FROM EDUCATIONAL DATA MINING TO AUTOMATED ANALYSIS OF SEMANTICS

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@ifenthaler
MY BACKGROUND ...
• www.springer.com/10758

• Digital learning
• Gamification
• Learning analytics
• Automated assessment

• Submission types
  • Original research
  • Work-in-progress
  • Integrative review
  • Emerging technology report
  • Book review

• Special Section: Learning with Data – Visualization to Support Teaching, Learning, and Assessment
  http://www.ifenthaler.info/?p=745
AGENDA

• PASS Learning Analytics Framework
• Automated Semantic Analysis
PASS

PERSONALISED ADAPTIVE STUDY SUCCESS
LINEAR MODEL – STATIC CURRICULUM AND SINGLE LEARNING PATH

Student A:
- Demonstrated competencies
- Passed exam

Student B:
- Failed to demonstrate competencies
- Failed exam

- Start again
- Move forward

- Week 1
- Week 2
- Week 3
- Week 4
- Week 5
- Week 6
- Week 7
- Week 8
- Week 9
- Week 10
- Week 11
- Week 12

- Lecture
- Tutorial

- ✔
- ✗
DYNAMIC MODEL – PERSONALISED AND ADAPTIVE LEARNING PATH

Demonstrated competencies

Failed to demonstrate competencies

Move forward

PASS EXAM

ACHIEVED
HOLISTIC REQUIREMENTS

(Mega) ---(GOVERNANCE)--- (Macro)

(Macro) ---(INSTITUTION)--- (Meso)

(Meso) ---(CURRICULUM)--- (Micro)

(Micro) ---(TEACHER TUTOR)--- (Micro)

(LRNER) ---(ONLINE LEARNING ENVIRONMENT)--- (Micro)

(PHYSICAL LEARNING ENVIRONMENT) ---(LEARNING ANALYTICS)--- (Macro)

(IFenthaler, in press)
### BENEFITS MATRIX

<table>
<thead>
<tr>
<th>Governance</th>
<th>Summative</th>
<th>Real-time</th>
<th>Predictive</th>
</tr>
</thead>
</table>
|            | o Apply cross-institutional comparisons  
|            | o Develop benchmarks  
|            | o Inform policy making  
|            | o Inform quality assurance processes  
|            | o Increase productivity  
|            | o Apply rapid response to critical incidents  
|            | o Analyse performance  
|            | o Model impact of organisational decision-making  
|            | o Plan for change management  

<table>
<thead>
<tr>
<th>Institution</th>
<th>Summative</th>
<th>Real-time</th>
<th>Predictive</th>
</tr>
</thead>
</table>
|             | o Analyse processes  
|             | o Optimise resource allocation  
|             | o Meet institutional standards  
|             | o Compare units across programs and faculties  
|             | o Monitor processes  
|             | o Evaluate resources  
|             | o Track enrolments  
|             | o Analyse churn  
|             | o Forecast processes  
|             | o Project attrition  
|             | o Model retention rates  
|             | o Identify gaps  

<table>
<thead>
<tr>
<th>Instructional design</th>
<th>Summative</th>
<th>Real-time</th>
<th>Predictive</th>
</tr>
</thead>
</table>
|                       | o Analyse pedagogical models  
|                       | o Measure impact of interventions  
|                       | o Increase quality of curriculum  
|                       | o Compare learning designs  
|                       | o Evaluate learning materials  
|                       | o Adjust difficulty levels  
|                       | o Provide resources required by learners  
|                       | o Identify learning preferences  
|                       | o Plan for future interventions  
|                       | o Model difficulty levels  
|                       | o Model pathways  

<table>
<thead>
<tr>
<th>Facilitator</th>
<th>Summative</th>
<th>Real-time</th>
<th>Predictive</th>
</tr>
</thead>
</table>
|             | o Compare learners, cohorts and courses  
|             | o Analyse teaching practises  
|             | o Increase quality of teaching  
|             | o Monitor learning progression  
|             | o Create meaningful interventions  
|             | o Increase interaction  
|             | o Modify content to meet cohorts' needs  
|             | o Identify learners at risk  
|             | o Forecast learning progression  
|             | o Plan interventions  
|             | o Model success rates  

<table>
<thead>
<tr>
<th>Learner</th>
<th>Summative</th>
<th>Real-time</th>
<th>Predictive</th>
</tr>
</thead>
</table>
|         | o Understand learning habits  
|         | o Compare learning paths  
|         | o Analyse learning outcomes  
|         | o Track progress towards goals  
|         | o Receive automated interventions and scaffolds  
|         | o Take assessments including just-in-time feedback  
|         | o Optimise learning paths  
|         | o Adapt to recommendations  
|         | o Increase engagement  
|         | o Increase success rates  

