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UNIVERSITY
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Modeling Knowledge Acquisition from Multiple Learning Resource Types



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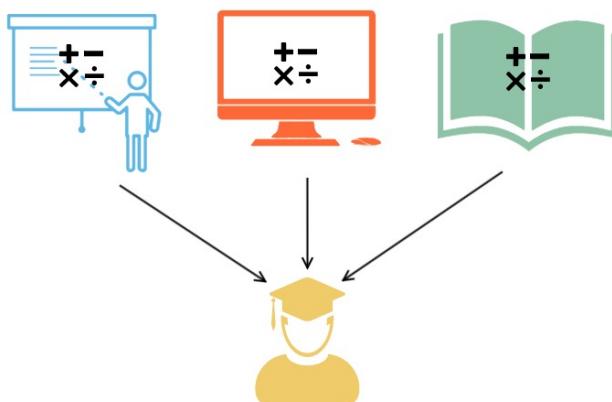
Content

- Introduction
- Model
- Experiments
- Conclusions



Introduction

- Motivation
 - Student knowledge modeling and domain knowledge modeling are important
 - Creating a coherent study plan,
 - Modeling students' knowledge,
 - Analyzing students' knowledge gaps
 - Ideally:
 - Student can learn from multiple types of learning materials
 - Relationships between various kinds of learning materials





Introduction

- Contribution
 - Propose a multi-view student knowledge model (MVKM)
 - Outperform on both synthetic and real-world datasets
 - Capture similarity between learning material types
 - Represent student knowledge



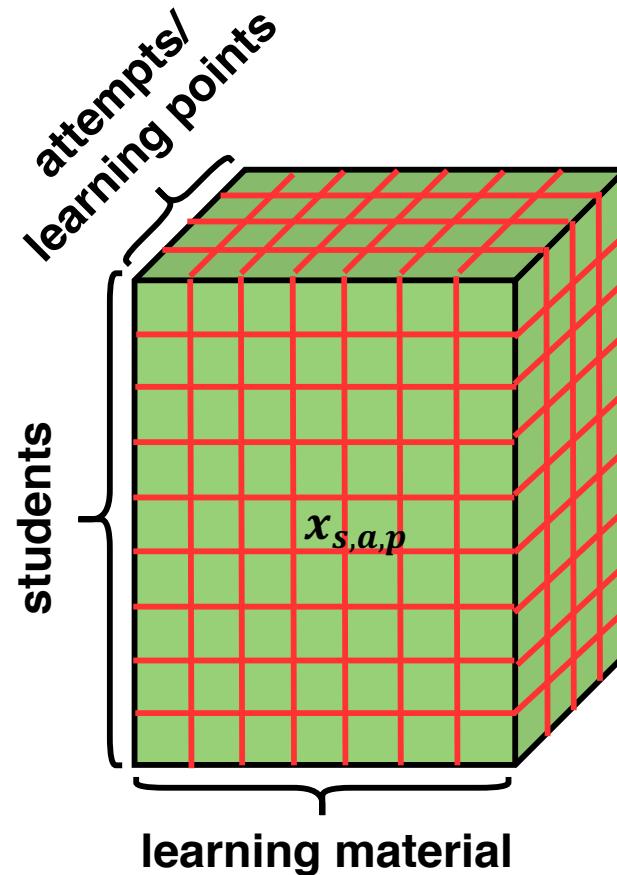
Model

- Problem formulation
- MVKM-Factorization part
- MVKM-Rank based constraint



Problem formulation

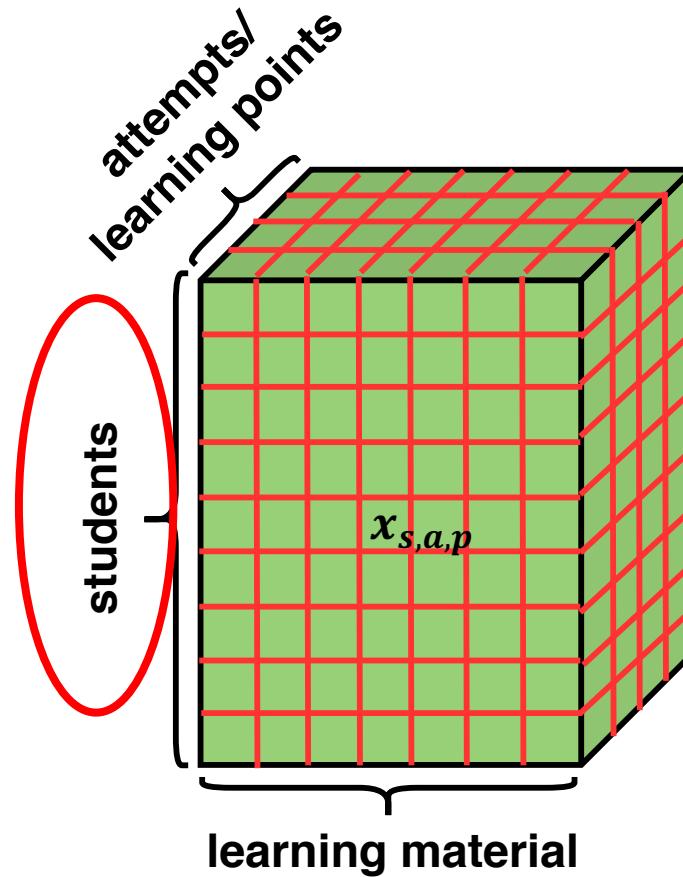
- Interactions of each learning material type - one tensor





Problem formulation

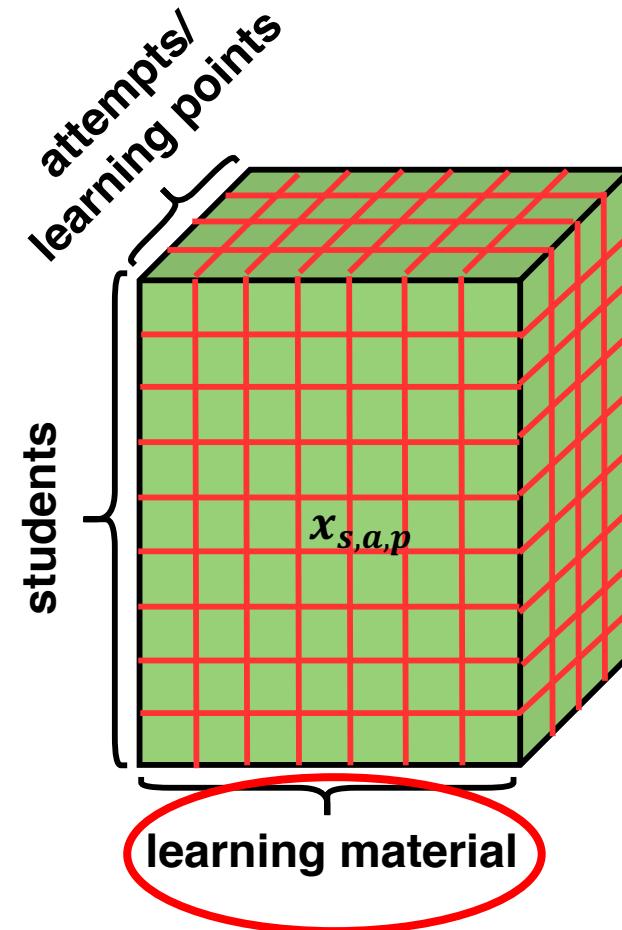
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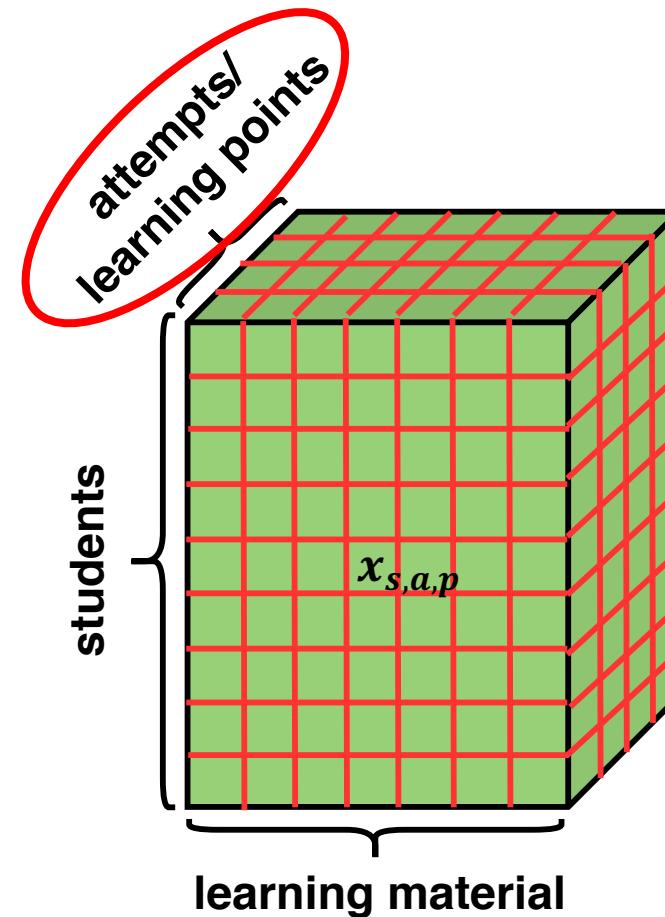
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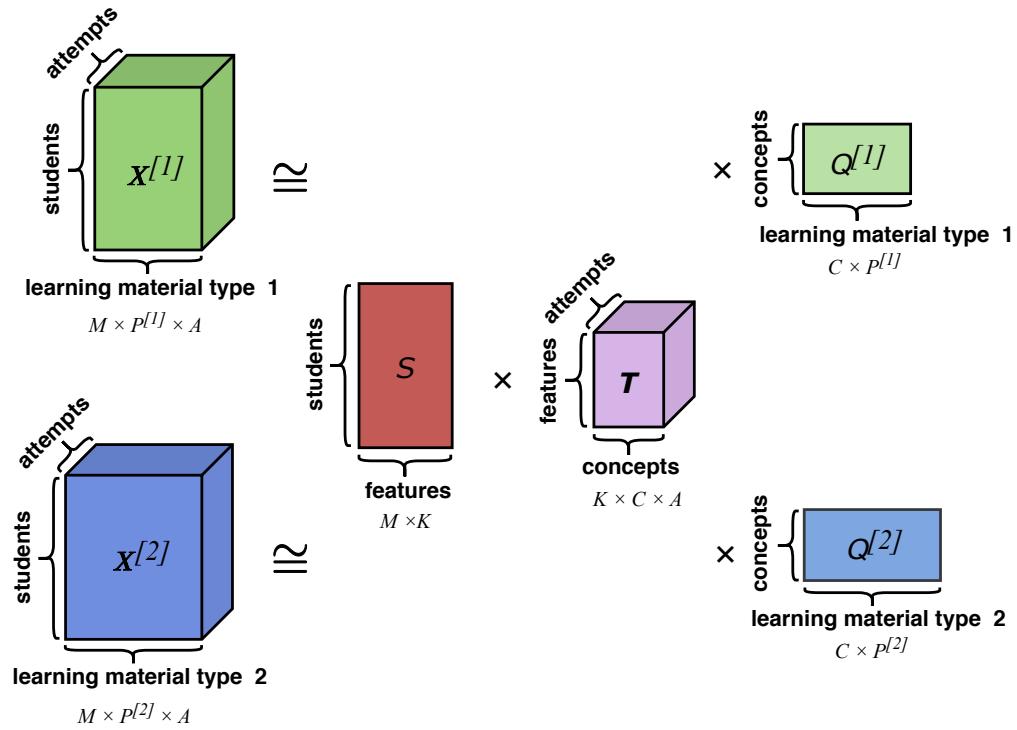
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MVKM-Factorization

