Find “Learning-Friends" in Online Social Networks

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Agenda

1. Project Mindstone
2. Social Network Integration
3. Computer Supported Collaborative Learning
4. Adaptive Systems
5. Mindstone Demonstrator Implementation

PROJECT MINDSTONE

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Project Mindstone

- Central goal:
  Content-centric contextual learning in social networks
- Point of departure:
  - Conversational enthusiasm in social networks
  - Computer-assisted knowledge acquisition
  - Peer-centric, lightweight communication technologies

Learning & the Internet-Paradigm

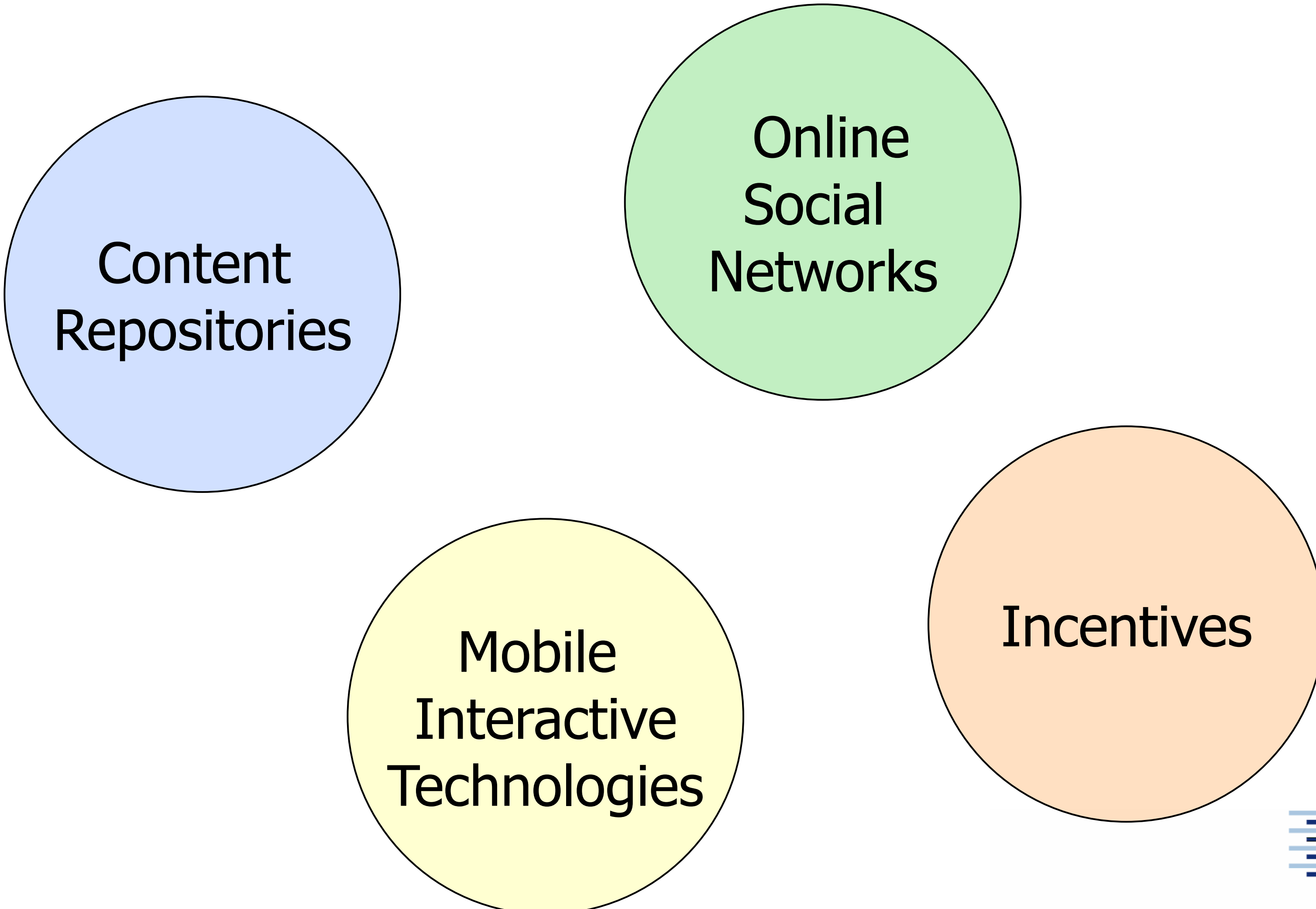
- Information is available
  - Everywhere, every time
- Information access is easy & fast
  - Unlimited, targeted, immediate & straightforward
- User actions follow an End-to-End paradigm
  - Intermediate regulation or mediation alienates
- Search & adaption remains self-determined
  - Personal trails through the net
  - Tools act as interfaces & (group) identifiers

eLearning Content – Traditional Management

- Learning Management System (LMS) manages
  - Download of scripts
  - Lecture recordings
  - Course composed like instructional films
  - Navigation serves as instructional design …

- Large, monolithic, rigid … directed
- Sender-oriented … impersonal

Aspects & Mindstones



Online Social Networks (OSN) Integration

- Develop a metric based approach in online social network (OSN) to measure
  - Distance in the sense of learning
  - Learning goal closeness
  - Learning style based group forming

SOCIAL NETWORK INTEGRATION

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Online Social Networks (OSN)