(Ienthaler, in press)
LEARNING ANALYTICS PROCESS

Feedback for optimisation

Access information

Validate, compute, and predict

Model using engine
DEFINING CONCEPTS

• **Educational data mining** (EDM) refers to the process of extracting useful information out of a large collection of complex educational datasets (Romero, Ventura, Pechenizkiy, & Baker, 2011)

• **Academic analytics** (AA) is the identification of meaningful patterns in educational data in order to inform academic issues (e.g., retention, success rates) and produce actionable strategies (e.g., budgeting, human resources) (Campbell, DeBlois, & Oblinger, 2010)

• **Learning analytics** (LA) uses dynamic information about learners and learning environments - assessing, eliciting and analysing them - for real-time modelling, prediction, and optimisation of learning processes and learning environments (Ifenthaler et al., 2014)
PASS FRAMEWORK

INDIVIDUAL CHARACTERISTICS
- Interest
- Prior knowledge
- Academic performance
- Standardised inventories
- Competencies
- Socio-demographic data

SOCIAL WEB
- Identity and sense of self
- Personal network
- Social ties
- Peer interaction
- Social media preferences

PHYSICAL DATA
- Current experiences
- Location
- Health
- Emotion
- Motivation

ONLINE LEARNING ENVIRONMENT
- Learning path & time
- Interaction data
- Content navigation
- Discussion activity
- Assessment
- Performance
- Ratings
- Satisfaction

LEARNING ANALYTICS ENGINE
- Pedagogical theories
- Data mining
- Structured data
- Unstructured data
- Natural language processing
- Algorithms
- Validation
- Comparison
- Patterns
- Prediction

PERSONALISATION AND ADAPTATION ENGINE
- Visualisation
- Prompts
- Scaffolding
- Feedback
- Recommendation
- Gamification

REPORTING ENGINE
- Dashboard
- Heatmap
- Statistics and graphs
- Automated report

CURRICULUM
- Requirements
- Learning design
- Sequencing
- Learning objectives
- Learning outcomes
- Assessment
- Evaluation

GOVERNANCE
- Decision-making

INSTITUTION
- Strategies

(Ifenthaler, in press)
PASS PROFILES

(Student profiles)  (Learning profiles)  (Curriculum profiles)

Static parameters  Dynamic parameters  Static parameters

Analytics

Intervention

(Ifenthaler & Widanapathirana, 2014)
Many research studies have clearly demonstrated the importance of cognitive structures as the building blocks of meaningful learning and retention of instructional materials. Identifying the learners' cognitive structures will help instructors to organize materials, identify knowledge gaps, and relate new materials to existing slots or anchors within the learners' cognitive structures. The purpose of our empirical investigation is to track the development of cognitive structures over time. Accordingly, we demonstrate how various indicators…
PASS PROTOTYPE – FACILITATOR VIEW

Learning environment usage

Individual student activity
Students without activity
Smith, Andrew
Taylor, Frank
Wagner, Steve

At risk

Assignment submissions

Top discussion topics

Learning materials

Satisfaction

Student at risk

Student monitoring

Personalise environment

Student engagement
PASS PROTOTYPE – INSTRUCTIONAL DESIGNER VIEW

Alignment of student behaviour and learning design

Student engagement
Dynamic reporting
Quality assurance
Personalise environment
Alignment of student behaviour and learning design
PASS VALIDATION STUDY FOR STUDENT AND LEARNING PROFILES
VALIDATION STUDENT PROFILE: HYPOTHESES

• Hypotheses 1a: It is hypothesized that student profile factors can be identified which explain at least 40% of variance of study unit outcomes.

• Hypothesis 1b: It is hypothesized that the student profile can predict study unit outcomes with at least 80% accuracy.

• Hypothesis 1c: It is hypothesized that the explained variance of the student profile differs across higher education institutions.