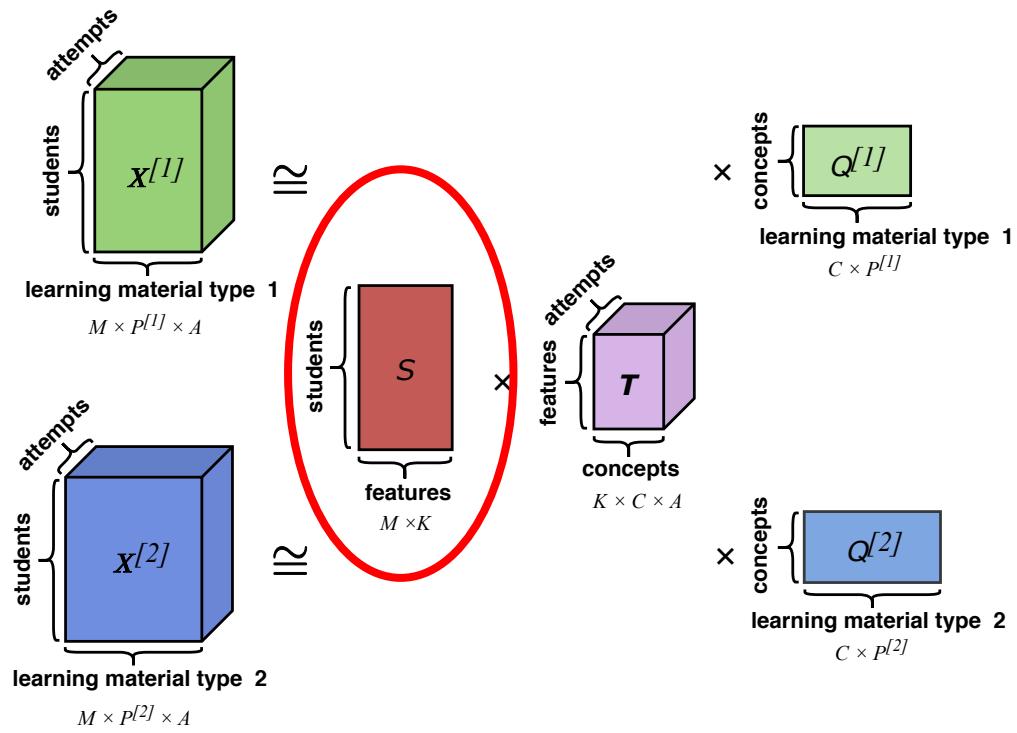
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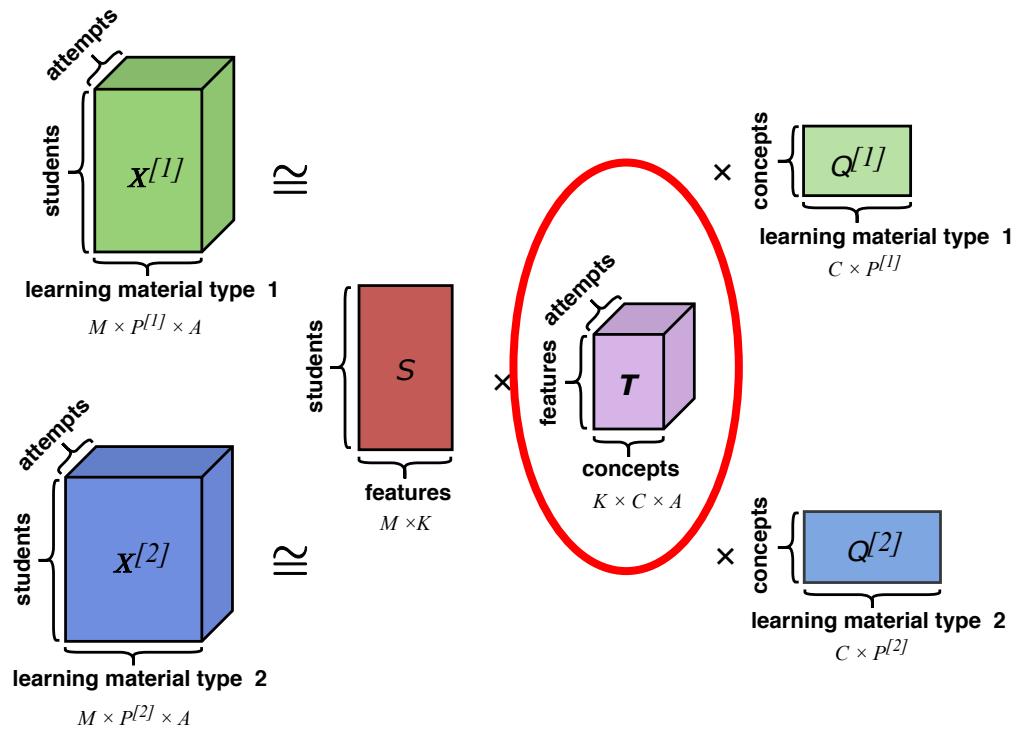
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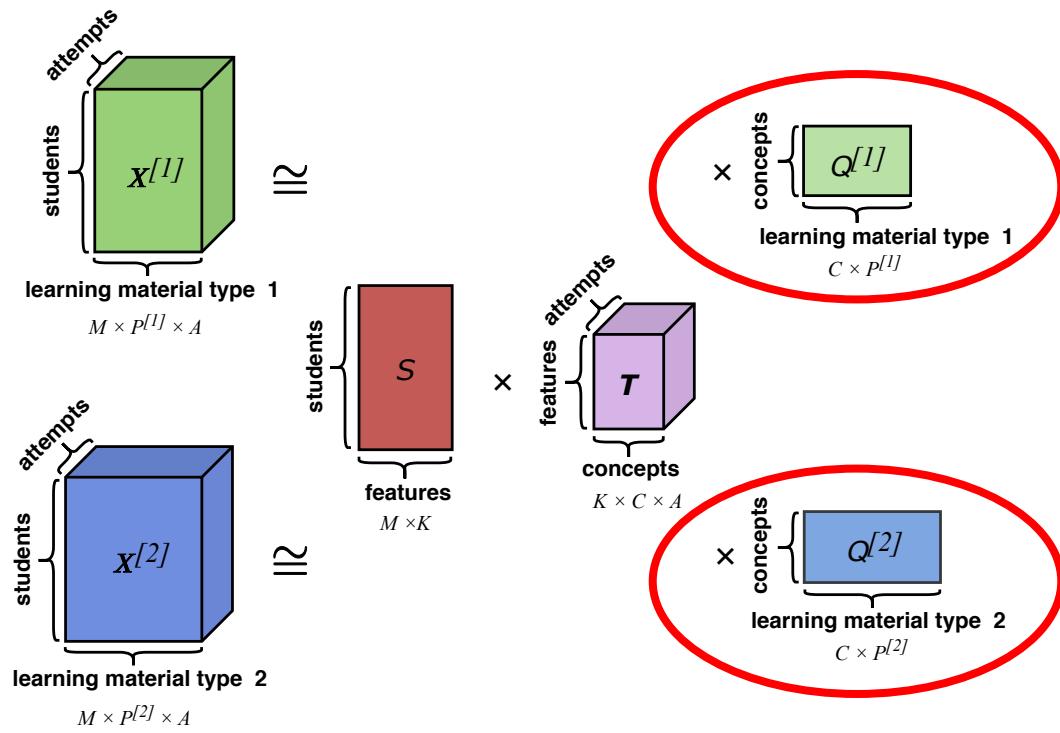
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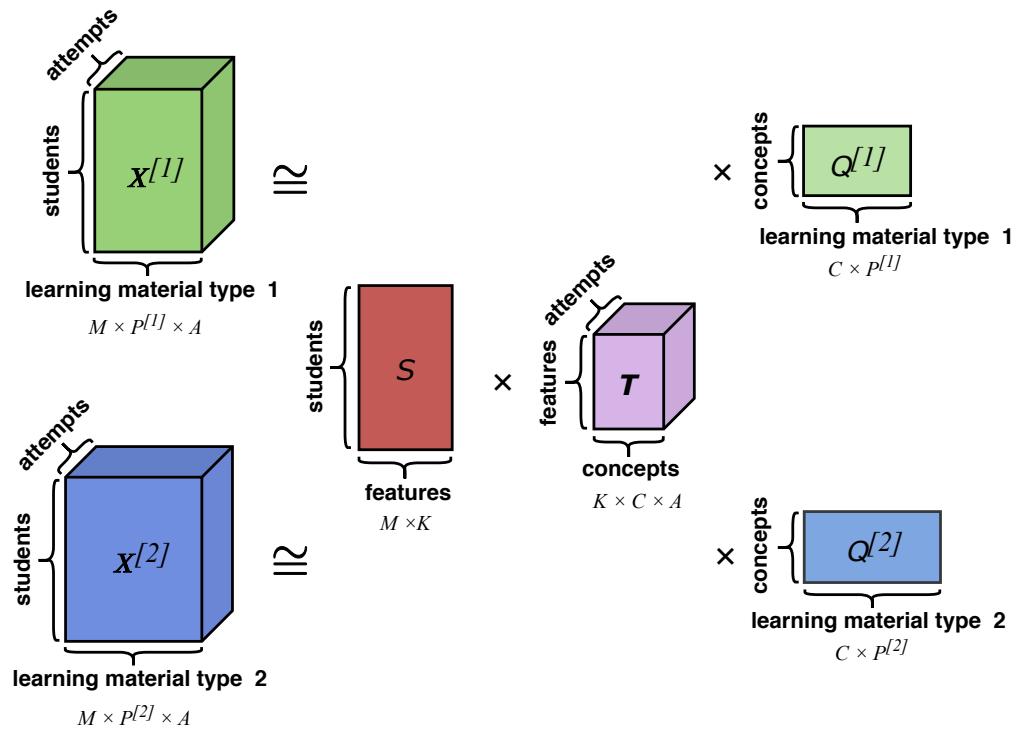
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MVKM-Factorization

