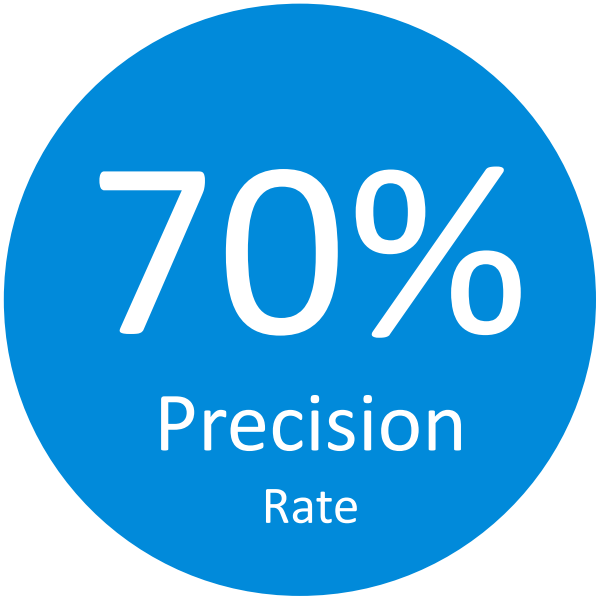
Learner's Performance vs. Activities in LMS

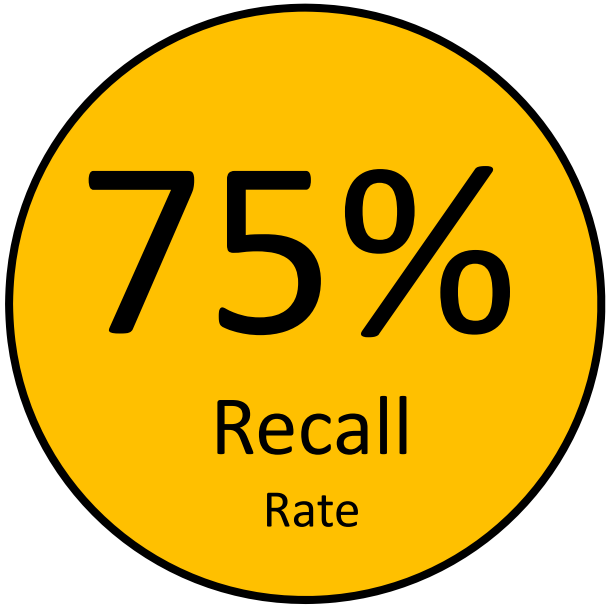
Results

33 prediction features

170 students (Train: 85, Eval:85)

SVM with Gaussian Kernel





EDUCON 2016, Abu Dhabi, UAE
April 10-13, 2016

Course Periodic Behavior Modelling and Its Application in LMS Activity Prediction

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***Abstract*—The use of technology in education has risen so rapidly that many of the e-learning tools have become a great source for data gathering. In response to the growth, learning analytics are developed to extract the meaning from extensively large datasets and optimize learning opportunities for learners. Understanding users' behaviors is one of the key factors that can help educational institutes improve their curriculum design or non-instructional intervention. This paper, therefore, explores LMS's user behaviors through the study of courses' periodic behaviors. It assumes that there is a weekly pattern in most college-level courses where classes meet on a weekly basis, and that the pattern is reflected through the number of daily activities the courses produce. Courses that share similar weekly patterns are grouped into the same cluster using an unsupervised clustering algorithm. The knowledge obtained from the clustering can be used to describe the pattern in other courses. This paper continues to demonstrate one of course periodic modelling's applications by proposing a method to predict the activities that occur in an LMS. As a result, the weekly pattern found in each course, when aggregated, can represent the weekly behavior of the overall system. It can also predict the future trend of activities with correct shape and accuracy within the range of 82-86 percent.**

Keywords—LMS, course periodic behavior, clustering, activity prediction

I. Introduction

Learning Management System (LMS) and Massive Open Online Course (MOOC). An educational institute might host an LMS to establish a communication channel between instructors and students and to assist learning in physical classroom. In contrast, an institute who targets mass education delivery might be more interested in building a MOOC platform.

Due to the amount of data these tools produce, researchers are able to analyze and discover many insights that can help them understand the nature of their education systems better. In other words, while a widespread use in e-learning tools create big data, big data is also a driver behind the rapid growth of e-learning tools; and consequently there is more development of learning analytics to extract value from large dataset [2]. In fact, the term *Learning Analytics* has been introduced to describe such study. Learning Analytic, as defined by [3], is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs. One of the main goals of learning analytics is to understand users' – or students' – behaviors to the extent that educators can adapt their teaching environment to accommodate such behaviors or to solve any existing problems.