• Hypothesis 1d: It is hypothesized that the explained variance of the student profile differs across area of studies.
VALIDATION STUDENT PROFILE: METHOD

- Data source: CRM database of Open Universities Australia

- $N = 1,030,778$ enrolments

- $N = 146,001$ students (54,073 male, 91,928 female)

- $N = 1,509$ study units

- $N = 650,179$ graded study units (359,849 passed, 290,330 failed)

- 3-step validation approach
  - Descriptive analysis
  - Multiple regression analysis
  - Support Vector Machines analysis
VALIDATION STUDENT PROFILE: DESCRIPTIVE ANALYSIS

Figure 1. Educational background and study success
VALIDATION STUDENT PROFILE: DESCRIPTIVE ANALYSIS

Figure 2. Socio-economic status and study success
VALIDATION STUDENT PROFILE: DESCRIPTIVE ANALYSIS

Figure 3. Study area and institution
VALIDATION STUDENT PROFILE: REGRESSION ANALYSIS

Table 1. Student profile – regression models

<table>
<thead>
<tr>
<th>Model</th>
<th>$R^2$</th>
<th>Adjusted $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>0.0567</td>
<td>0.0567***</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.1281</td>
<td>0.1280***</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.1867</td>
<td>0.1865***</td>
</tr>
<tr>
<td>Model 4</td>
<td>0.3613</td>
<td>0.3611***</td>
</tr>
<tr>
<td>Model 5</td>
<td>0.4408</td>
<td>0.4457***</td>
</tr>
<tr>
<td>Model 6</td>
<td>0.4435</td>
<td>0.4354***</td>
</tr>
</tbody>
</table>

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

- Model 1: Demographic data
- Model 2: + educational background
- Model 3: + educational background parents
- Model 4: + enrollment data
- Model 5: + past study history
- Model 6: + past study success
VALIDATION STUDENT PROFILE: REGRESSION ANALYSIS

Figure 4. Most important predictors of Model 6 (all \( p < .001 \))
VALIDATION STUDENT PROFILE: SUPPORT VECTOR MACHINES

Table 2. Student profile – Comparison of SVM Models

<table>
<thead>
<tr>
<th></th>
<th>R²</th>
<th>Adjusted R²</th>
<th>R²-SVR</th>
<th>Predictive accuracy (SVM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>0.0567</td>
<td>0.0567***</td>
<td>0.0592</td>
<td>0.586</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.1281</td>
<td>0.1280***</td>
<td>0.1296</td>
<td>0.638</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.1867</td>
<td>0.1865***</td>
<td>0.1918</td>
<td>0.675</td>
</tr>
<tr>
<td>Model 4</td>
<td>0.3613</td>
<td>0.3611***</td>
<td>0.424</td>
<td>0.795</td>
</tr>
<tr>
<td>Model 5</td>
<td>0.4408</td>
<td>0.4457***</td>
<td>0.4378</td>
<td>0.797</td>
</tr>
<tr>
<td>Model 6</td>
<td>0.4435</td>
<td>0.4354***</td>
<td>0.4505</td>
<td><strong>0.803</strong></td>
</tr>
</tbody>
</table>

Note. * p < .05, ** p < .01, *** p < .001
### Table 3. Student profile – comparison of institutions

<table>
<thead>
<tr>
<th>Institution</th>
<th>N</th>
<th>R²</th>
<th>Adjusted R²</th>
<th>R²-SVR</th>
<th>Predictive accuracy (SVM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRT</td>
<td>244494</td>
<td>0.4635</td>
<td><strong>0.4633</strong>*</td>
<td>0.4889</td>
<td><strong>0.817</strong></td>
</tr>
<tr>
<td>GRF</td>
<td>217039</td>
<td>0.4528</td>
<td><strong>0.4526</strong>*</td>
<td>0.4603</td>
<td>0.796</td>
</tr>
<tr>
<td>SWI</td>
<td>127218</td>
<td>0.431</td>
<td><strong>0.4306</strong>*</td>
<td>0.4595</td>
<td>0.796</td>
</tr>
<tr>
<td>USA</td>
<td>114432</td>
<td>0.372</td>
<td><strong>0.3716</strong>*</td>
<td>0.3807</td>
<td>0.766</td>
</tr>
<tr>
<td>MAQ</td>
<td>88026</td>
<td>0.4379</td>
<td><strong>0.4374</strong>*</td>
<td>0.4430</td>
<td>0.807</td>
</tr>
<tr>
<td>RMT</td>
<td>84510</td>
<td>0.3641</td>
<td><strong>0.3635</strong>*</td>
<td>0.3530</td>
<td><strong>0.763</strong></td>
</tr>
<tr>
<td>MON</td>
<td>76278</td>
<td>0.434</td>
<td><strong>0.4334</strong>*</td>
<td>0.4604</td>
<td>0.803</td>
</tr>
<tr>
<td>MUR</td>
<td>73043</td>
<td>0.3718</td>
<td><strong>0.3711</strong>*</td>
<td>0.3562</td>
<td>0.783</td>
</tr>
<tr>
<td>SD</td>
<td></td>
<td>0.096</td>
<td>0.097</td>
<td>0.126</td>
<td>0.024</td>
</tr>
</tbody>
</table>