- Interactions of each learning material type - one tensor



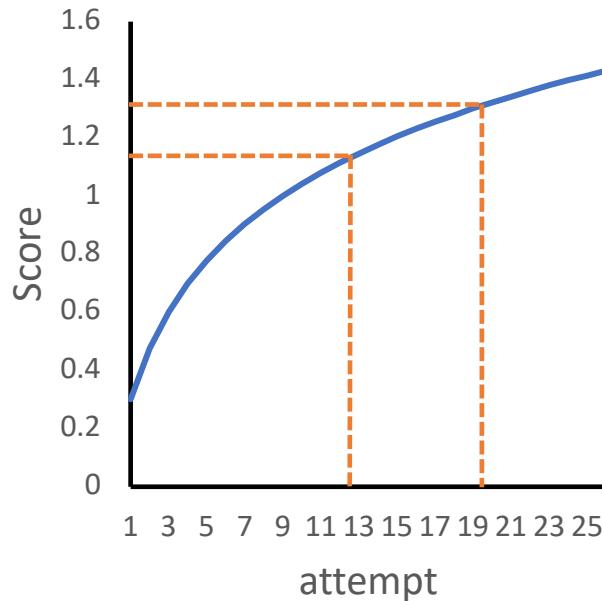
$$\hat{x}_{s,a,p}^{[r]} \approx s_s \cdot T_a \cdot q_p^{[r]} + b_s + b_p^{[r]} + b_a$$

biases



MVKM-Rank based constraint

- Students' knowledge increase



$$s_s \cdot T_{a+1} \cdot q_p^{[r]} - s_s \cdot T_a \cdot q_p^{[r]} \geq 0$$



Experiments

- We evaluate our model with three sets of experiments:



Student Performance Prediction - to validate if the model captures the variability of observed data



Student Knowledge Modeling - to check if our model represents valid student knowledge growth



Learning Resource Modeling - to study if the model meaningfully recovers learning materials' latent concepts

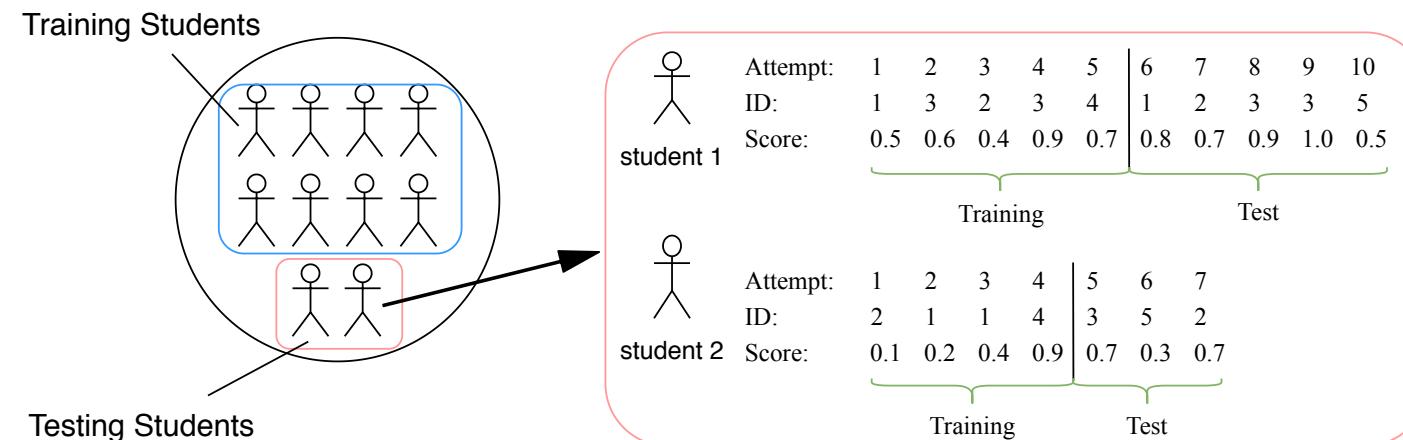


Datasets & Experiment Setup

- Datasets
 - Three synthetic datasets
 - Canvas Network Platform
 - MOOC Replication Framework (MORF)
- Experiment Setup
 - We use 5-fold student stratified cross-validation

Dataset	material type 1 (#)	material type 2 (#)	#stu	act. seq. len.	#rcds.	avg. sco.
Synthetic_NG	quiz (10)	discussion (15)	1000	20	19991	0.6230
Synthetic_NG2	quiz (10)	discussion (15)	1000	20	19991	0.6984
Synthetic_G	quiz (10)	assignment (15)	1000	20	19980	0.6255
MORF_QD	assignment (18)	discussion (525)	459	25	6800	0.8693
MORF_QL	assignment (10)	lecture (52)	1329	76	58956	0.7731
Canvas_H	quiz (10)	discussion (43)	1091	20	13633	0.8648

Statistics for each datasets





Baselines & Metrics

- Baselines
 - Educational Data mining: **IBKT, DKT, FDTF, TFWL, RBTF**
 - Recommendation System: **BPTF**
 - Different settings of proposed model
 - **MVKM-Base**: MVKM with single learning material type
 - **MVKM-W /O-P**: MVKM without knowledge increase constraint
 - **[method name]-MV**: Baselines ‘Multiview’ setting
 - **AVG**
- Metrics
 - Root Mean Squared Error (RMSE)
 - Mean Absolute Error (MAE)



Does MVKM outperform other baselines?

Methods	Synthetic_NG		Synthetic_NG2		Synthetic_G	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
AVG	0.3084±0.0072	0.2820±0.0093	0.5059±0.0115	0.4005±0.0115	0.3070±0.0039	0.2811±0.0050
RBTF	0.2515±0.0126	0.2027±0.0081	0.3374±0.0234	0.2681±0.0146	0.2628±0.0113	0.2103±0.0080
FDTF	0.4906±0.0172	0.4410±0.0207	0.6588±0.0215	0.5529±0.0226	0.5041±0.0184	0.4537±0.0213
TFWL	0.5283±0.0168	0.4632±0.0178	0.6919±0.0132	0.5883±0.0156	0.5490±0.0053	0.5130±0.0076
BPTF	0.1675±0.0048	0.1256±0.0061	0.3454±0.0140	0.2589±0.0072	0.1825±0.0064	0.1381±0.0050
IBKT	0.4744±0.0118	0.4197±0.0140	0.6630±0.0122	0.5494±0.0152	0.4748±0.0076	0.4233±0.0098
DKT	0.2694±0.0275	0.1911±0.0241	0.4536±0.0404	0.3569±0.0413	0.2716±0.0209	0.2047±0.0178
RBTF-MV	0.2920±0.0069	0.2305±0.0078	0.4064±0.0213	0.3227±0.0147	0.2618±0.0155	0.2126±0.0130
FDTF-MV	0.4078±0.0168	0.3402±0.0167	0.5861±0.0211	0.4688±0.0135	0.4888±0.0112	0.4538±0.0131
TFWL-MV	0.4337±0.0139	0.3896±0.0133	0.6386±0.0161	0.5450±0.0194	0.5312±0.0137	0.4626±0.0145
BPTF-MV	0.1718±0.0037	0.1457±0.0055	0.3438±0.0158	0.2603±0.0120	0.1533±0.0055	0.1184±0.0044
IBKT-MV	0.4257±0.0142	0.3585±0.0155	0.6019±0.0124	0.4892±0.0165	0.4844±0.0068	0.4275±0.0089
DKT-MV	0.4278±0.0313	0.3613±0.0318	0.6399±0.0515	0.5320±0.0526	0.3390±0.0252	0.2892±0.0245
MVKM-Base	0.2007±0.1069	0.1498±0.0809	0.3026±0.0697	0.2273±0.0356	0.2097±0.0485	0.1565±0.0348
MVKM-W /O-P	0.1714±0.0089	0.1306±0.0089	0.2817±0.0316	0.2213±0.0245	0.1796±0.0345	0.1357±0.0190
Our Method (MVKM)	0.1388±0.0048	0.1049±0.0056	0.2221±0.0074	0.1739±0.0048	0.1532±0.0128	0.1171±0.0097

Performance Prediction results on synthetic datasets

Methods	MORF_QD		MORF_QL		CANVAS_H	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
AVG	0.2410±0.0227	0.1913±0.0161	0.2420±0.0108	0.1957±0.0067	0.0767±0.0121	0.0555±0.0040
RBTF	0.2711±0.0229	0.2132±0.0147	0.2572±0.0114	0.1980±0.0074	0.1571±0.0172	0.1235±0.0103
FDTF	0.3081±0.0437	0.2401±0.0329	0.3006±0.0194	0.2324±0.0151	0.1395±0.0259	0.0929±0.0119
TFWL	0.2750±0.0529	0.2003±0.0249	0.3090±0.3090	0.2237±0.0099	0.2377±0.0803	0.1186±0.0513
BPTF	0.2172±0.0128	0.1776±0.0082	0.2302±0.0068	0.1953±0.0048	0.1114±0.0120	0.0946±0.0082
IBKT	0.2756±0.0070	0.2281±0.0053	0.2646±0.0147	0.2174±0.0096	0.0856±0.0105	0.0692±0.0042
DKT	0.3169±0.0374	0.2498±0.0313	0.2859±0.0061	0.2158±0.0075	0.0911±0.0322	0.0616±0.0173
RBTF-MV	0.2814±0.0282	0.2177±0.0222	0.2624±0.0193	0.1977±0.0136	0.1484±0.0098	0.1171±0.0054
FDTF-MV	0.3138±0.0441	0.2453±0.0387	0.2398±0.0137	0.1866±0.0091	0.1149±0.0085	0.0907±0.0068
TFWL-MV	0.2919±0.0275	0.1975±0.0160	0.3222±0.0208	0.2178±0.0165	0.1748±0.0600	0.0784±0.0269
BPTF-MV	0.2615±0.0129	0.2286±0.0114	0.2313±0.0070	0.1960±0.0041	0.1452±0.0100	0.1343±0.0081
IBKT-MV	0.2774±0.0204	0.2177±0.0099	0.2904±0.0098	0.2137±0.0062	0.0834±0.0125	0.0425±0.0049
DKT-MV	0.2938±0.0310	0.2352±0.0236	0.2540±0.0065	0.2185±0.0047	0.079±0.0247	0.0496±0.0065
MVKM-Base	0.2242±0.0328	0.1669±0.0207	0.2277±0.0119	0.1724±0.0081	0.0666±0.0159	0.0411±0.0040
MVKM-W /O-P	0.2385±0.0196	0.1771±0.0104	0.2450±0.0145	0.1814±0.009	0.0649±0.0111	0.0388±0.0027
Our Method (MVKM)	0.2088±0.0229	0.1603±0.0142	0.2150±0.0127	0.1654±0.0104	0.0613±0.0112	0.0362±0.0028

Performance Prediction results on real datasets



Does MVKM outperform other baselines?

