

Measuring Similarity of Educational Items Using Data on Learners' Performance

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Adaptive practice systems

- **items** — simple questions
- practice — rapid sequence of items

$$17 \times 10 =$$



tvořiv_ch studentech

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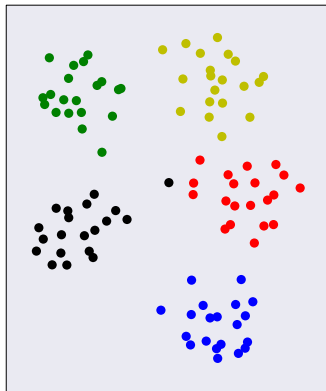
Large pool of items

- How to organize these items?
- What knowledge components should be use?
- Are there some anomalies?
- ...

Motivation

Large pool of items

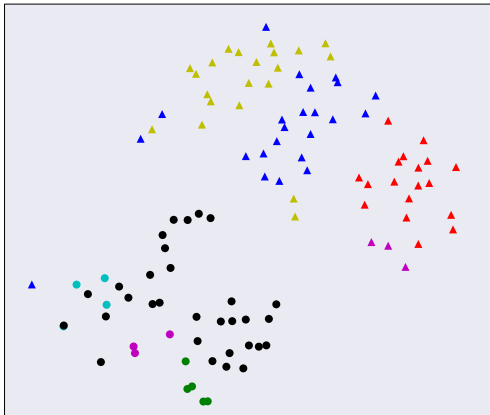
- **clustering**
- visualization
- outlier detection
- ...



Motivation

Large pool of items

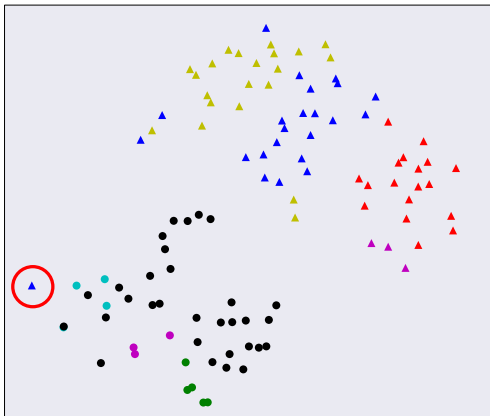
- clustering
- **visualization**
- outlier detection
- ...



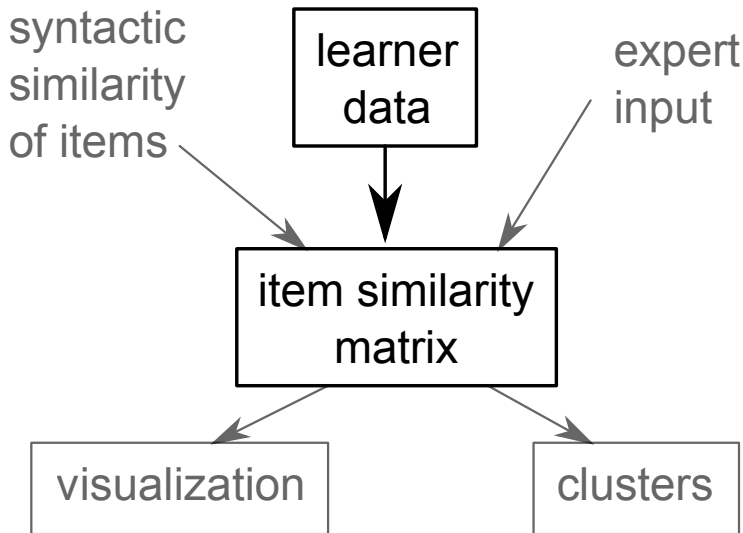
Motivation

Large pool of items

- clustering
- visualization
- **outlier detection**
- ...



General approach



Similarity measures

matrix of answers					similarity matrix			
	i_1	i_m	i_n	i_I		i_m	i_n	
l_1	1	1	1	0	\vdots			
l_2	-	1	0	-	i_m	1	0.63	
l_3	1	0	-	0	\vdots			
\vdots	\vdots	\vdots	\vdots	\vdots	i_n	0.63	1	
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots			
l_L	0	-	1	-				

similarity measure

Similarity measures

binary data

- 1 — correct
- 0 — incorrect
- input can be simplified:

		item i	
		incorrect	correct
item j	incorrect	a	b
	correct	c	d

Similarity measures

Yule $S_y = (ad - bc)/(ad + bc)$

Pearson $S_p = (ad - bc)/\sqrt{(a + b)(a + c)(b + d)(c + d)}$

Cohen $S_c = (P_o - P_e)/(1 - P_e)$

$$P_o = (a + d)/n$$

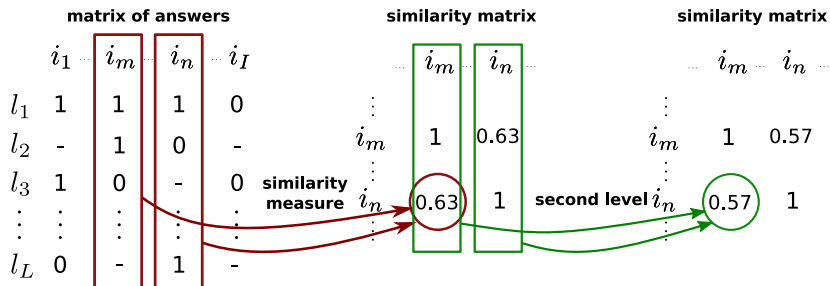
$$P_e = ((a + b)(a + c) + (b + d)(c + d))/n^2$$

Sokal $S_s = (a + d)/(a + b + c + d)$

Jaccard $S_j = a/(a + b + c)$

Ochiai $S_o = a/\sqrt{(a + b)(a + c)}$

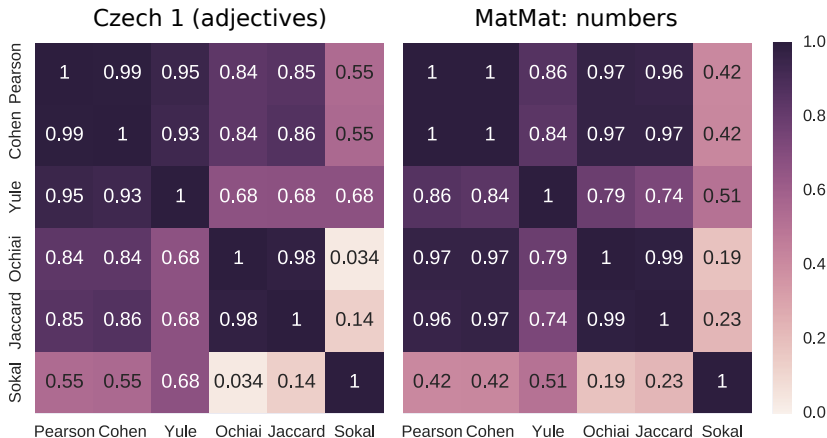
Second level of similarity



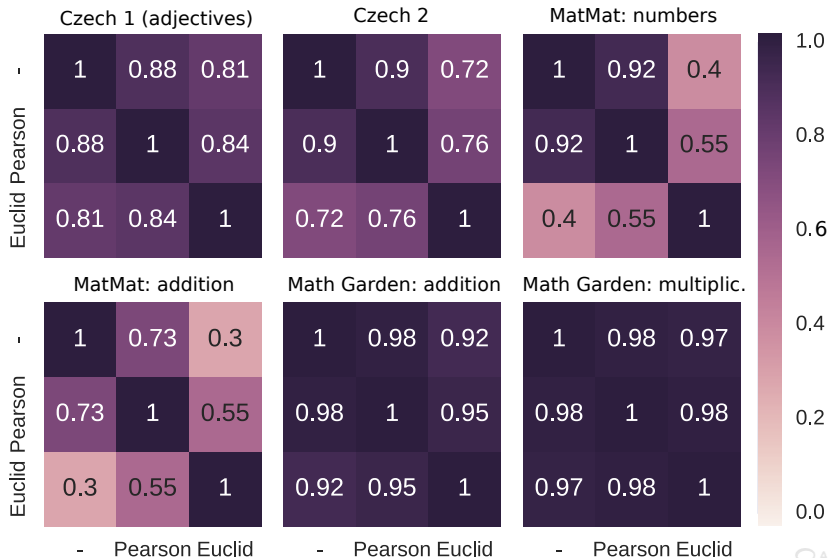
Second level of similarity

- 2 items are similar if they are *similarly* similar to other items
- more information used
- noise reduction
- necessary for some follow up algorithms