*Note. *p < .05, **p < .01, ***p < .001*
VALIDATION STUDENT PROFILE: SUPPORT VECTOR MACHINES

Table 4. Student profile – comparison of areas of study

<table>
<thead>
<tr>
<th>Areas of study</th>
<th>N</th>
<th>R²</th>
<th>Adjusted R²</th>
<th>R²-SVR</th>
<th>Predictive accuracy (SVM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arts &amp; Humanities</td>
<td>386059</td>
<td>0.4299</td>
<td>0.4297</td>
<td>0.45039</td>
<td>0.799</td>
</tr>
<tr>
<td>Business</td>
<td>269410</td>
<td>0.4054</td>
<td>0.4053</td>
<td>0.4360</td>
<td>0.780</td>
</tr>
<tr>
<td>Education</td>
<td>157693</td>
<td>0.4887</td>
<td>0.4885</td>
<td>0.5049</td>
<td>0.824</td>
</tr>
<tr>
<td>Law &amp; Justice</td>
<td>84663</td>
<td>0.4900</td>
<td><strong>0.4896</strong></td>
<td>0.5166</td>
<td><strong>0.827</strong></td>
</tr>
<tr>
<td>IT</td>
<td>57371</td>
<td>0.3732</td>
<td><strong>0.3726</strong></td>
<td>0.3586</td>
<td><strong>0.776</strong></td>
</tr>
<tr>
<td>Science &amp; Engineering</td>
<td>57234</td>
<td>0.4228</td>
<td>0.422</td>
<td>0.4234</td>
<td>0.800</td>
</tr>
<tr>
<td>SD</td>
<td></td>
<td>0.107</td>
<td>0.107</td>
<td>0.129</td>
<td>0.027</td>
</tr>
</tbody>
</table>

*Note.* *p < .05, **p < .01, ***p < .001
A CHALLENGE FOR ESTABLISHING A LA FRAMEWORK IS THE INTERACTION AND FRAGMENTATION OF INFORMATION AS WELL AS ITS CONTEXTUAL IDIOSYNCRASIES
VALIDATION LEARNING PROFILE: HYPOTHESES

• Hypotheses 2a: It is hypothesized that learning profile factors can be identified which explain at least 80% of variance of study unit outcomes.

• Hypothesis 2b: It is hypothesized that the learning profile can predict study unit outcomes with at least 80% accuracy.

• Hypothesis 2c: It is hypothesized that the explained variance of the learning profile increases over the course of the study period.

• Hypothesis 2d: It is hypothesized that the predictive accuracy of the learning profile increases over the course of the study period.
VALIDATION LEARNING PROFILE: METHOD

• Data source: Learning Management System (LMS)

• $N = 12,002$ students (4,201 male, 7,801 female)

• $n_1 = 7,024$ students in *Principles of Project Management*

• $n_2 = 4,978$ students in *Writing for the Web*

• 4 study periods, 4 weeks each (total 16 weeks)

• 3-step validation approach
  – Descriptive analysis
  – Multiple regression analysis
  – Support Vector Machines analysis
VALIDATION LEARNING PROFILE: DESCRIPTIVE ANALYSIS

Figure 5. Enrollment, unit version and study success for Principles of Project Management
VALIDATION LEARNING PROFILE: DESCRIPTIVE ANALYSIS