Traits of user behaviors could be found in the activity logs

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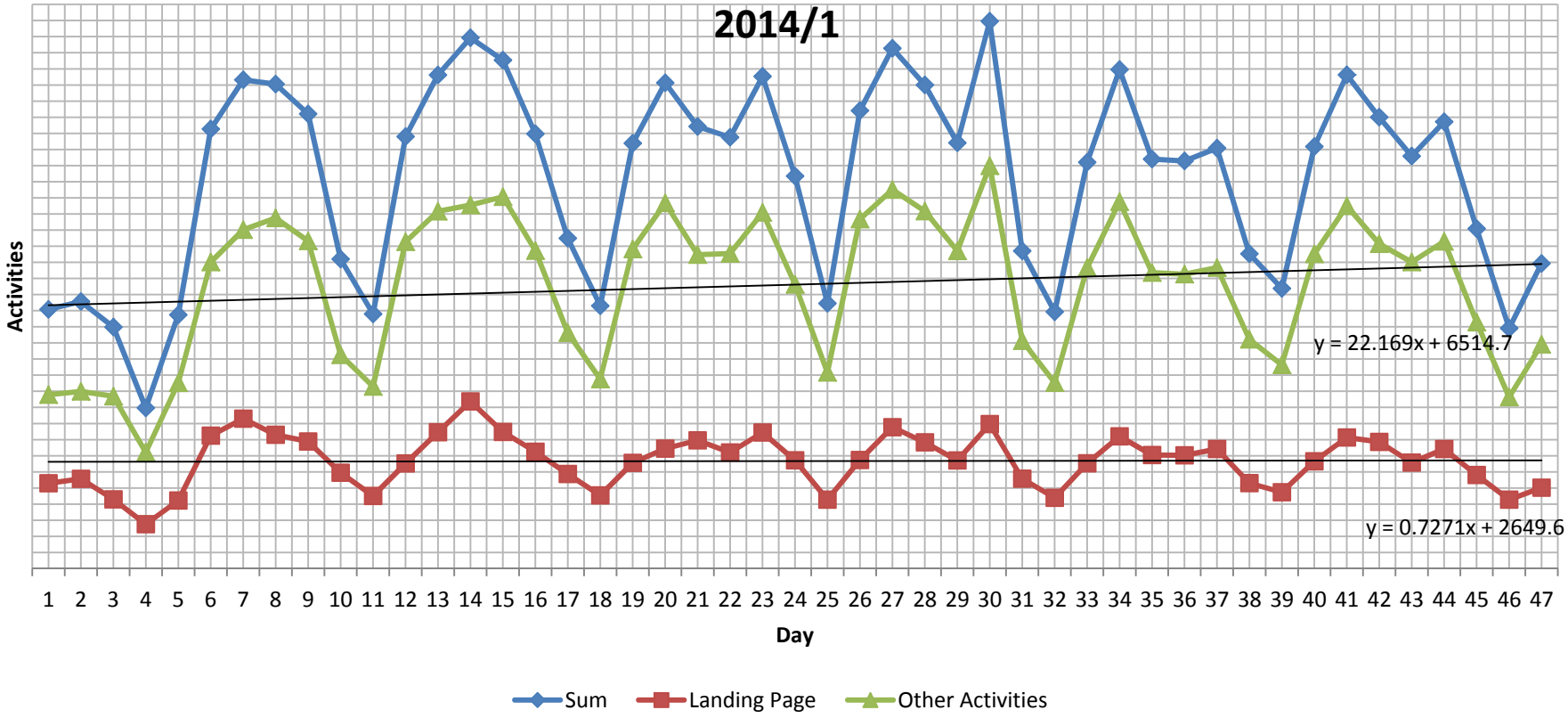
Course Periodic Behavior Modelling

Observation (Training Set)



N Temiyasathit, P Punyabukkana, A Suchato, “Course periodic behavior modelling and its application in LMS activity prediction”, 2016 IEEE Global Engineering Education Conference (EDUCON), 1164-1174