- Two anchor points
  - The people involve (presence and relations)
  - Topics in focus (network of content bricks)
- Can we integrate traditional learning approaches into social platforms?
  - Requires view on external contents
  - Requires incentives „learning as part of living"
  - Programming interfaces available (→ Facebook)

Integration Approach 1/2

- Create LMS integration for online social network
- Allows automatic measurements to asses learning goals or find collaborators
  - Measure from data persisted in social networks which learning style a user prefers
  - Find metrics which determine the "distance" between user in the sense of learning
  - Propose each user that someone is learning on the same topic

Integration Approach 2/2

- Allow metric result to be used by and metric input data gathered from social „apps“
  - M-Learning
  - E-Learning
  - Virtual Classroom (through chat...)
  - Serious games (game apps, like the sims social)

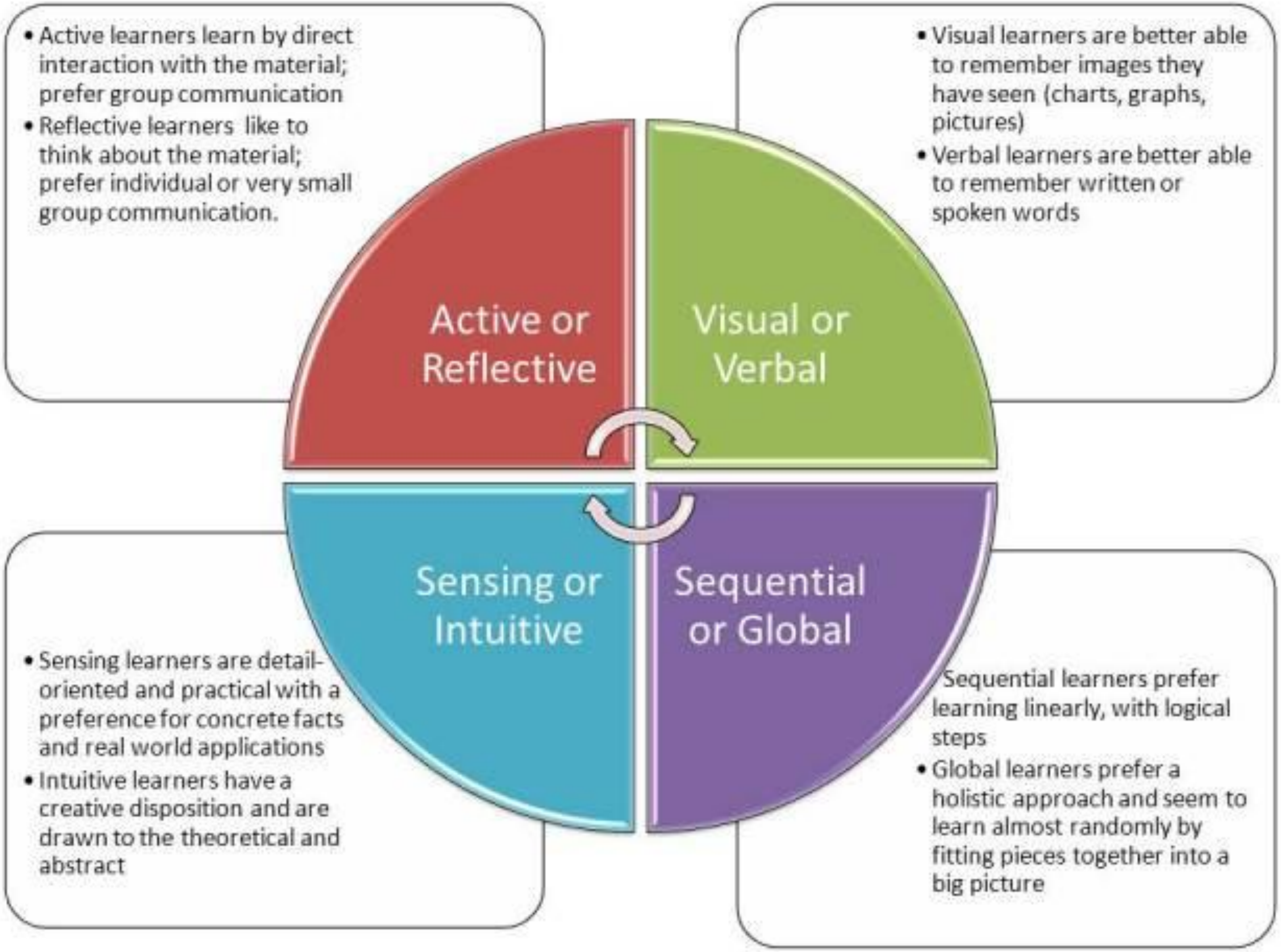
Current Research

- No research community in online social network learning
- Research is done in
  - Computer-supported Collaborative learning (CSCL)
  - Adaptive Educational Hypermedia (AEH)
- Both research areas discuss taxonomies / metrics to qualify
  - Learning style and skill recognition
  - Group forming

Learning Styles

- Learning style are widely used to adapt content or form group
- Widely accepted Learning style theory by Felder and Silverman [1]
- 4 Dimensions which can be qualified numerical
  - Scale between –11 and +11 per dimension
  - Questionnaire is mostly used to calculate the dimension

Felder & Silverman Dimension



[2]