Evaluation - correlation of measures



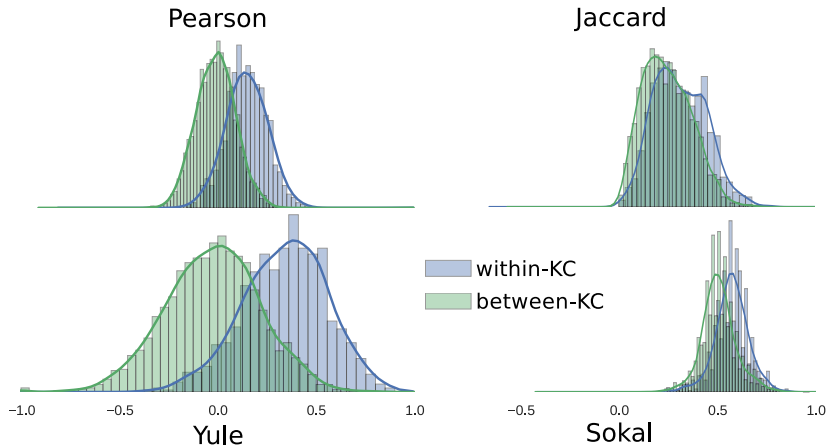
Evaluation - correlation of measures



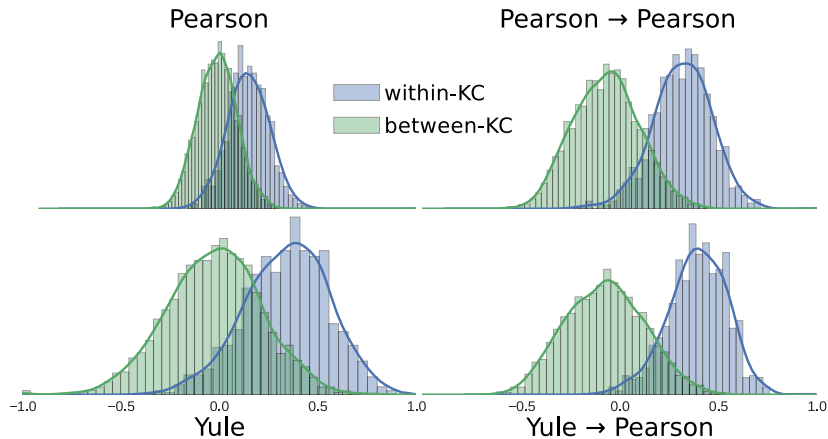
Simulated data

- we know *right answer*
- logistic model
 - learners have skills
 - items have difficulty
- typical setting
 - 100 learners
 - 5 knowledge components
 - 20 items per KC