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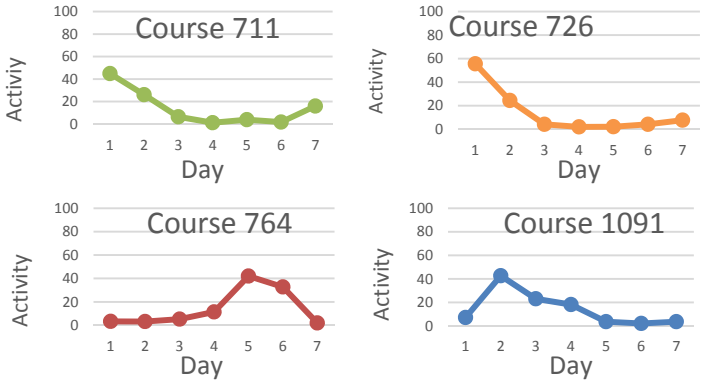
Course Periodic Behavior Modelling



Test Data (2015/1)

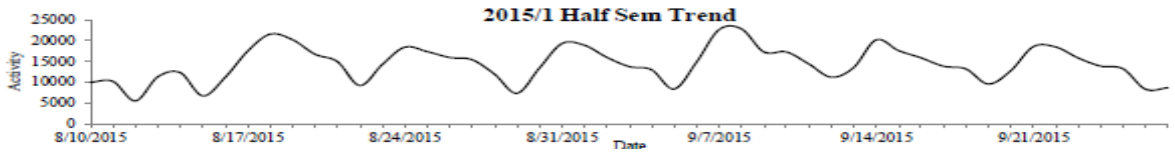
Pattern Normalization

Course Clustering

Training Data (2014/1)

Activity Prediction / Aggregation

Prediction Result



N Temiyasathit, P Punyabukkana, A Suchato, “Course periodic behavior modelling and its application in LMS activity prediction”, 2016 IEEE Global Engineering Education Conference (EDUCON), 1164-1174

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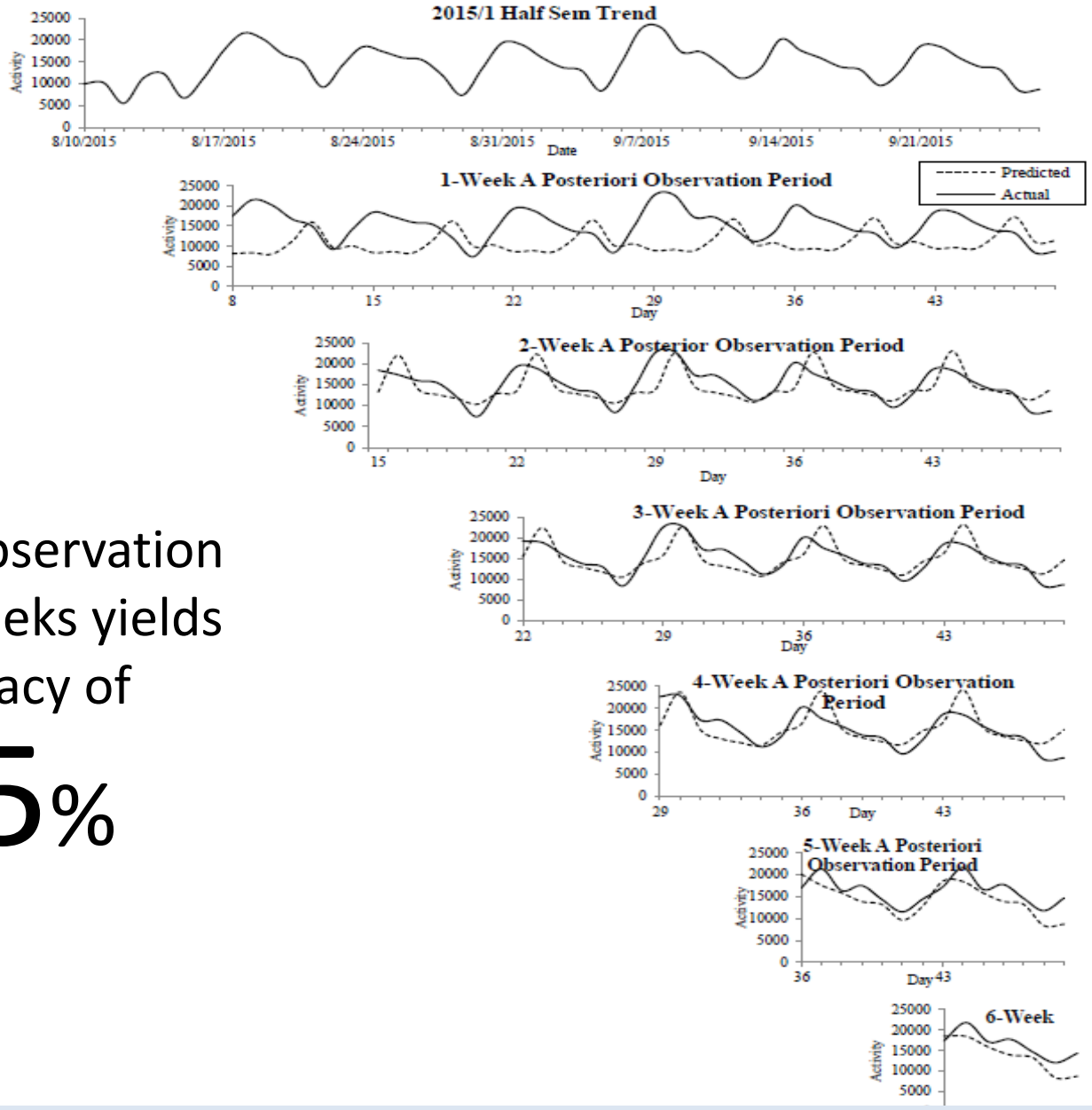
Learning Analytics