COMPUTER SUPPORTED COLLABORATIVE LEARNING

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CSCL

- Computer-supported collaborative Learning (CSCL) aims to allow students to learn in a group of physically distributed students
- It is focused on the learning experience
- „Possibility of improving collaborative learning by grouping students in specific ways“ and „set of good rules for grouping students could be different for distinct disciplines“ [3]

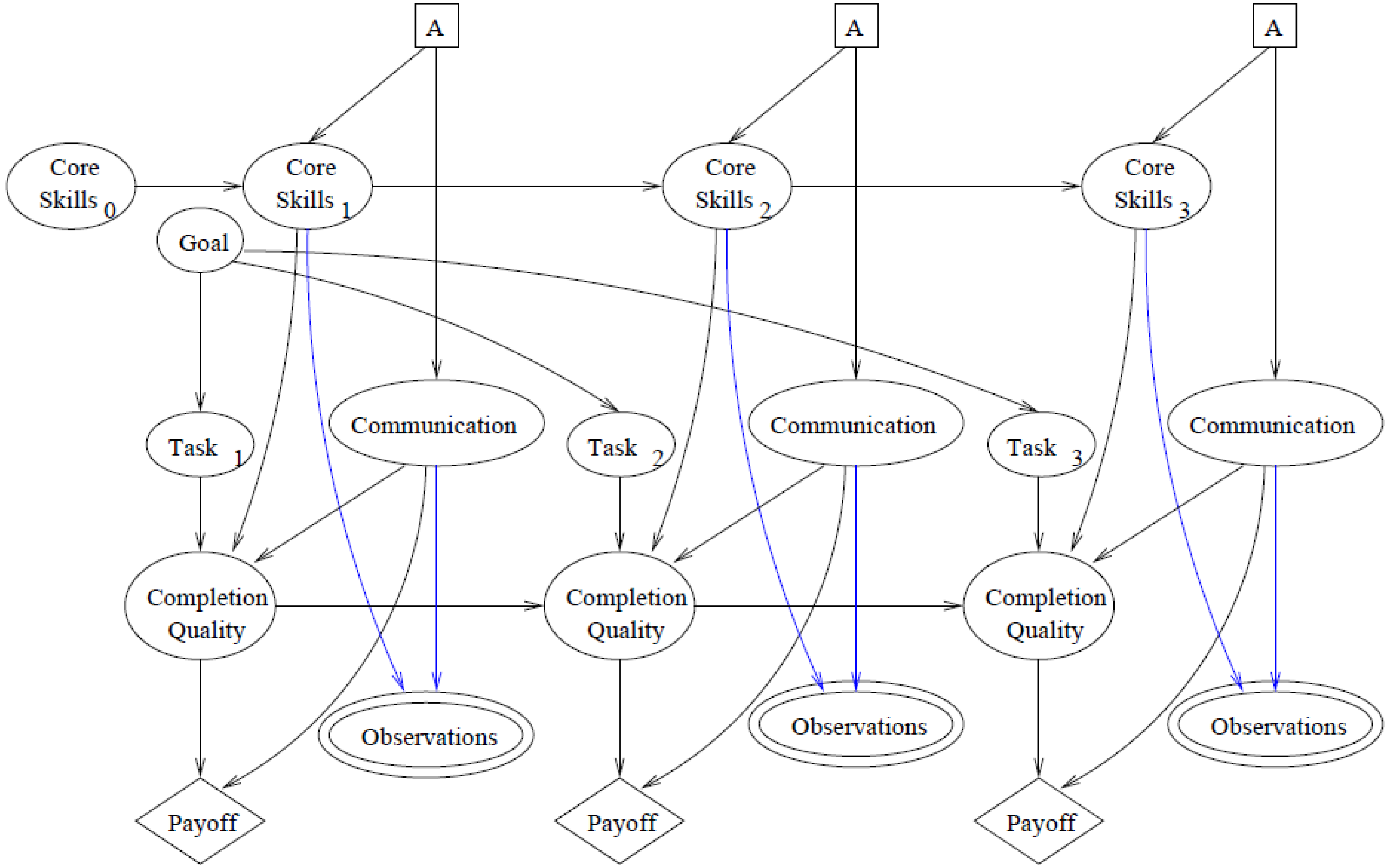
Learning Style Usage in CSCL

- Common to all approaches in CSCL research is measurement of certain key indicators to form a group of collaborator
- Often, learning style (e.g. Felder and Silverman theory) is a measure to achieve automatic grouping

One‘s Decision to Collaborate 1/3

- “Quantitative model of once decision to collaborate with others” [4]
- Available input to implement mechanism in adaptive system
  - Core skills i = skills of all users at time I
  - A = Set of actions enable user to collaborate with others
  - Completion Quality = yield a payoff for the user
  - Observation = User does not know his skills and communication abilities – has to be measured