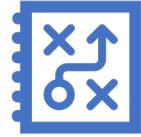
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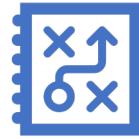
Does Multiview help improve prediction performance?

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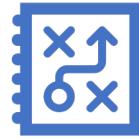
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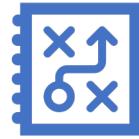
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Methods	MORF_QD		MORF_QL		CANVAS_H	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
MVKM-Base	0.2242±0.0328	0.1669±0.0207	0.2277±0.0119	0.1724±0.0081	0.0666±0.0159	0.0411±0.0040
MVKM-W /O-P	0.2385±0.0196	0.1771±0.0104	0.2450±0.0145	0.1814±0.009	0.0649±0.0111	0.0388±0.0027
Our Method (MVKM)	0.2088±0.0229	0.1603±0.0142	0.2150±0.0127	0.1654±0.0104	0.0613±0.0112	0.0362±0.0028

Performance Prediction results on real datasets



Is the Knowledge increase constraint essential? Yes!

Methods	Synthetic_NG		Synthetic_NG2		Synthetic_G	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
MVKM-Base	0.2007±0.1069	0.1498±0.0809	0.3026±0.0697	0.2273±0.0356	0.2097±0.0485	0.1565±0.0348
MVKM-W /O-P	0.1714±0.0089	0.1306±0.0089	0.2817±0.0316	0.2213±0.0245	0.1796±0.0345	0.1357±0.0190
Our Method (MVKM)	0.1388±0.0048	0.1049±0.0056	0.2221±0.0074	0.1739±0.0048	0.1532±0.0128	0.1171±0.0097

Performance Prediction results on synthetic datasets

Methods	MORF_QD		MORF_QL		CANVAS_H	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
MVKM-Base	0.2242±0.0328	0.1669±0.0207	0.2277±0.0119	0.1724±0.0081	0.0666±0.0159	0.0411±0.0040
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Performance Prediction results on real datasets

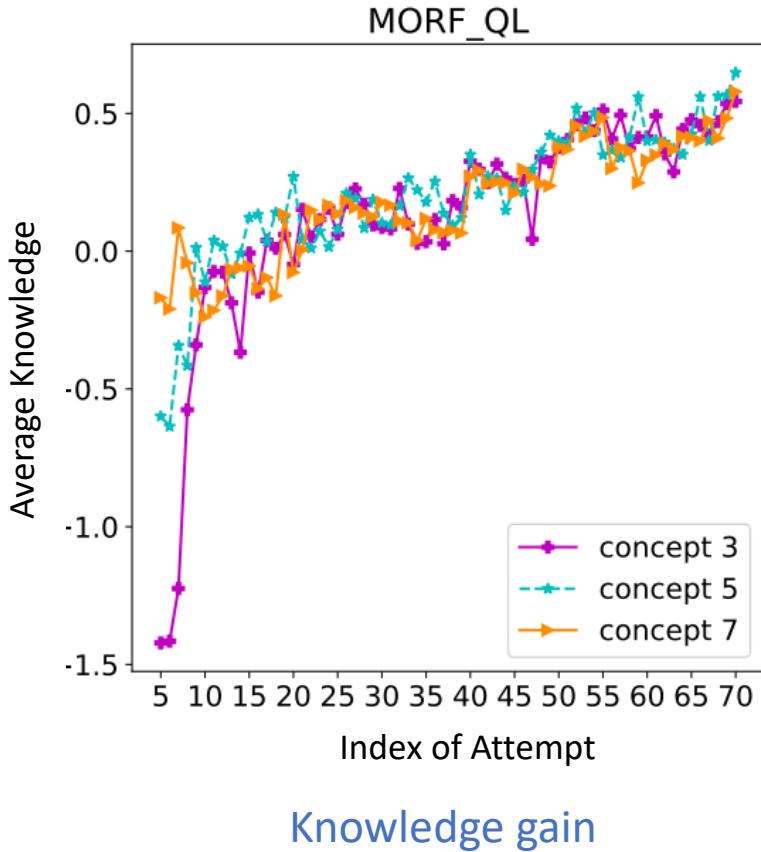


Student Knowledge Modeling

- Students Knowledge gain
- Knowledge increase constraint

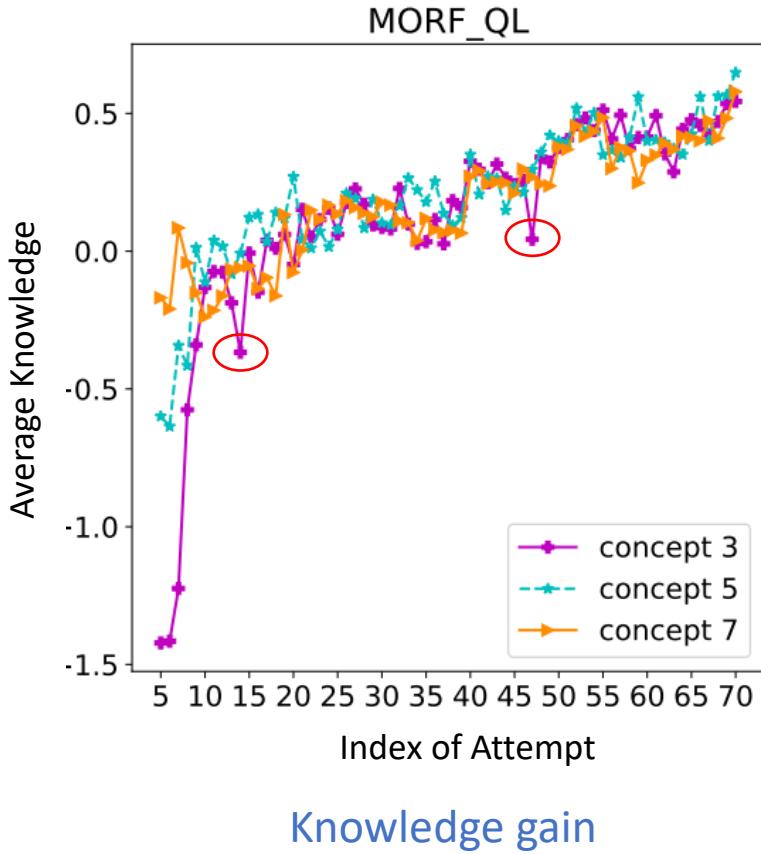


Students' knowledge increase, but not strict



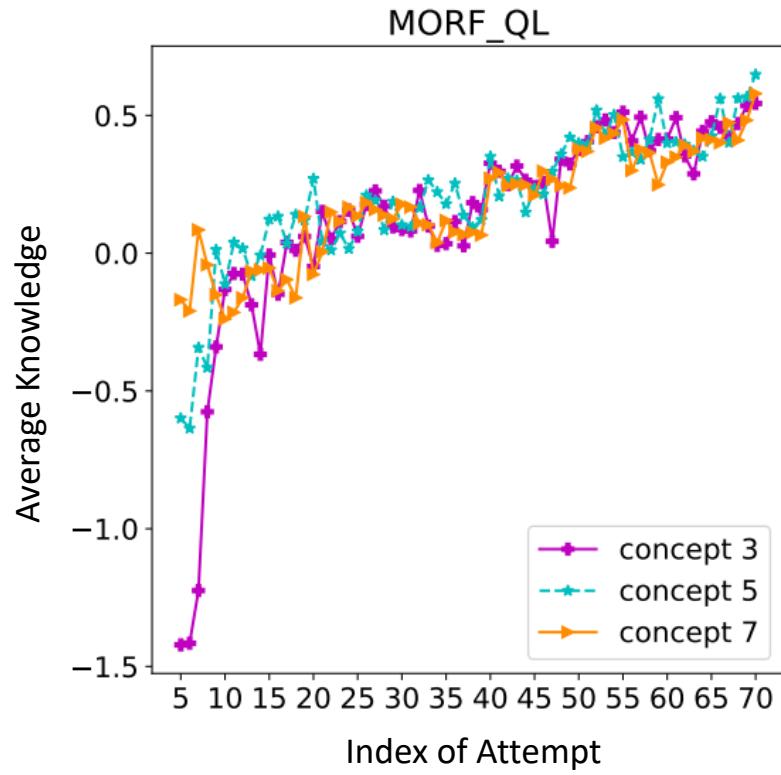


Students' knowledge increase, but not strict

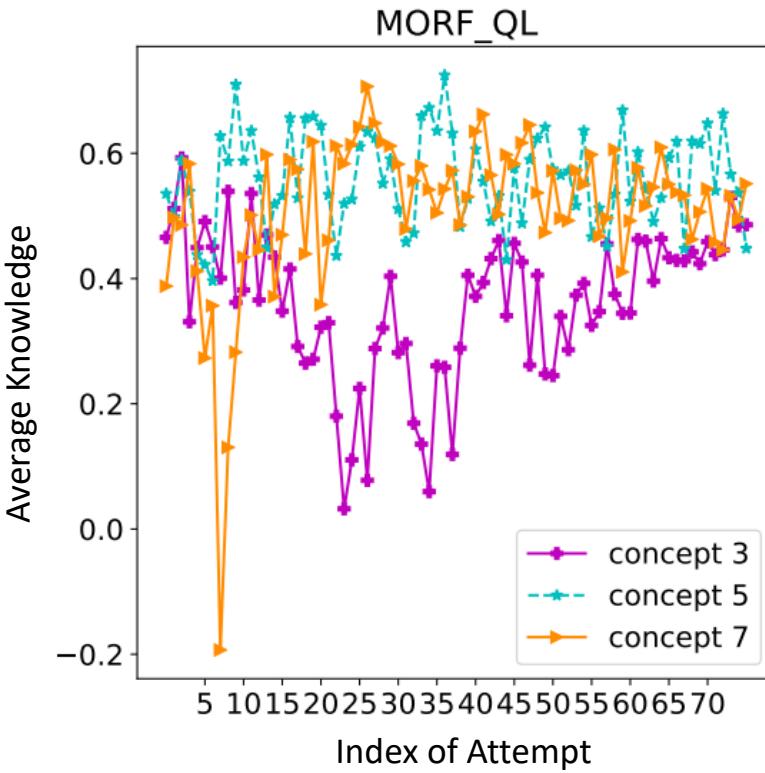




What if we remove the knowledge increase constraint?