- A posteriori observation period of 3 weeks yields the best accuracy of

84.35%

N Temiyasathit, P Punyabukkana, A Suchato, “Course periodic behavior modelling and its application in LMS activity prediction”, 2016 IEEE Global Engineering Education Conference (EDUCON), 1164-1174

TALE 2016, Bangkok, Thailand
December 7-9, 2016

Understanding Knowledge Areas in Curriculum through Text Mining from Course Materials

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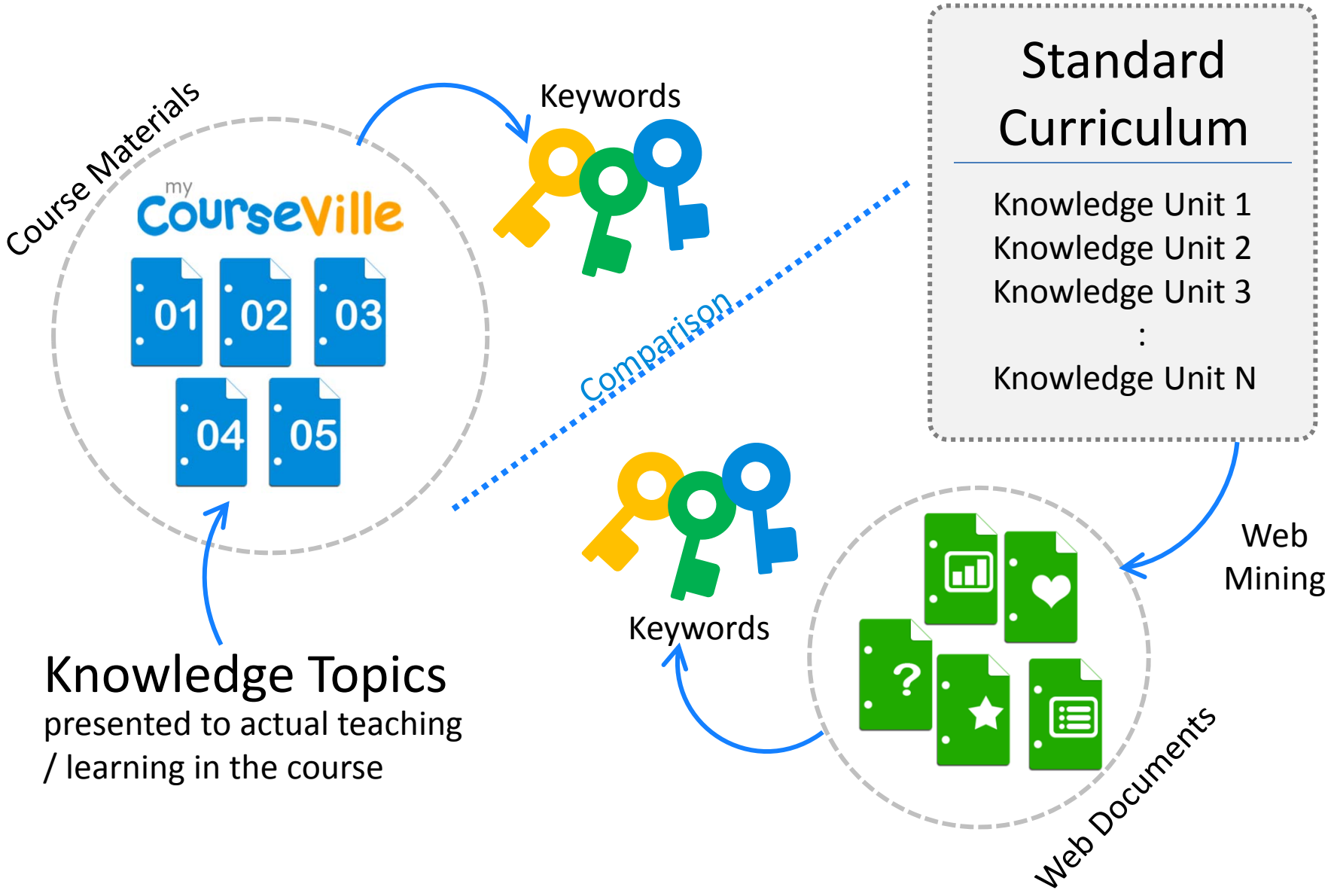
***Abstract*—Curriculum analysis is attracting widespread interest in educational field. There are two main approaches: (*i*) human-based and (*ii*) text-based assessments. Although an evaluation by teachers and learners are widely used, it is inconvenient and time-consuming. Also, the results absolutely rely on individual attitude. The text-based approach aims to directly evaluate the course syllabus; however, there is only a course description in the syllabus, so this cannot really express the actual course contents. In this paper, we present an automatic text-based curriculum analysis that straightforwardly assesses entire course materials. Our approach employs a well-known text-mining technique that extracts keywords using TF-IDF. The analysis is based on keywords from the course materials matching to the keywords from online documents, which is similar to the domain expert. Moreover, a new measurement is proposed to quantify associations between course materials and online documents using amounts of matching keywords. The experiment was conducted on materials of three subjects collected from five top universities mapping to the latest Computer Engineering Curricular Guideline (CE2016). The results illustrate significant relations among courses from different universities and CE2016. To further analyze the courses, each of them are visualized using radar charts.**