One‘s Decision to Collaborate 2/3



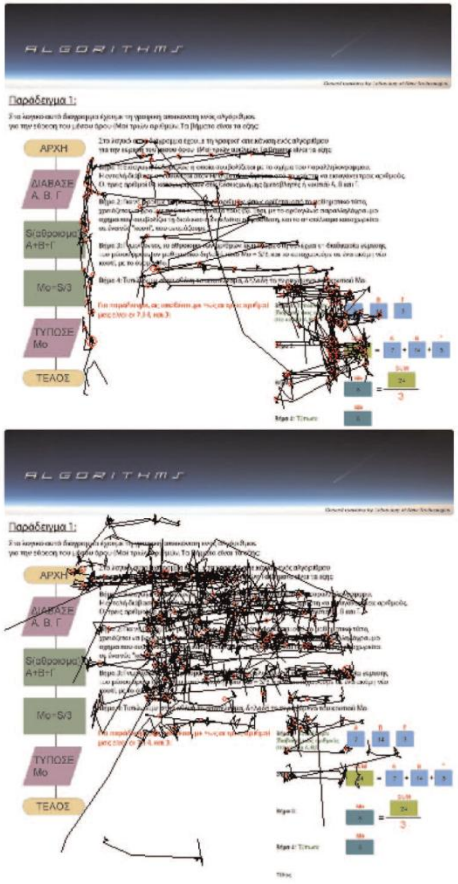
[4]

One‘s Decision to Collaborate 3/3

- Observations a often done using questionnaires
- OSN integration should not require manual input
  - Wouldn’t allow evenly benchmark of each user
  - Wouldn’t fit to a automatic proposal mechanism
  - Wouldn’t allow the user to evolve over time
- Techniques for automatic benchmarking / measurements are required

Measuring Through User Interaction 1/2

- [5] measures cognitive style by eye gaze movement measurement
- Imager (above) and verbalizer (below) (visual <-> verbal)
- Tested in Adaptive System Adaptive Web
- "Adaptive Web generally shows correlation between of match conditions and performance" [6]



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Measuring Through User Interaction 2/2

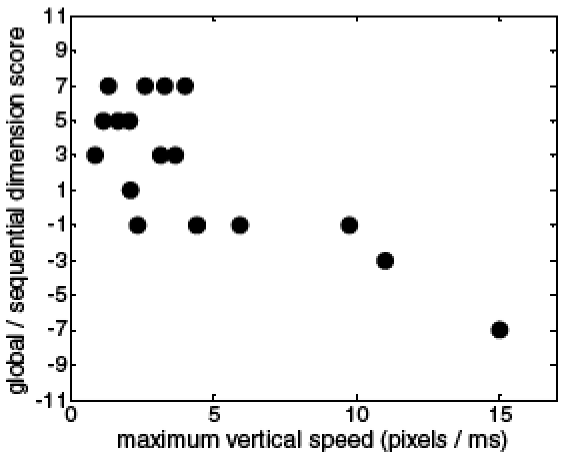


Fig. 1. Maximum vertical speed versus global/sequential dimension score

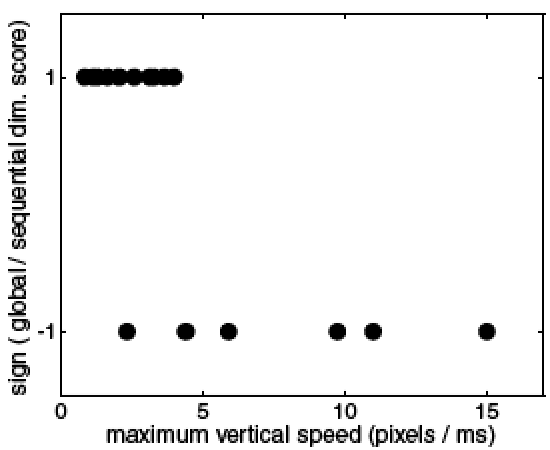
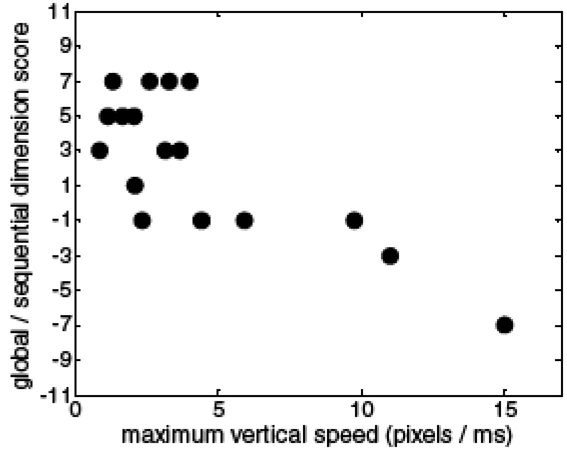


Fig. 2. Maximum vertical speed versus sign of sequential/global dimension score

- [7] presents an approach to link mouse movement patterns to learning style
- The result of the study found a correlation between global / sequential of Felder and Silverman dimensions [1] and the mouse movement

Measuring Through User Interaction 2/2



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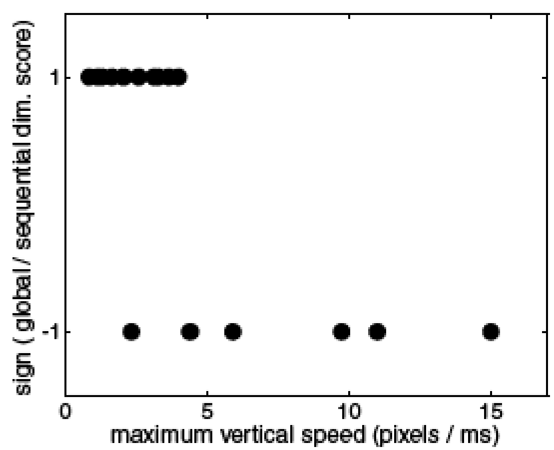