Figure 6. Enrollment, unit version and study success for Writing for the Web
<table>
<thead>
<tr>
<th></th>
<th>Period 1</th>
<th>Period 3</th>
<th>Period 3</th>
<th>Period 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Writing for the Web</strong></td>
<td>0.4673</td>
<td>0.7613</td>
<td>0.8366</td>
<td>0.8592</td>
</tr>
<tr>
<td><strong>Project management</strong></td>
<td>0.4971</td>
<td>0.7572</td>
<td>0.8206</td>
<td>0.8359</td>
</tr>
<tr>
<td><strong>Combined</strong></td>
<td>0.4880***</td>
<td>0.7593***</td>
<td><strong>0.8273</strong>*</td>
<td><strong>0.8439</strong>*</td>
</tr>
<tr>
<td><strong>R²-SVR</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Writing for the Web</strong></td>
<td>0.4972</td>
<td>0.7571</td>
<td>0.8403</td>
<td>0.8563</td>
</tr>
<tr>
<td><strong>Project management</strong></td>
<td>0.5423</td>
<td>0.7856</td>
<td>0.8449</td>
<td>0.869</td>
</tr>
<tr>
<td><strong>Combined</strong></td>
<td>0.5284</td>
<td>0.7841</td>
<td>0.8602</td>
<td>0.8777</td>
</tr>
<tr>
<td><strong>Predictive accuracy (SVM)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Writing for the Web</strong></td>
<td>0.7498</td>
<td>0.8754</td>
<td>0.9326</td>
<td>0.9467</td>
</tr>
<tr>
<td><strong>Project management</strong></td>
<td>0.7694</td>
<td>0.8807</td>
<td>0.9351</td>
<td>0.9433</td>
</tr>
<tr>
<td><strong>Combined</strong></td>
<td>0.7644</td>
<td><strong>0.8879</strong></td>
<td><strong>0.9383</strong></td>
<td><strong>0.9463</strong></td>
</tr>
</tbody>
</table>
NOT ALL EDUCATIONAL DATA IS RELEVANT AND EQUIVALENT FOR LEARNING ANALYTICS
ETHICAL ISSUES ARE ASSOCIATED WITH THE USE OF EDUCATIONAL DATA FOR LEARNING ANALYTICS
LIMITED ACCESS TO EDUCATIONAL DATA GENERATES DISADVANTAGES FOR INVOLVED STAKEHOLDERS
THE PREPARATION OF STAKEHOLDERS FOR APPLYING INSIGHTS FROM LEARNING ANALYTICS IN A MEANINGFUL WAY IS VITAL
INFORMATION FROM DISTRIBUTED NETWORKS AND UNSTRUCTURED DATA CANNOT BE DIRECTLY LINKED TO EDUCATIONAL DATA COLLECTED WITHIN AN INSTITUTION’S ENVIRONMENT
AN OPTIMAL SEQUENCE OF DATA COLLECTION AND ECONOMIC RESPONSE TIMES (SECONDS, MINUTES, HOURS, DAYS, WEEKS) OF LEARNING ANALYTICS HAVE YET TO BE DETERMINED
BESIDES THE ANALYSIS OF NUMERICAL DATA (E.G., CLICK STREAMS), A QUALITATIVE ANALYSIS OF SEMANTIC RICH DATA (E.G., DISCUSSION FORUMS, RESPONSES TO OPEN-ENDED ASSESSMENTS) ENABLES A BETTER UNDERSTANDING OF LEARNERS’ KNOWLEDGE AND NEEDS.
AGENDA

• PASS Learning Analytics Framework

• Automated Semantic Analysis
WHAT IS THE PURPOSE OF AN ONLINE DISCUSSION FORUM?
ONLINE DISCUSSION FORUM?

• Community building / social interaction
• Organisation and elaboration of subject matter
• In-depth reflection
• Problem solving, critical thinking
• Peer- and facilitator feedback
• Alternative assessment
• ....

(e.g., Ko & Rossen, 2010)
IS AN ONLINE DISCUSSION FORUM A KEY COMPONENT TO ACHIEVE LEARNING OUTCOMES?
ONLINE DISCUSSION FORUM?

(e.g., Ko & Rossen, 2010)

Interindividual differences for modules
- Assignment, $Z = 1.856, p = .002$
- Chat, $Z = 2.582, p < .001$
- Course, $Z = 2.545, p < .001$
- Forum, $Z = 3.078, p < .001$
- Page, $Z = 2.034, p = .001$
- Quiz, $Z = 1.843, p = .002$
- Resource, $Z = 1.906, p = .001$
- User, $Z = 3.013, p < .001$
(N = 1342; \( R^2 = .325; \)
\( F = 2.988, p = .004 \))
ARE STUDENTS WHO ARE ENGAGED IN ONLINE DISCUSSION FORUMS MORE LIKELY TO PASS AN ONLINE COURSE?
Top 5 new courses wanted!
by Jennifer C1 - Fri, 17 May 2013, 3:37 PM

Hi everyone! What would be your top 5 courses you would like to use on open2study?

Mine would be:
1. Philosophy/History of science
2. Australian Aboriginal history and culture
3. Documentary Film making
4. Writing and publishing
5. Introduction to Law

Do you agree? What is your top 5?

Re: Top 5 new courses wanted!
by Harrie1D - Sun, 19 May 2013, 5:47 PM

Australian Aboriginal history and culture would be a subject I would be interested in. Environmental studies interesting. And more health and fitness subjects!

Re: Top 5 new courses wanted!
by L. Jansen - Wed, 29 Jun 2013, 5:29 AM

Concepts of physics. Not the pure mathematical approach, but the conceptual. With a focus on quantum mechanics. Like:
- Gravity
- Light
- Relativity theory
- Schrödinger's cat
- Silt-experiment
- Hadron collider
- Entanglement
- Superposition

Principles of Project Management
by cryptons - Fri, 10 May 2013, 8:28 AM

Ref: Module 2 - Topic 1: Project Manager Role

Have any of my fellow classmates tried out the MBTI Survey in the readings?