MVKM



MVKM-W/O-P

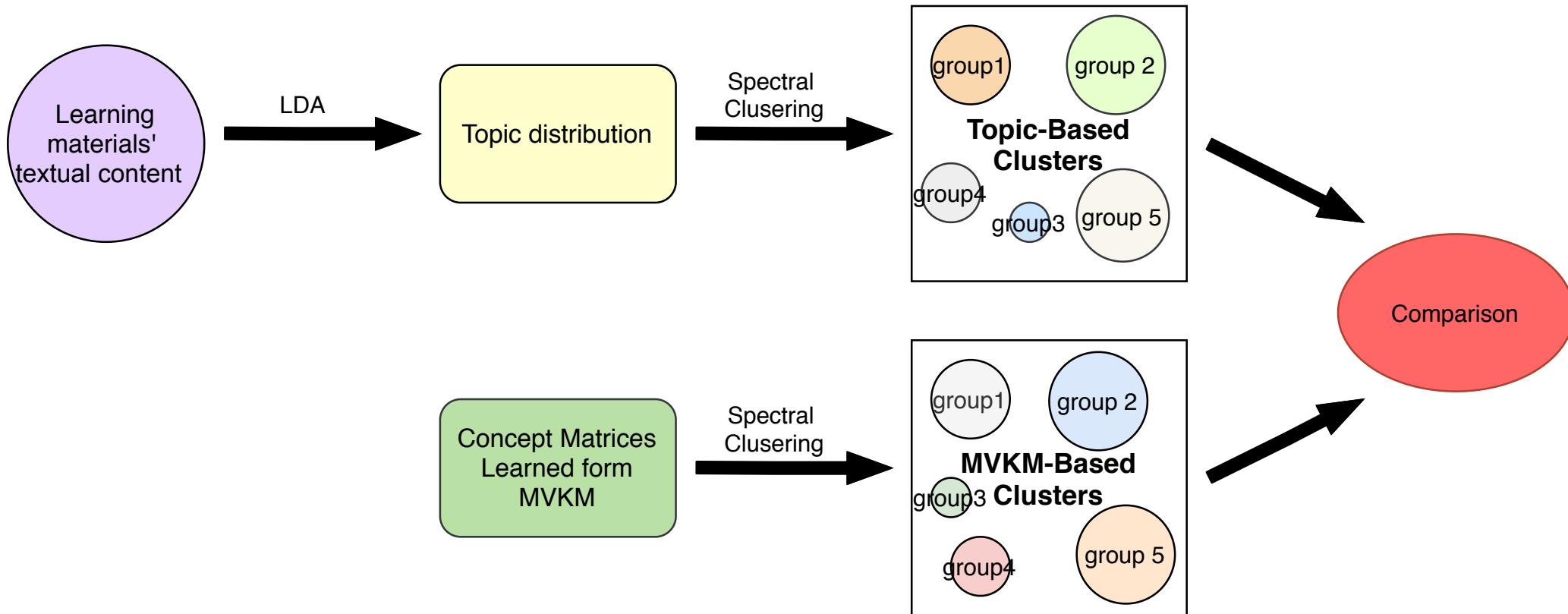


Learning Resource Modeling

- Within-Type Concept Evaluation
- Between-Type Concept Evaluation



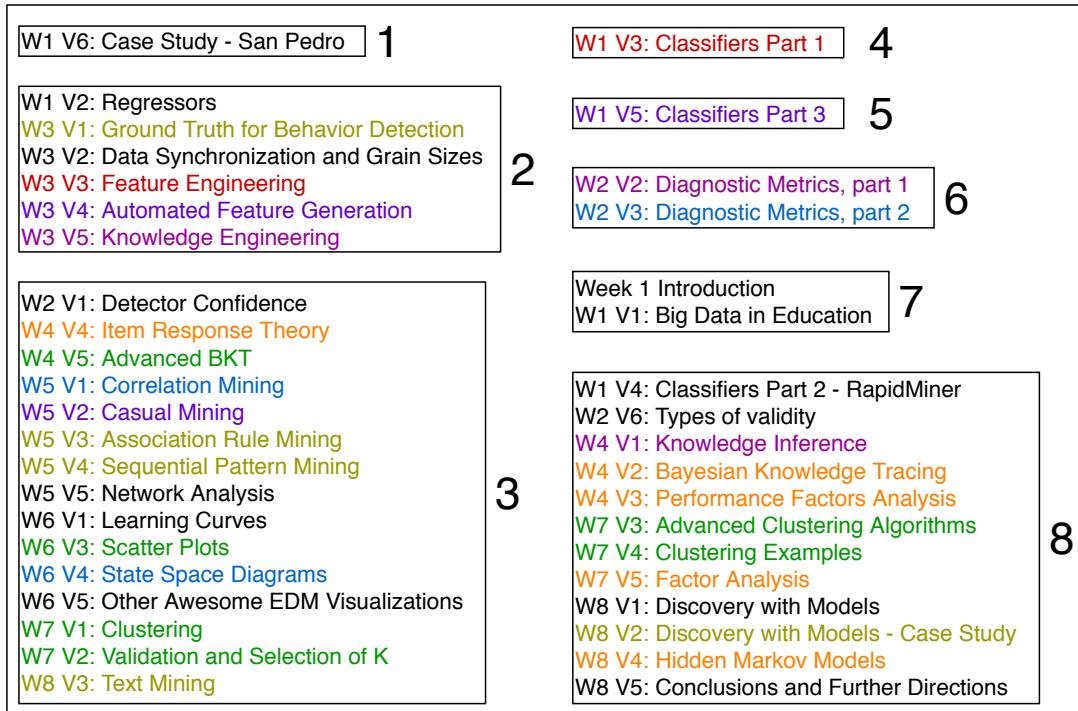
Learning Resource Modeling



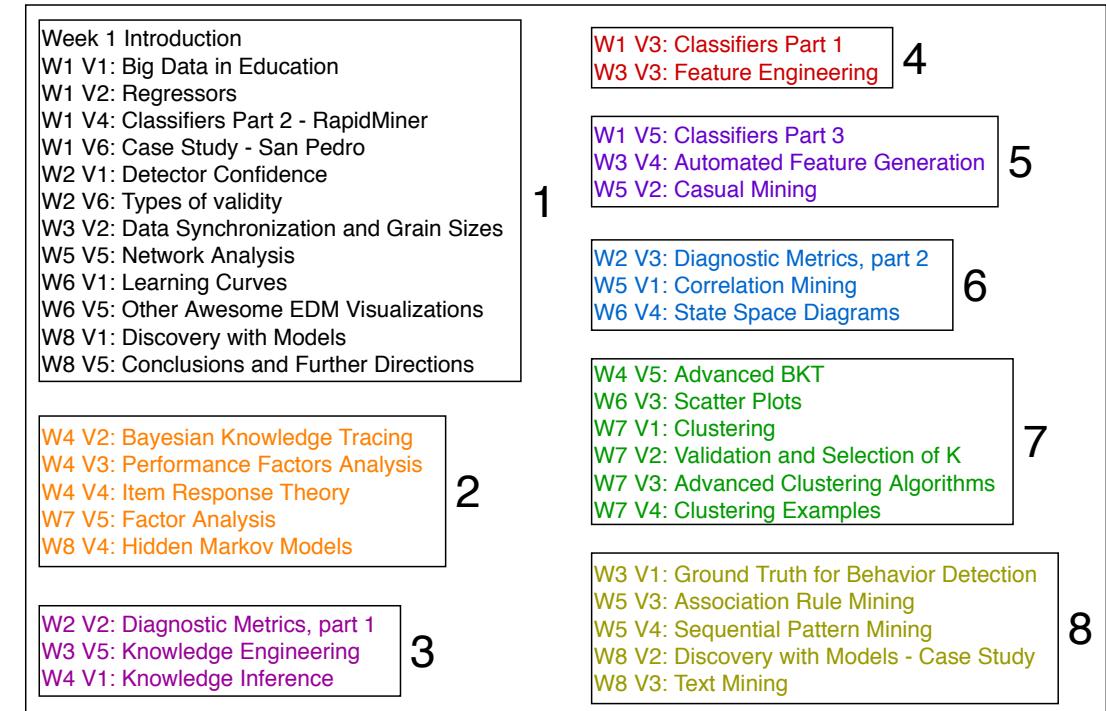


Within-Type Concept Evaluation

Both structural similarities and content similarities exist



Clusters that were discovered by using MVKM

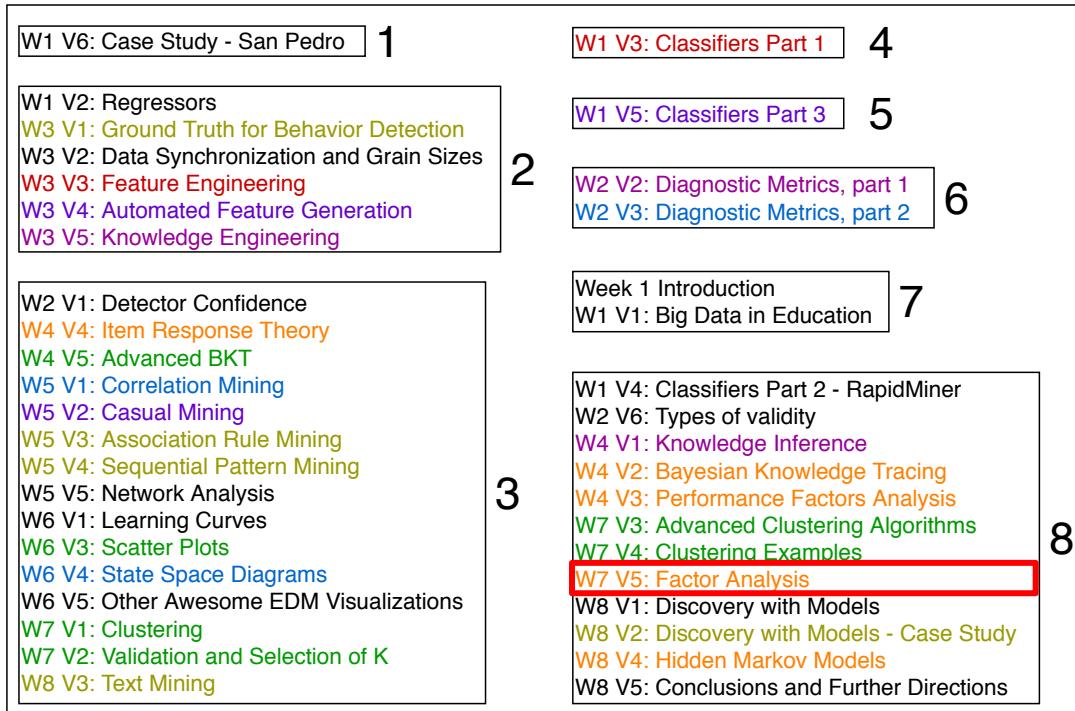


Clusters discovered by using LDA topics

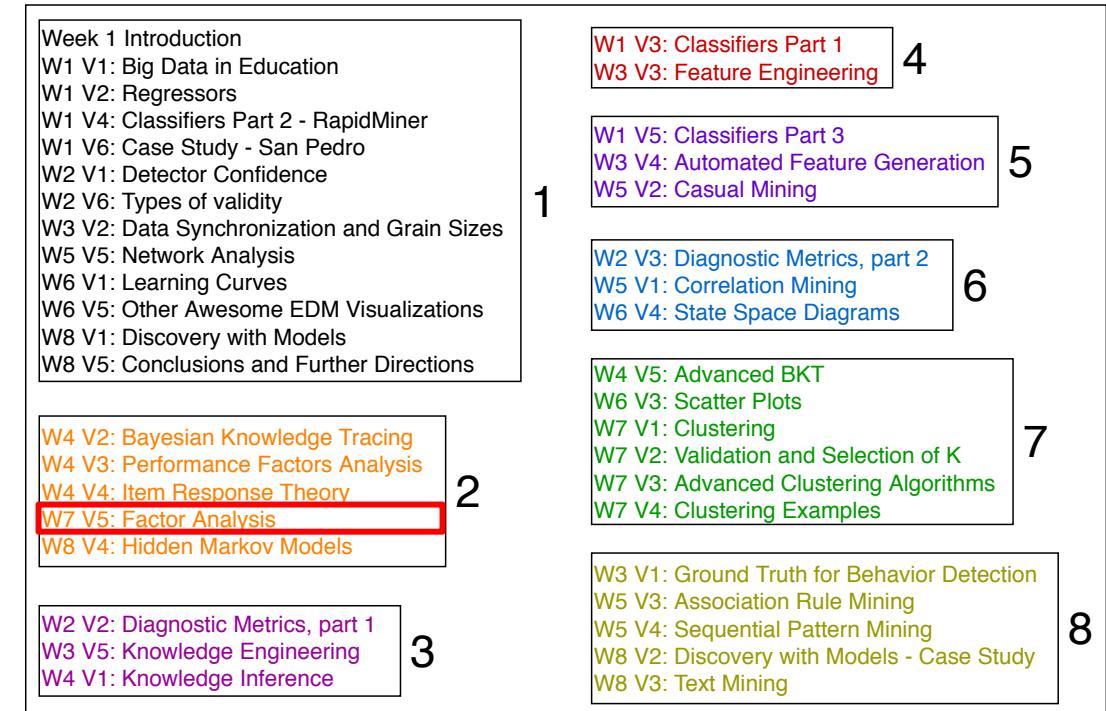


Within-Type Concept Evaluation

Both structural similarities and content similarities exist



Clusters that were discovered by using MVKM

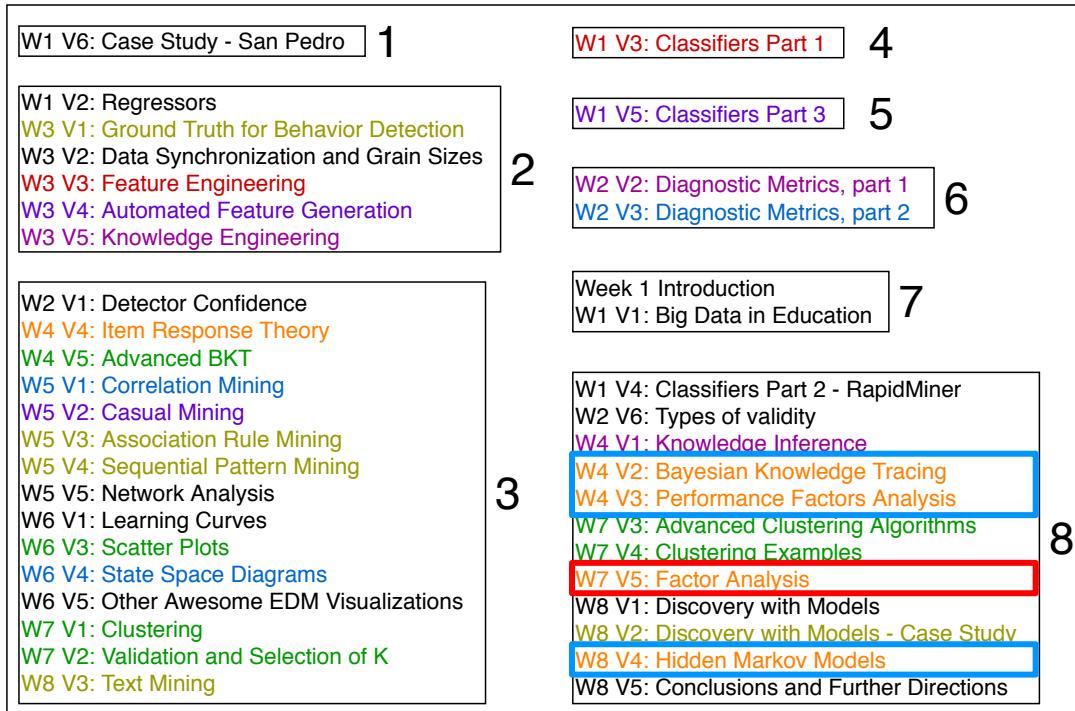


Clusters discovered by using LDA topics

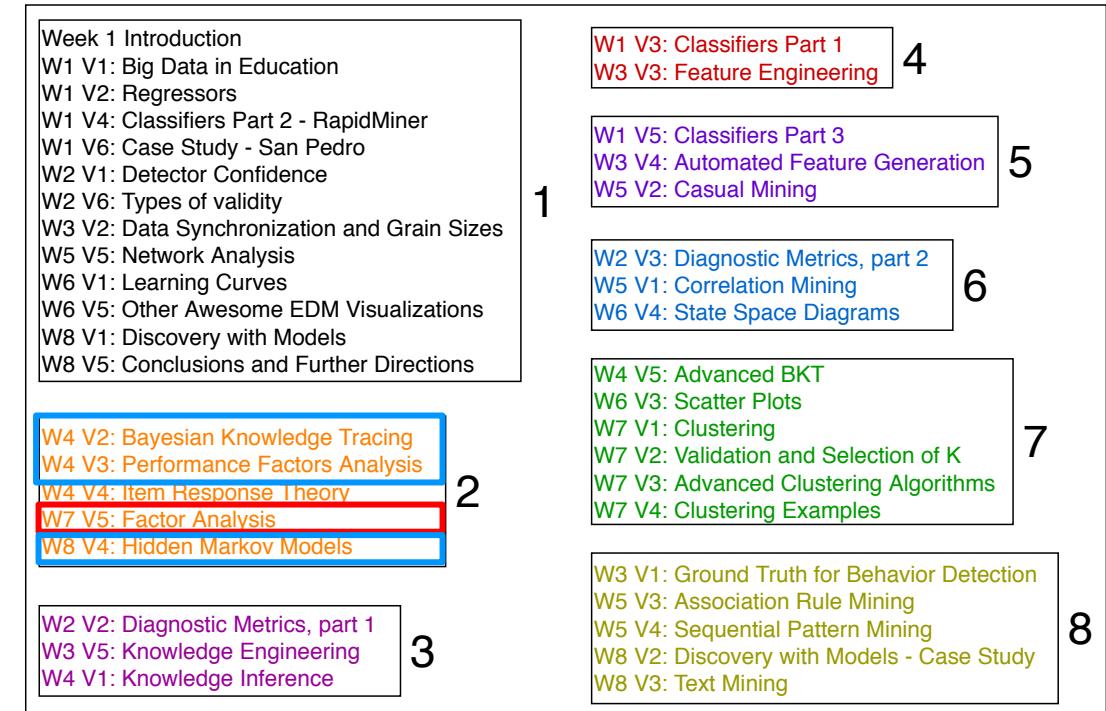


Within-Type Concept Evaluation

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Clusters that were discovered by using MVKM