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Neural Networks 1/2

- [8] Felder – Silverman model
- Artificial Neural Networks (ANN)
- One Input neurons per action in system:
  - Reading material, access to examples, answer changes, exercises, exam delivery time, exam revision, chat usage, mail usage forum usage, information access (linear or random)
- Generalized Delta Rule (GDR) for weight adjustment

Neural Networks 2/2

- 24 Neurons in hidden layer
- Network is trained by simulated student data
  - Students learning style
  - Access to certain resources according to his learning style
- Best accuracy 69,3 %

Group Cohesion

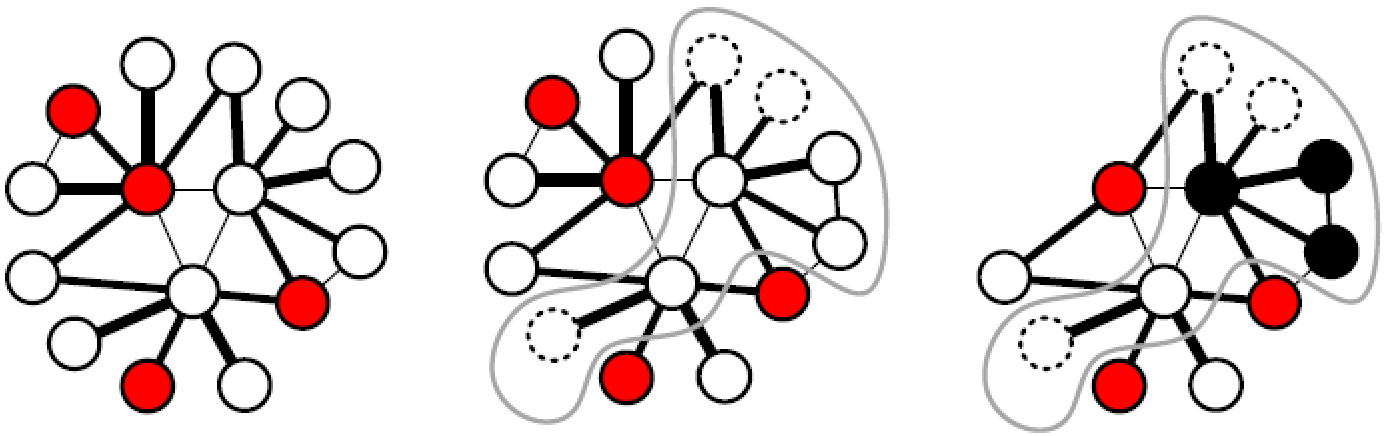
- Group cohesion to describes the quality of collaboration
- [9] use lexical markers to determine group cohesion
- First Person Singular (FPS) “I”, Second Person Plural (SPP) “you”, First Person Plural(FPP) “we”
- Number of occurrence of FPP implies group cohesion

→ Could be used to gather input data from chat in OSN

Team Formation 1/5

- [10] proposes a team composition discovery metric
- Aim: Find optimal team to solve a problem
  → Could be used to distribute good learning matches among possible candidates
- Aspects
  - Skills: sum of all involvements to a certain activity
  - Interaction Distance: count(collaboration in joint activities)
  - Load: true or false

Team Formation 2/5



a) Expert Network b) Candidates c) Team Composition

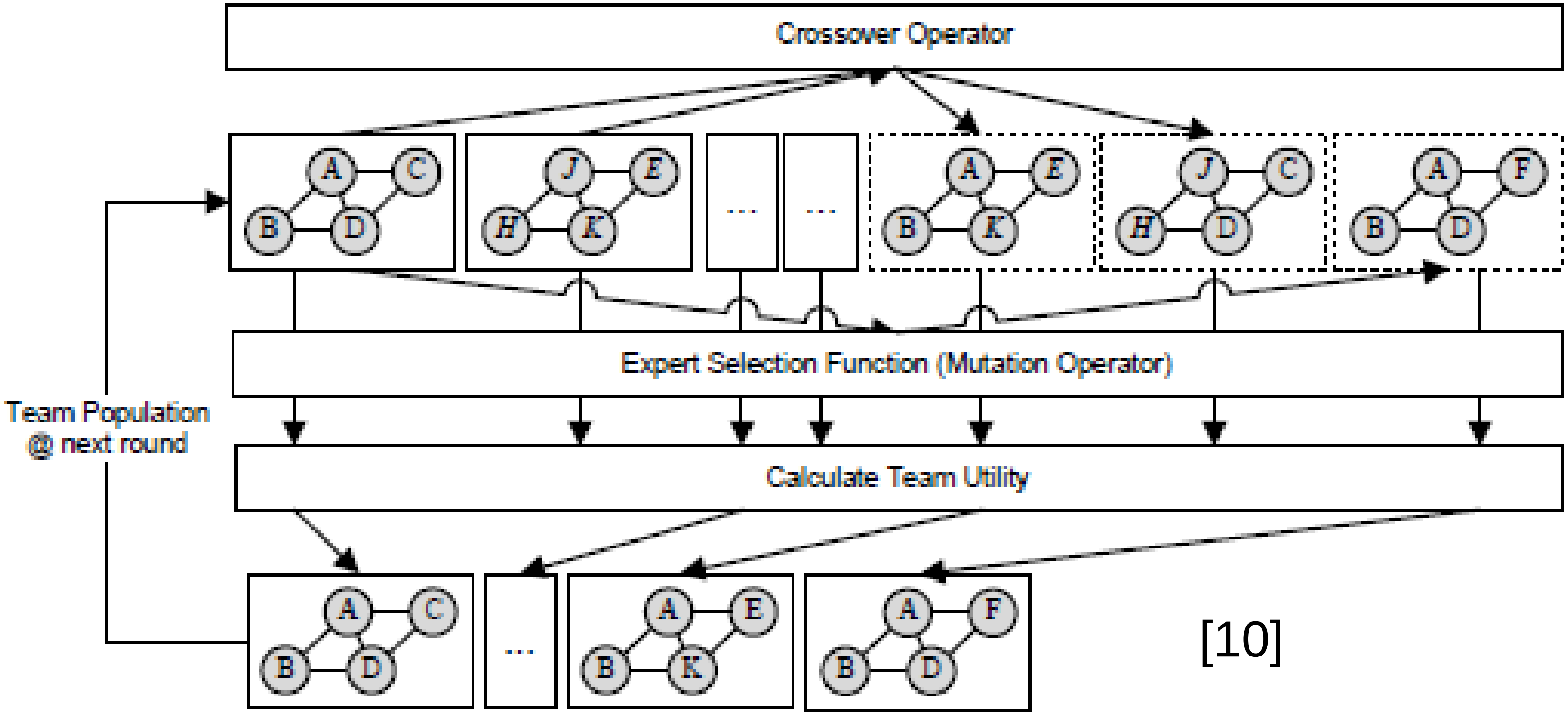
[10]