MBTI Style Questionnaire:
http://www.humanmetrics.com/cgi-win/1Types2.asp

This is related to the Myers-Briggs Type Indicator (MBTI)

The Personality Types:
Introvert, Sensing, Thinking, Judging, Extravert, Intuitive, Feeling, Perceiving.

The Presenter stated she was: Sue Drewson = ENFJ

Myself cryptons = INFP (Which obviously isn’t a great role for PM, but it does link to other career choices, which I think is more accurate to my personality type.

I would love to hear what my fellow classmate’s personality types were and if they felt it resembled their personality in anyway.
HOW TO AUTOMATE THE ANALYSIS OF SEMANTIC INFORMATION IN DISCUSSION FORUMS?
A LANGUAGE-ORIENTED APPROACH
Why online discussion forums?

- Builds class community by promoting discussion on course topics
- Allows me for in-depth reflection; students have more time to reflect, research & compose their thoughts before participating in the discussion
- Facilitates learning by allowing students to view & respond to the work of others
- Develops thinking & writing skills
- Allows guest experts to participate in the course by posing information & responding to questions

A language-oriented approach?
WHAT IS CLOSELY RELATED IS ALSO CLOSELY EXTERNALIZED

(POLLIO, 1966)
CLOSER RELATIONS TEND TO BE PRESENTED MORE CLOSELY WITHIN A TEXT

(PIRNAY-DUMMER & IFENTHALER, 2011)
TEXTS WHICH CONTAIN 300 OR MORE WORDS MAY BE USED TO GENERATE ASSOCIATIVE NETWORKS AS GRAPHS
(IFENTHALER, 2014)
<p>My name is Elizabeth; I am currently living in Sydney with my husband, and will.<p>With my uncertain work schedule I plan to spend 5 minutes every Sunday looking</p>

<p>Hi Elizabeth,</p>

<p>It is nice to see someone who has a world or job rather in the same industry as</p>

<p>The schedule is something I can totally relate to and would love to get an upda</p>
LANGUAGE-ORIENTED APPROACH

Syntactic analysis
- Cleaning (HTML, etc.)
- Tokenizing (sentences)
- Tagging (text corpus)
- Stemming (word stem)

Association measures
- Define length of sentence
- Identify pairs of words
- Distance for pairs of words and sentences
- Weight (shortest distance)

(e.g., Ifenthaler & Pirnay-Dummer, 2014)
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<th>node2</th>
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<tr>
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<tr>
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<tr>
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<td>33</td>
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<tr>
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<td>size</td>
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Student B
Student C
AKOVIA HAS

7 SIMILARITY MEASURES
0 \leq s \leq 1
0 = exclusion
1 = identity
Concept Matching

\[ \bigcup (v_i) \]

Propositional Matching

\[ \bigcup (v_i, e_j, v_k) \]

Balanced Semantic Matching

\[
\tau = \frac{s_{A,B} \left( \bigcup (v_{1,i}, e_{1,j}, v_{1,k}), \bigcup (v_{2,i}, e_{2,j}, v_{2,k}) \right)}{s_{A,B} \left( \bigcup (e_{1,i}), \bigcup (e_{1,m}) \right)}
\]

Surface Matching

\[ \theta = f(e_i) \]

Graphical Matching

\[
\mu = \max_{i,j} \left\{ d(KSpT(e_{i,j})) \right\}
\]

Structural Matching

\[
\Gamma_{v,i}^V(V_v) = \bigcup_{u=i+2}^{i+v} \Gamma_{v,u}
\]

Gamma Matching

\[
\frac{n}{n!} \leq \gamma \leq \frac{2}{2 \cdot (n-2)!}
\]

(Ifenthaler & Pirnay-Dummer, 2014; Pirnay-Dummer, Ifenthaler, & Spector, 2010)
SURFACE MATCHING - SFM

- Size of the representation = sum of propositions

\[ s_{sfm} = 1 - \frac{|f_1 - f_2|}{\max(f_1, f_2)} = 1 - \frac{8 - 4}{8} \approx .50 \]

(Ifenthaler, 2010-a, 2014; Ifenthaler & Pirnay-Dummer, 2014)
GRAPHICAL MATCHING - GRM

- Complexity of a representation = diameter of the spanning tree of a model
- Diameter = longest shortest path of a spanning tree (Kruskal, 1957)

\[
\mu = \max_{i,j} \left\{ d(KSpT(e_{i,j}) \right\}
\]

\[
S_{grm} = 1 - \frac{|f_1 - f_2|}{\max(f_1, f_2)} = 1 - \frac{4 - 4}{4} \approx 1.00
\]