***Keywords*—curriculum analysis; curriculum evaluation; course content analysis; keyword extraction; TF-IDF;**

The well-known institution of educational society named "ACM Education Board and the IEEE Computer Society's Education", which have been working to establish curricular guideline for over 40 years, has released Computer Engineering Curricula CE2016 in October 2015 [9] to be a guideline for Undergraduate Degree Programs in Computer Engineering. In the guideline, 13 Knowledge Areas (KAs) were defined as related areas of computer engineering as shown in Table I. Moreover, each KA was divided into many sub topics termed Knowledge Units (KUs); the number of KUs corresponding to each KA is varied with extent of the KA. A number of researchers concentrated to examine the guideline document for various objectives. Sekiya, et al., tried to map linkages between two different guidelines and also between guideline and course syllabi [1] whereas Marshall quantified differences of structure among the guideline series [6].

TABLE I. KNOWLEDGE AREAS OF COMPUTER ENGINEERING IN CE2016

ID	Abbreviation	Knowledge Area
01	CAE	Circuits and Electronics
02	CAL	Computing Algorithms
03	CAO	Computer Architecture and Organization
04	DIG	Digital Design


Course Materials
my CourseVille
01
02
03
04
05
Keywords
Comparison
Standard Curriculum
Knowledge Unit 1
Knowledge Unit 2
Knowledge Unit 3
:
Knowledge Unit N
Web Mining
Keywords
Web Documents
Knowledge Topics
presented to actual teaching / learning in the course

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Inferring Coverage of Knowledge Units from Course Materials

Sample Results

Course materials collected from

5

institutes

- Chulalongkorn University
- University of Cambridge
- MIT
- Carnegie-Mellon University
- Stanford University

Knowledge Units defined by the **Association for Computing Machinery (ACM)**

Selected equivalent courses in

Computer Networks

and

Operating Systems

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Knowledge Units defined by the **Association for Computing Machinery (ACM)**

Computer Networks

Knowledge Units
Authentication
Computer Networks
Data communications
Local and wide area networks
Network and web security
Network applications
Network architecture
Network management
Network protocols
Performance evaluation
Wireless and mobile networks