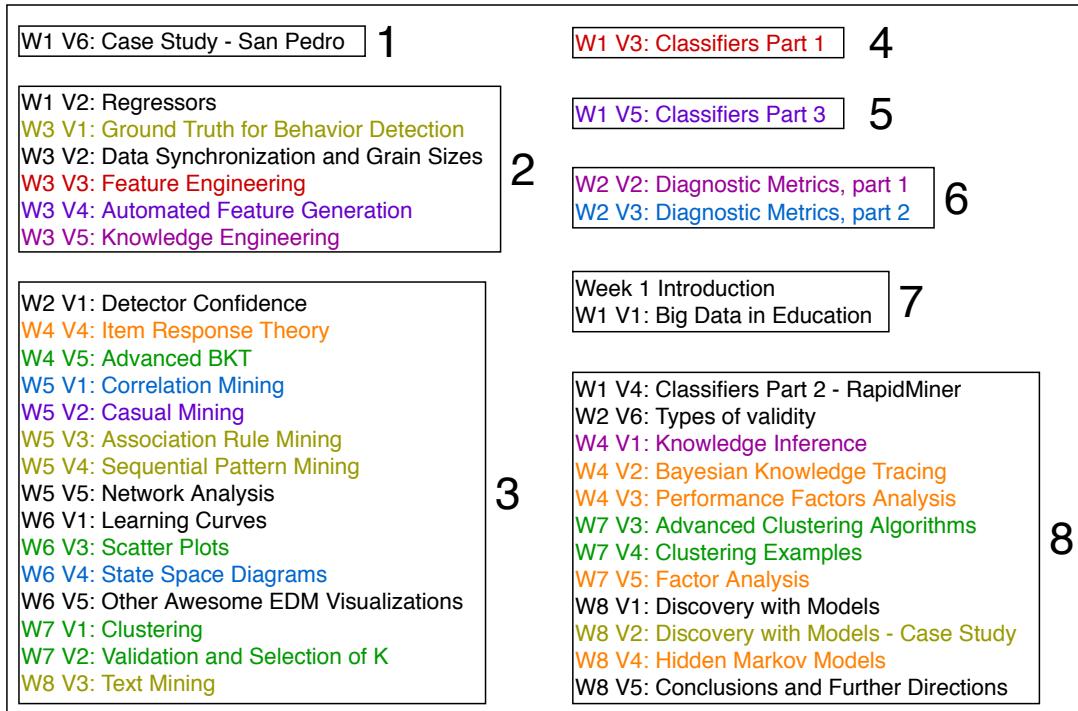


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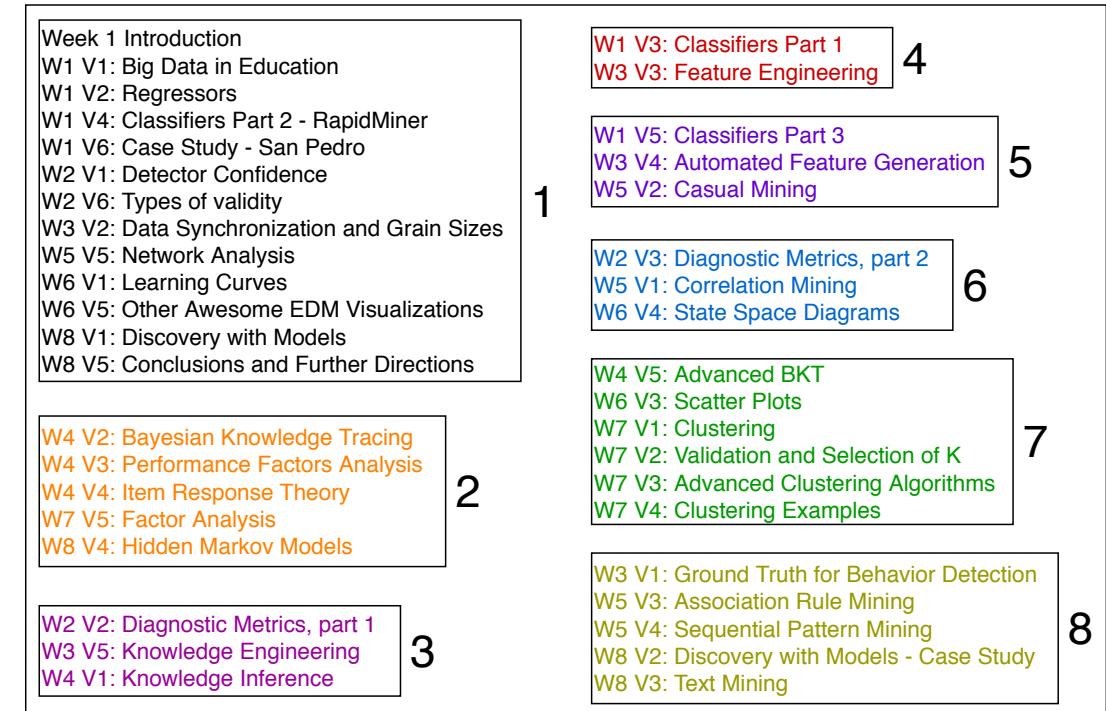