Proposed algorithm is related to determine a clique in a weighted graph → paper proves NP completeness

→ Heuristics based genetic algorithms and simulated annealing

Team Formation 3/5

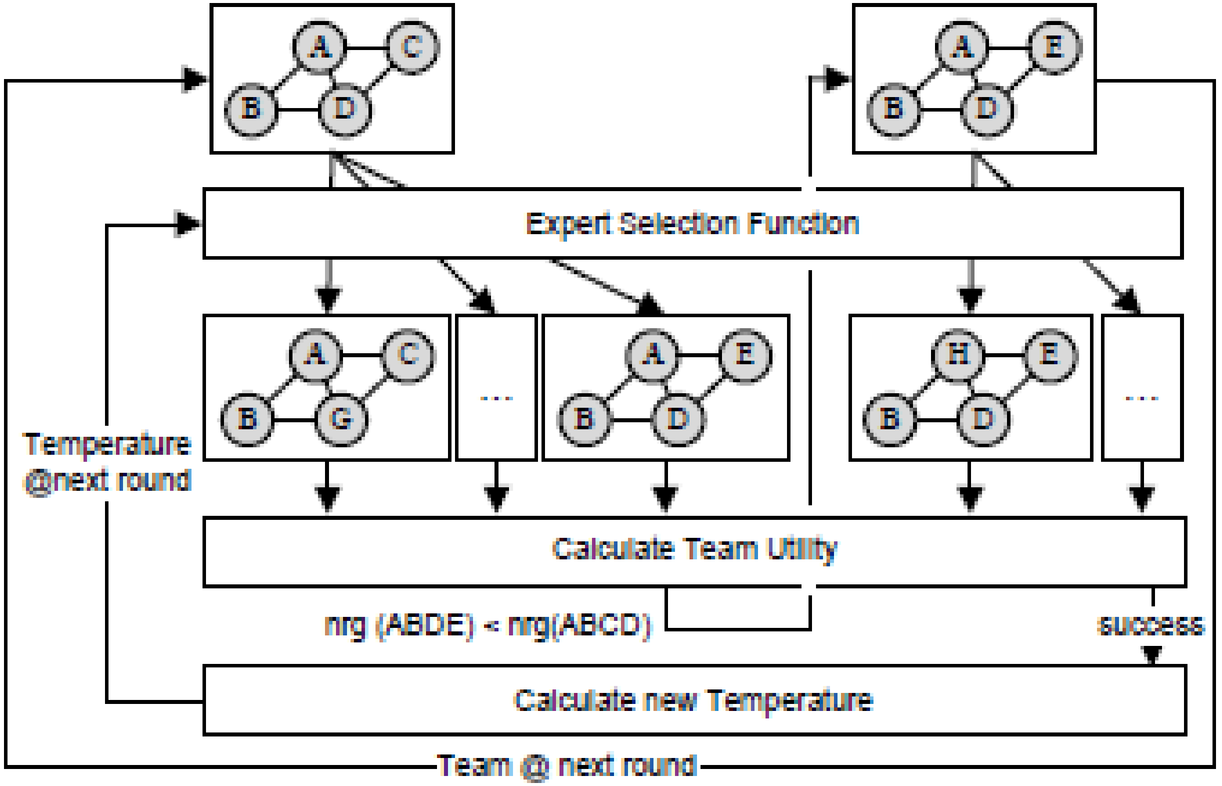
- Genetic algorithm



[10]

Team Formation 4/5

- Simulated annealing



[10]

Team Formation 5/5

- Expert selection function
  - Traverse search space in short time
  - Find similar neighboring configuration
- A evaluation in [10] figures out that
  - GA is better than SA for smaller worlds
  - Runtime of GA depends on population size