Operating System

Knowledge Units
Additional emerging technologies
Applied emerging technologies
Conceptual emerging technologies
Managing system resources
Operating systems for mobile devices
Real-time operating system design
Scheduling algorithms
Support for concurrent processing
Support for virtualization
System performance evaluation
System Resource Management

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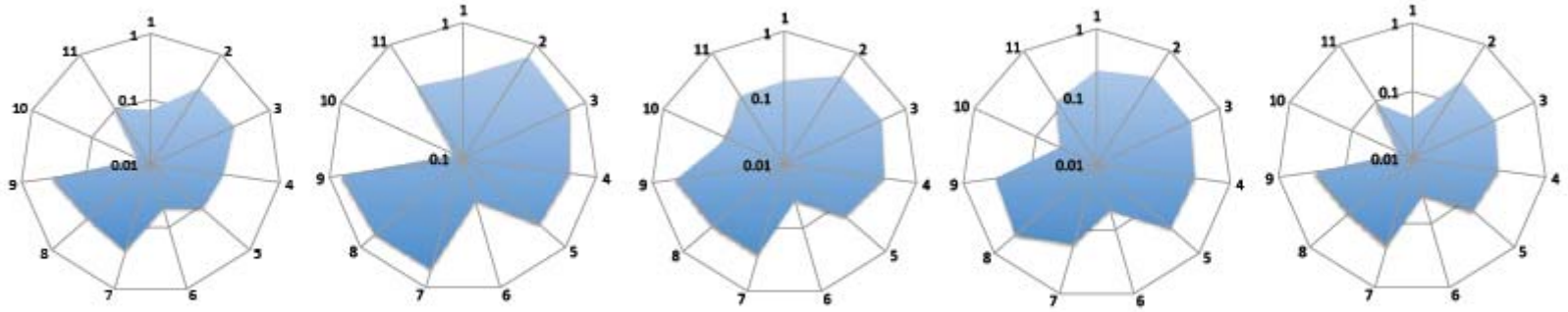
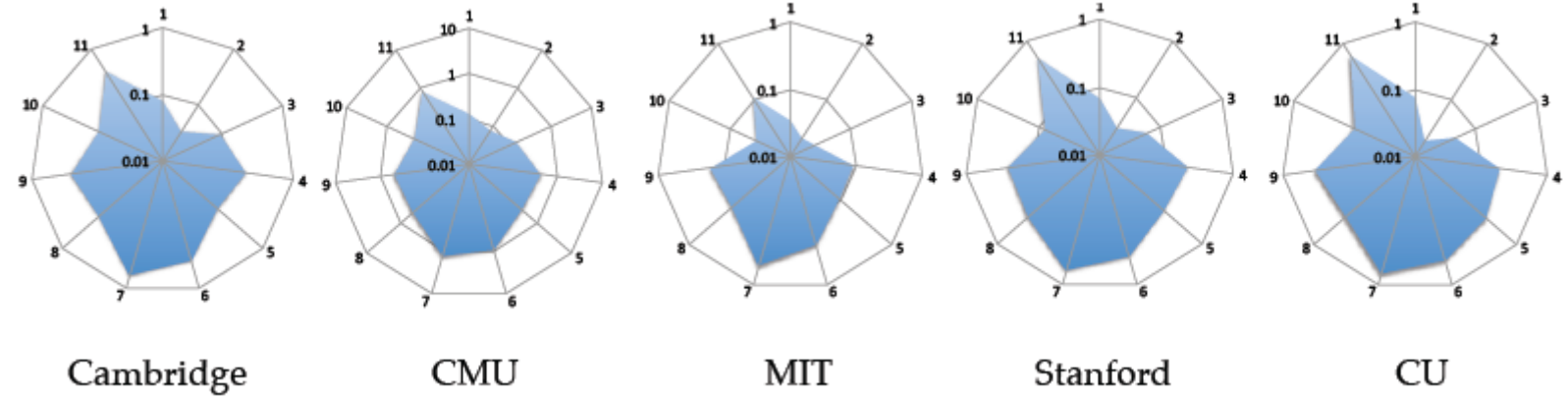
Inferring Coverage of Knowledge Units from Course Materials

Sample Results

Computer Networks



Operating Systems



Immediate Directions

- Online Course Platform
  - Life-long Learning
  - Blended Learning
- Outcome-based
  - E-portfolios of students / Curricular / Courses
  - Accreditations
- Learning Analytics