Within-Type Concept Evaluation

MVKM mostly represent the course structure similarity



Clusters that were discovered by using MVKM

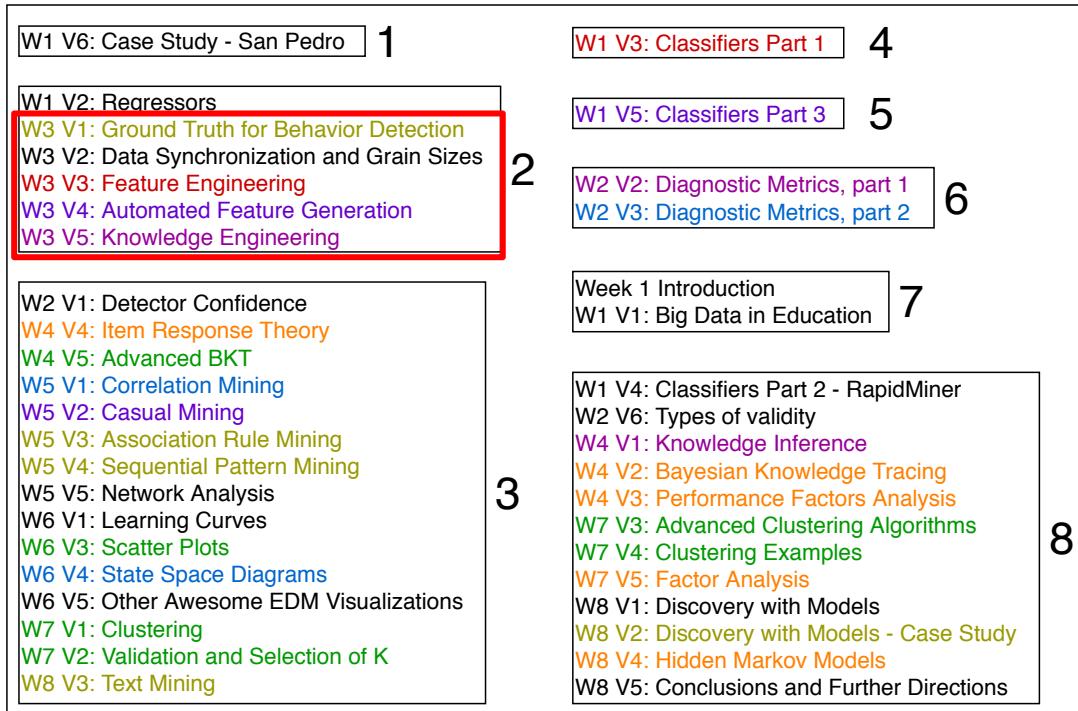


Clusters discovered by using LDA topics

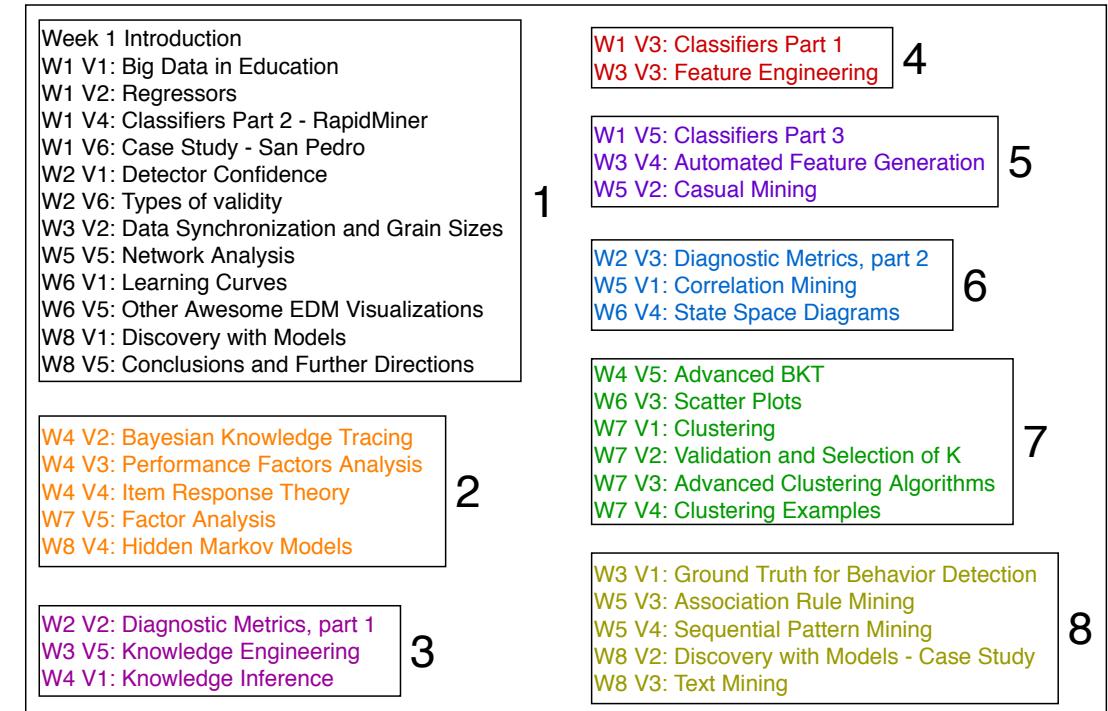


Within-Type Concept Evaluation

MVKM mostly represent the course structure similarity



Clusters that were discovered by using MVKM

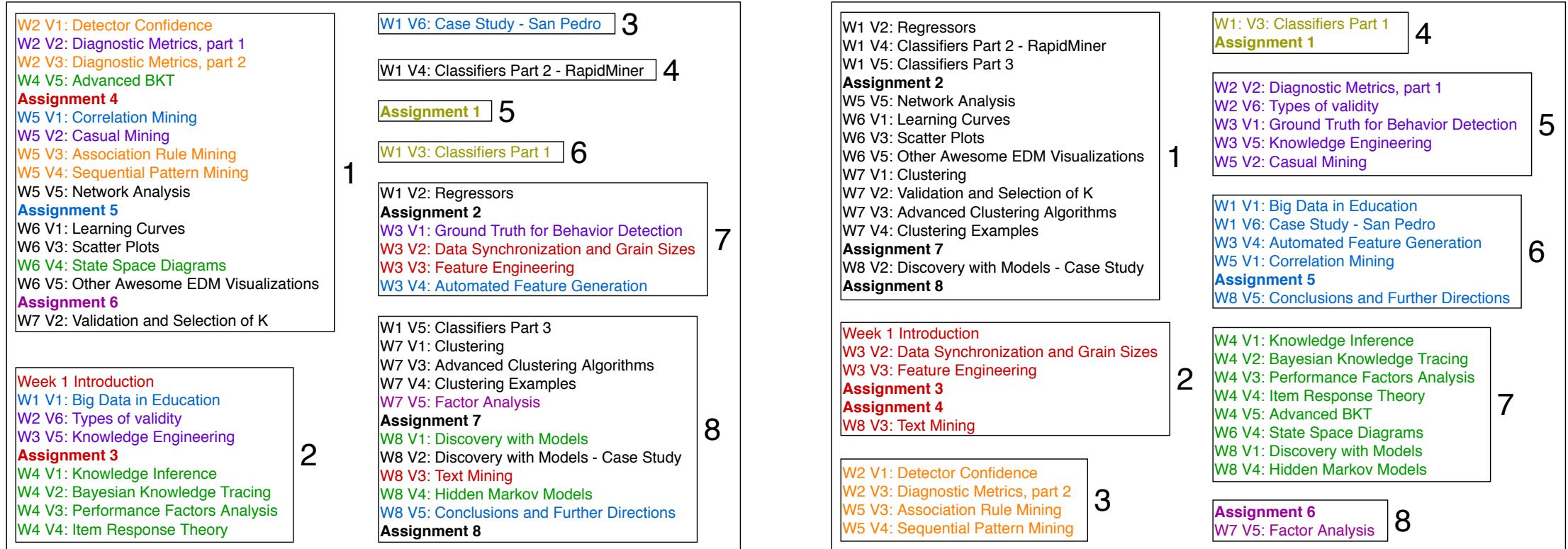


Clusters discovered by using LDA topics



Between-Type Concept Evaluation

Both structural similarities and content similarities exist