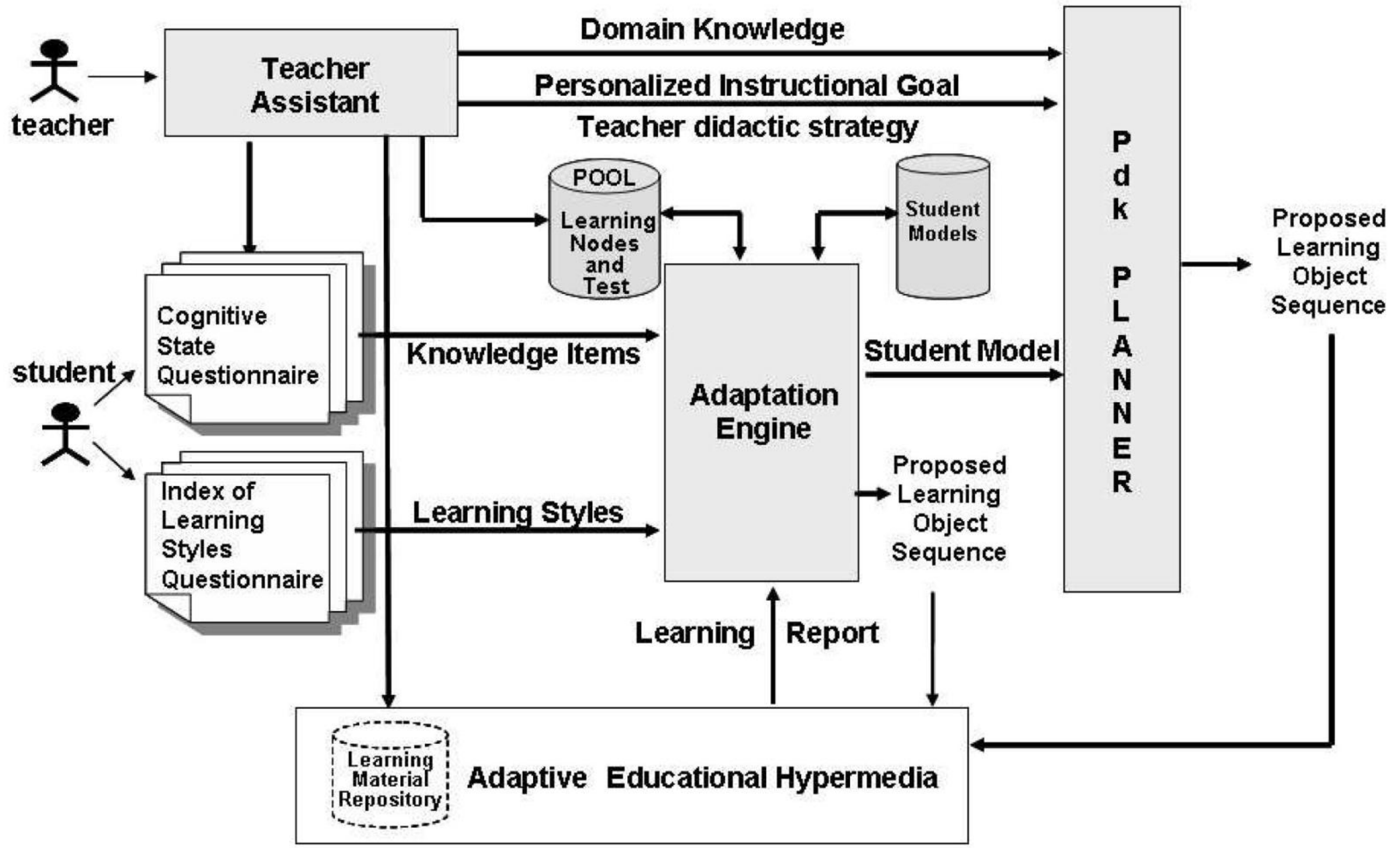
ADAPTIVE SYSTEMS

Adaptive Educational Hypermedia (AEH)

- AEH Systems try to adapt learning content (presentation) to the learners need
- Issue: “It does seem that personalization to show a statistically significant benefit in educational systems is much harder to create than first envisaged” [11]
- Adaption is done by analyzing knowledge, learning style cognitive style
  → Measurements can be used for social network metric

Knowledge Estimation 1/2

- AEH-System LS-Plan [12]