(Ifenthaler, 2010-a, 2014; Ifenthaler & Pirnay-Dummer, 2014)
**GAMMA MATCHING - GAM**

- Connectedness of the representation: concepts per link
- Corrected gamma (scale of gamma between 0 and 1)

\[
\gamma_{\text{min}} = \frac{n_{\text{con}}}{n_{\text{con}}} \leq \gamma_{\text{min}} \leq 2
\]

\[
\gamma_{\text{cor}} = \frac{(\gamma - \gamma_{\text{min}})}{(2 - \gamma_{\text{min}})}
\]

\[
\gamma = \frac{6}{3} = 2
\]

\[
\gamma = \frac{15}{6} = 2.5
\]

\[
\gamma_{\text{min}} = 15; \gamma_{\text{cor}} = 0
\]

\[
\gamma_{\text{min}} = 15; \gamma_{\text{cor}} = .96
\]

\[
s_{\text{gam}} = 1 - \frac{|f_1 - f_2|}{\max(f_1, f_2)} = 1 - \frac{.96 - 0}{.96} \approx .00
\]

(Ifenthaler, 2010-a, 2014; Ifenthaler & Pirnay-Dummer, 2014)
STRUCTURAL MATCHING - STM

- Inner structure comparison
- Decomposition into sub-models

\[ s_{stm} = \frac{f(H \cap I)}{f(H \cap I) + \alpha \cdot f(H - I) + \beta \cdot f(I - H)} \]

\[ s_{smHI} = .32; s_{stmiJ} = .71; s_{stmlJ} = .47 \]

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<th>Sub graph</th>
<th>Trace-String</th>
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</tbody>
</table>

(Ifenthaler, 2010-a, 2014; Ifenthaler & Pirnay-Dummer, 2014)
CONCEPT MATCHING - CCM

- Semantic similarity of concepts
- Tversky similarity (Tversky, 1977)

\[
s_{ccm} = \frac{f(M \cap N)}{f(M \cap N) + \alpha \cdot f(M - N) + \beta \cdot f(N - M)}
\]

\[
s_{ccm} = \frac{7}{7 + 0.5 \cdot 1 + 0.5 \cdot 2} \approx 0.82
\]

(Ifenthaler, 2010-a, 2014; Ifenthaler & Pirnay-Dummer, 2014)
PROPOSITION MATCHING - PPM

- Semantic similarity of propositions (concept-link-concept)
- Tversky similarity (Tversky, 1977)

\[
s_{ppm} = \frac{f(M \cap N)}{f(M \cap N) + \alpha \cdot f(M - N) + \beta \cdot f(N - M)}
\]

\[
s_{ppm} = \frac{6}{6 + 0.5 \cdot 3 + 0.5 \cdot 4} \approx .63
\]

(Ifenthaler, 2010-a, 2014; Ifenthaler & Pirnay-Dummer, 2014)
BALANCED SEMANTIC MATCHING - BSM

• Combination of CCM and PPM

\[
\begin{align*}
S_{ppm} &= \frac{6}{6 + 0.5 \cdot 3 + 0.5 \cdot 4} \approx 0.63 \\
S_{ccm} &= \frac{7}{7 + 0.5 \cdot 1 + 0.5 \cdot 2} \approx 0.82
\end{align*}
\]

\[
S_{bsm} = \begin{cases} 
S_{ppm}, & S_{ccm} > 0 \\
0, & \text{else}
\end{cases}
\]

(Ifenthaler, 2010-a, 2014; Ifenthaler & Pirnay-Dummer, 2014)
WEBINTERFACE

Scientific Background!
What is knowledge? How can it be successfully assessed? How can we best use the results? As questions such as these continue to be discussed and the learning sciences continue to deal with expanding amounts of data, the challenge of applying theory to diagnostic methods takes on more complexity.

Read Online »

(Ifenthaler, 2014; Ifenthaler & Pirnay-Dummer, 2014)
WEB INTERFACE

(Afenthaler, 2014; Ifenthaler & Pirnay-Dummer, 2014)
SERVER FRAMEWORK

Raw data

E-Mail

Protocol

Analysis results

Analysis Server A

Analysis Server B

Analysis Server C

(Ifenthaler & Pirnay-Dummer, 2014; Pirnay-Dummer & Ifenthaler, 2010)
ARCHITECTURE

(Textfiles (1..n) UTF-8)

(tmitocar.xls)

(listform.xls)

(akoviacomm ands.xls)

(Upload)

(Validation)

(Valid?)