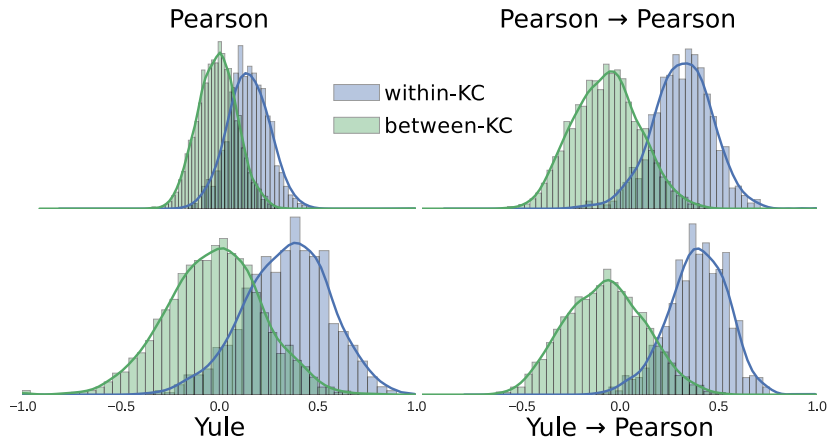
Evaluation



Evaluation



Evaluation



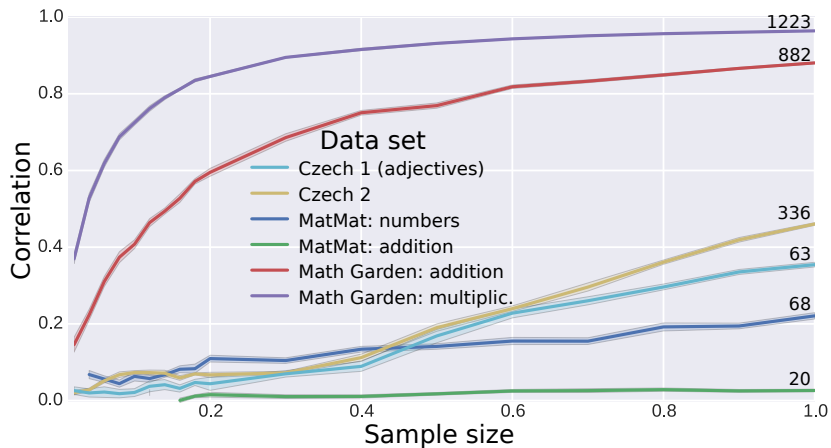
Evaluation - clustering

	Czech adjectives	100L 5KC	200L 5KC
Pearson	0.32 ± 0.02	0.48 ± 0.05	0.84 ± 0.05
Jaccard	0.31 ± 0.03	0.15 ± 0.04	0.29 ± 0.08
Yule	0.31 ± 0.03	0.43 ± 0.05	0.77 ± 0.07
Sokal	0.15 ± 0.06	0.18 ± 0.03	0.25 ± 0.05
Pearson \rightarrow Euclid	0.43 ± 0.01	0.80 ± 0.06	0.98 ± 0.01
Yule \rightarrow Euclid	0.32 ± 0.02	0.65 ± 0.07	0.94 ± 0.04
Pearson \rightarrow Pearson	0.41 ± 0.03	0.73 ± 0.06	0.96 ± 0.02
Yule \rightarrow Pearson	0.32 ± 0.03	0.72 ± 0.06	0.97 ± 0.02

Do We Have Enough Data?

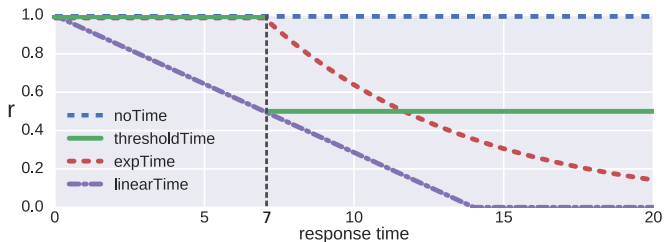
- stability of results
- split data to two halves
- how similarity measures correlate on these halves?

Do We Have Enough Data?



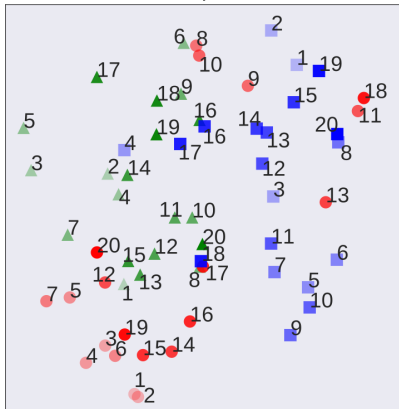
Response times

- additional information
- correctness and response time to one measure of success



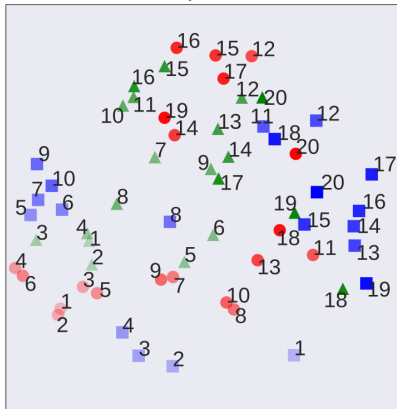
Response times - MathMat

without response times



● number → objects ▲ objects → number

with response times

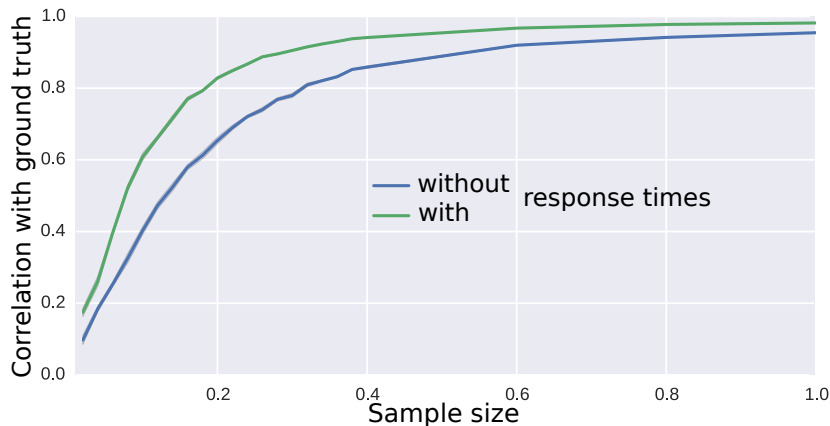


■ number line

Response times - Math Garden

- Math Garden - large datasets: $\sim 1M$ of answer on 30 items
- small impact of time information - correlation > 0.9
- but what we have not such large dataset

Response times - MathGarden



Conclusion

- Pearson (Cohen) and Yule are better
- second level improve results
- we should check that we have sufficient data
- response time can give different point of view
- response time can help with small datasets