Knowledge Estimation 2/2

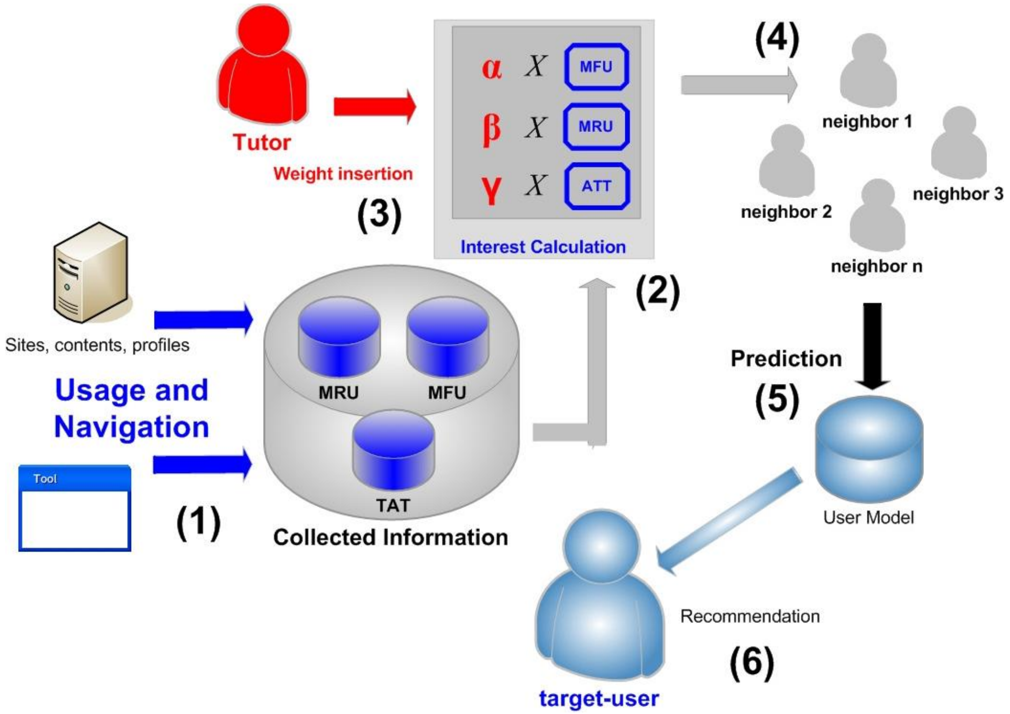
- Student model (SM) consist of
  - Learning Style (LS): Felder and Silverman model
  - Cognitive State (CS): Each Knowledge item processed by the student in a given domain
- Student models are updated after student studies a learning object
  - [12] proposes update CS through questionnaires and access time of learning objects
    → Access Time could be measured by OSN analysis

Predict User Interest 1/2

- Usage mining, e.g. done by [13]
  - Information measured: Total Access Time, Most Recently Used, Most Frequently Used
  - Collaborative Filtering: infer from other users�much measured information possible future interest of current user

Predict User Interest 2/2

- Architecture image from[13]



→ Case Study shows "small error on prediction"

→ Possible OSN metric

MINDSTONE DEMONSTRATOR IMPLEMENTATION

Development Idea

- Create a social network based or integrated LMS
- 2 Approaches
  - Integration into existing social network (FB, G+)
  - Modifying of an open source social networking engine (Diaspora)
- Open Problem: Data acquisition

Data Acquisition 1/4

- Social networks differ from closed communities like moodle
  - # of users
  - Connection and communication between users
- Research interest in mass data analysis to use synergies in large user groups
- Privacy and legal issues avoid simple fetching of the user graph

Data Acquisition 2/4

- Studies require graph data from social network
- Can be gathered from real instances
  - Facebook Graph API
  - Upcoming Google+ API
- Can be created and load to a OSN database
  - Currently possible with FOS Diaspora

Data Acquisition 3/4

- [14]propose an algorithm that creates a graph similar to real-world graphs
- Metrics are used to determine differences between real-world and simulated data
  - Degree Distribution: Power Law exponent of distribution
  - Diameter & Average Path length
  - Clustering: ij and jk linked: P(ik)?
  - Betweenness Centrality: # of occurrences of a node in the shortest path between other nodes

Data Acquisition 4/4

- Metrics are used to determine differences between real-world and simulated data (continuation of 3/4)
  - Assortativity Coefficient: Similarity factor of degrees of neighbors
- Comparison results in [14]

Table 1. Comparisons of Facebook graphs and our algorithm

	Princeton	Georgetown	Oklahoma	UNC	our model (1)	our model (2)	Forest Fire
Number of nodes	6596	9414	17425	18163	9000	18000	9000
Number of edges	293320	425638	892528	766800	394512	917512	300130
Average degree	88.93	90.42	102.442	84.43	87.66	100.275	66.69
Max Degree	628	1235	2568	3795	847	1313	4330
Degree exponent (γ)	-1.13	-1.26	-1.40	-1.46	-1.19	-1.34	-0.99
Average neighbour degree exponent	2.62	2.47	2.22	2.77	1.97	2.17	1.265
Assortativity coefficient	0.091	0.075	0.073	0.0007	0.066	0.085	-0.34
Avg Node Betweenness	2.525E-4	1.856E-4	1.01E-4	9.913E-5	1.031E-4	6.002E-5	1.856E-4
Betweenness Slope	4.652E-6	4.49E-6	2.77E-6	6.051E-6	2.751E-6	1.306E-6	4.49E-6
Clustering coefficient	0.244	0.231	0.235	0.206	0.21	0.256	0.561
Diameter	9	11	9	7	7	7	10
Average path length	2.67	2.75	2.767	2.801	2.27	2.42	2.67

Resume

- Research of integration into social networks is needed to
  - Connect people learning on the same topic
  - Propose learning topics based on communication
  - Ensure completeness and consistency of learned information
- It is required to transfer research in CSCL and AEH to online social network learning technologies by
  - Modify techniques of both areas to fit into OSN paradigms
  - Develop a experimental software platform to
    - Test techniques
    - Find most appropriate OSN implementation
    - Use the platform to make studies with students

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link-lab

Thank You – Questions?

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Further Information:

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http://www.haw-hamburg.de/inet

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