(no → Error Protocol)

(yes → Analysis & Visualisation)

(Results & Protocol) → Notification & Download (.zip)

(Ifenthaler & Pirnay-Dummer, 2014; Pirnay-Dummer & Ifenthaler, 2010)
AKOVIA OUTPUT

(compare, ganalyze)

results.xls

vis1.png, vis2.png, vis3.png, vis3.svg

protocol.txt

yourticket.zip

(Ifenthaler, 2014; Ifenthaler & Pirnay-Dummer, 2014)
### EASY SCRIPTING COMMANDS

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(Ifenthaler, 2014; Ifenthaler & Pirmay-Dummer, 2014)
## EASY SCRIPTING COMMANDS

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(Ifenthaler, 2014; Ifenthaler & Pirnay-Dummer, 2014)
(Ifenthaler, 2014; Ifenthaler & Pirnay-Dummer, 2014)
GRAPHICAL REPRESENTATIONS

(Ifenthaler, 2014; Ifenthaler & Pirnay-Dummer, 2014)
QUANTITATIVE INDICATORS

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</table>

(Ifenthaler, 2014; Ifenthaler & Pirnay-Dummer, 2014)
**EFECTIVITY OF DISCUSSION VISUALISATION**

\[ F(2.83, 144.15) = 97.37, p < .001, \eta^2 = .656 \]

\[ Z_{12} = 5.73, p < .001 \]
\[ Z_{23} = 5.59, p < .001 \]
\[ Z_{34} = 6.00, p < .001 \]
\[ Z_{45} = 6.25, p < .001 \]

(Ifenthaler, 2011; Pirnay-Dummer & Ifenthaler, 2011)
Repeated-measures
\[ F(4.13, 289.31) = 9.52, \]
\[ p < .001, \eta^2 = .120 \]

Interaction time x group
\[ F(8.27, 289.31) = 2.52, \]
\[ p = .006, \eta^2 = .067 \]
## RELIABILITY OF AKOVIA

Table 1. Test-retest reliability of AKOVIA measures

<table>
<thead>
<tr>
<th>Measure</th>
<th>Test-retest reliability</th>
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<td>Graphical Matching [GRM]</td>
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<td>Structural Matching [STM]</td>
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<td>Gamma Matching [GAM]</td>
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<tr>
<td>Concept Matching [CCM]</td>
<td>-</td>
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<tr>
<td>Propositional Matching [PPM]</td>
<td>.901**</td>
</tr>
<tr>
<td>Balanced Semantic Matching [BSM]</td>
<td>-</td>
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*Note.* **$p < .01$*
## VALIDITY OF AKOVIA

Table 2. Convergent and divergent validity of AKOVIA measures \((N = 1.849.296)\)

<table>
<thead>
<tr>
<th></th>
<th>1. BSM</th>
<th>2. CCM</th>
<th>3. PPM</th>
<th>4. SFM</th>
<th>5. GRM</th>
<th>6. STM</th>
<th>7. GAM</th>
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<td>1. Balanced Semantic Matching</td>
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<td>2. Concept Matching</td>
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<td>3. Propositional Matching</td>
<td>.91***</td>
<td>.68***</td>
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<td>4. Surface Matching</td>
<td>.20***</td>
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<td>.15***</td>
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*** \( p < .001 \)

(Pirnay-Dummer, Ifenthaler, & Spector, 2010)
THE OPPORTUNITY AND CHALLENGE OF LEARNING ANALYTICS IS THE VALID COMBINATION OF INSTRUCTIONAL DESIGN, PEDAGOGICAL MODELS, AS WELL AS EDUCATIONAL DATA (INCLUDING INDIVIDUAL LEARNER NEEDS AND CHARACTERISTICS) IN REAL TIME
IF THE ASSESSMENT AND ANALYSIS CAN BE CARRIED OUT AUTOMATICALLY AND IN REAL TIME...
... then its results can be used to inform both the decision-makers and the learners during an ongoing learning process.
STUDENT ENGAGEMENT AND SUCCESS DOES NOT ARISE BY CHANCE
(TINTO, 2009)
Learning Analytics
SELECTED REFERENCES


Ifenthaler, D., Masduki, I., & Seel, N. M. (2011). The mystery of cognitive structure and how we can detect it. Tracking the development of cognitive structures over time. *Instructional Science, 39*(1), 41-61. doi: 10.1007/s11251-009-9097-6


REFERENZEN


FROM EDUCATIONAL DATA MINING TO AUTOMATED ANALYSIS OF SEMANTICS

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