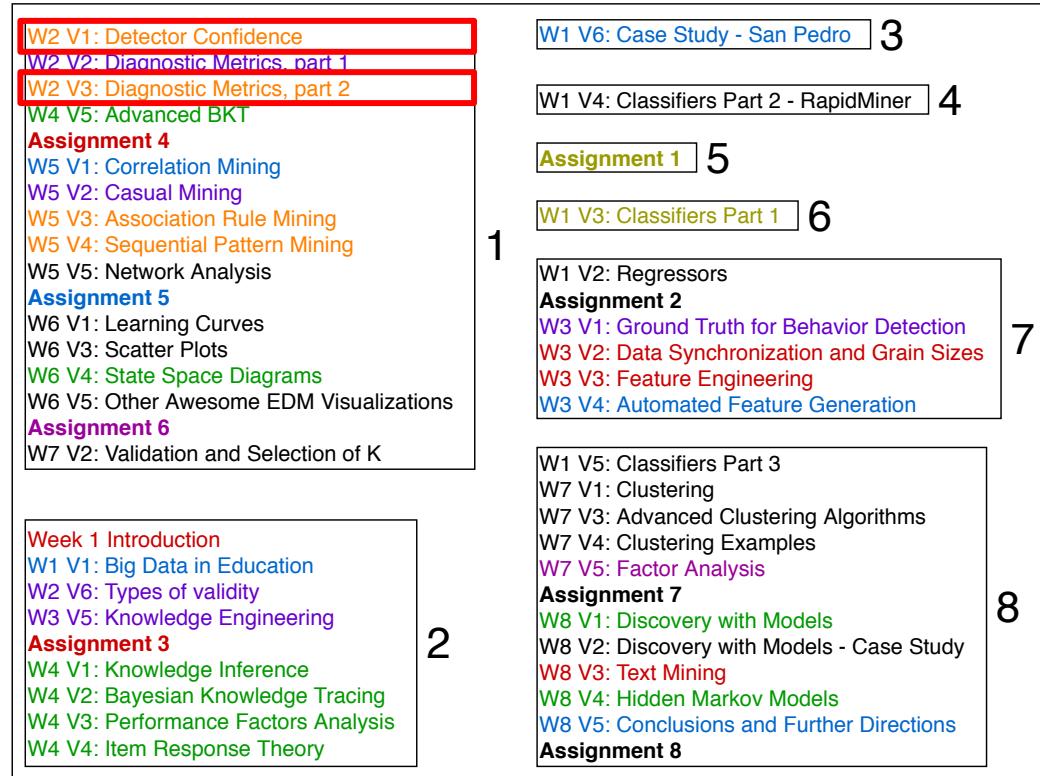
Clusters that were discovered by using MVKM

Clusters discovered by using LDA topics

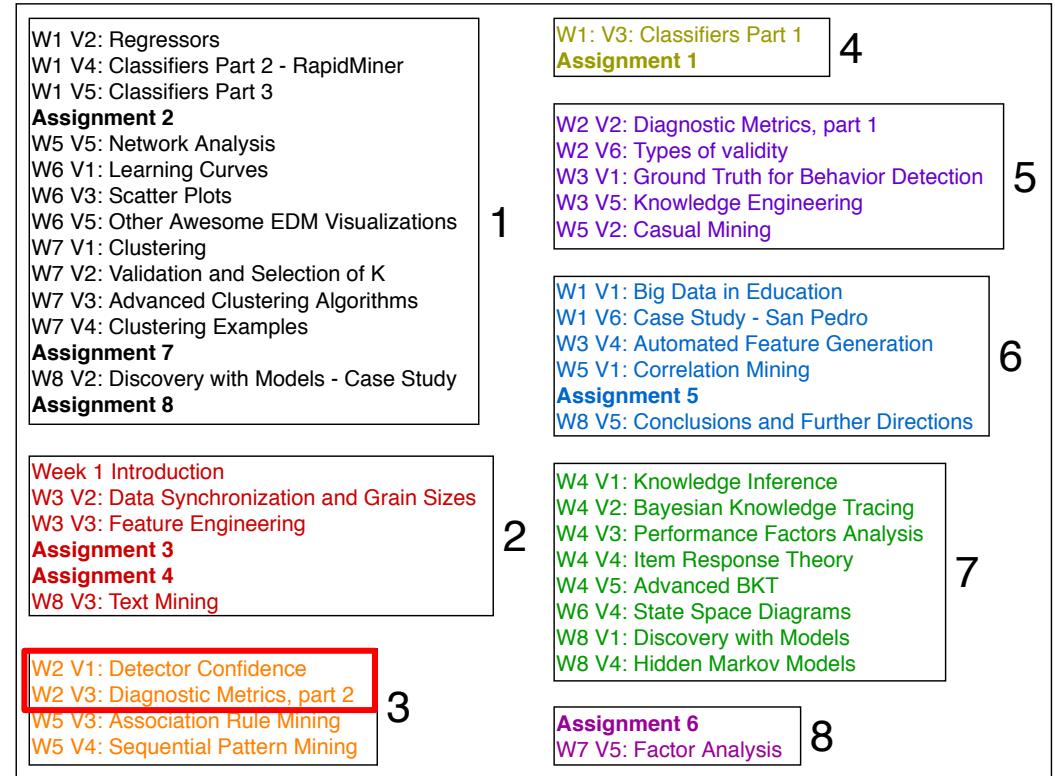


Between-Type Concept Evaluation

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Clusters that were discovered by using MVKM

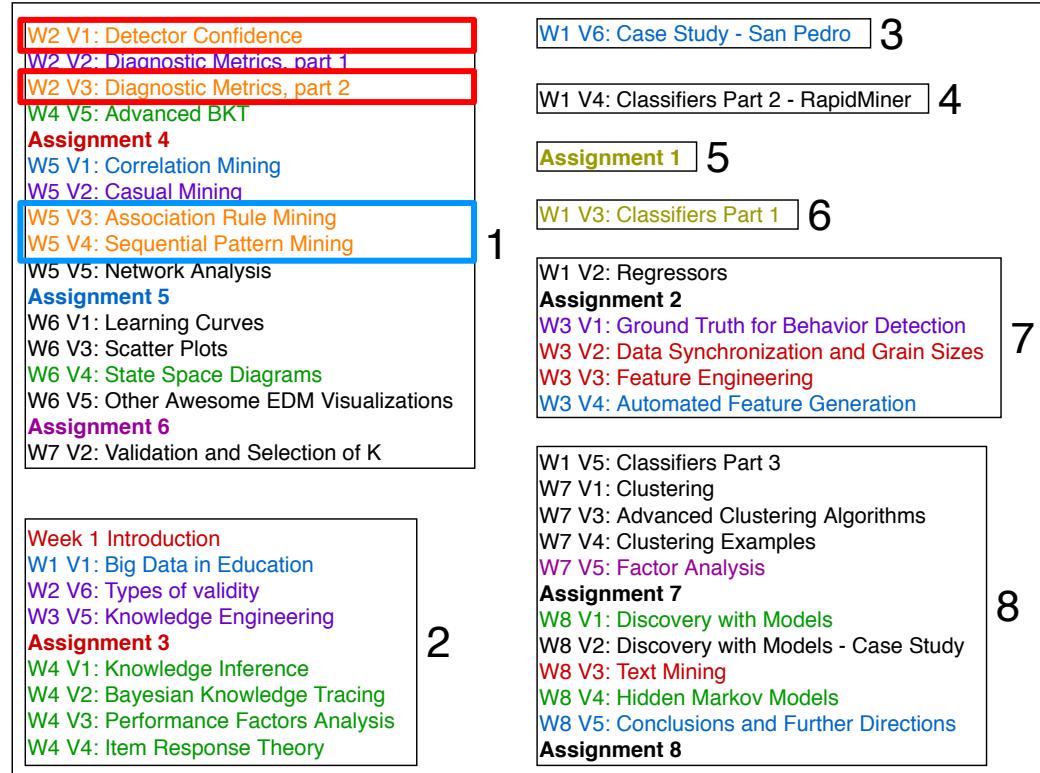


Clusters discovered by using LDA topics

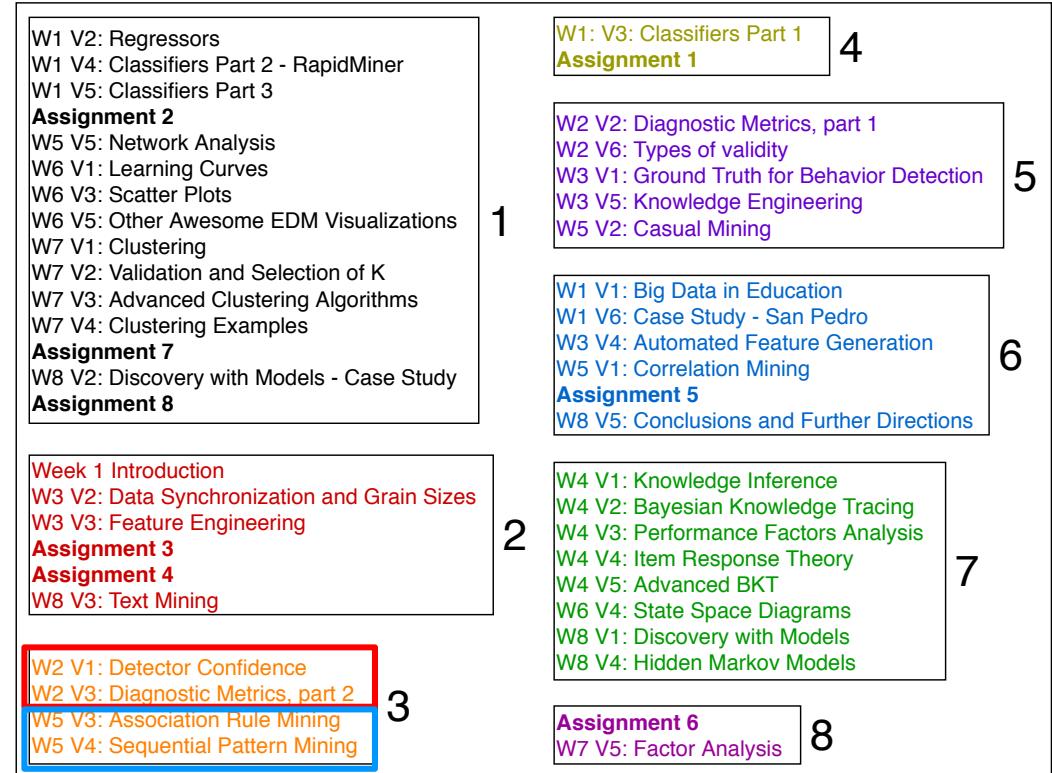


Between-Type Concept Evaluation

Both structural similarities and content similarities exist



Clusters that were discovered by using MVKM

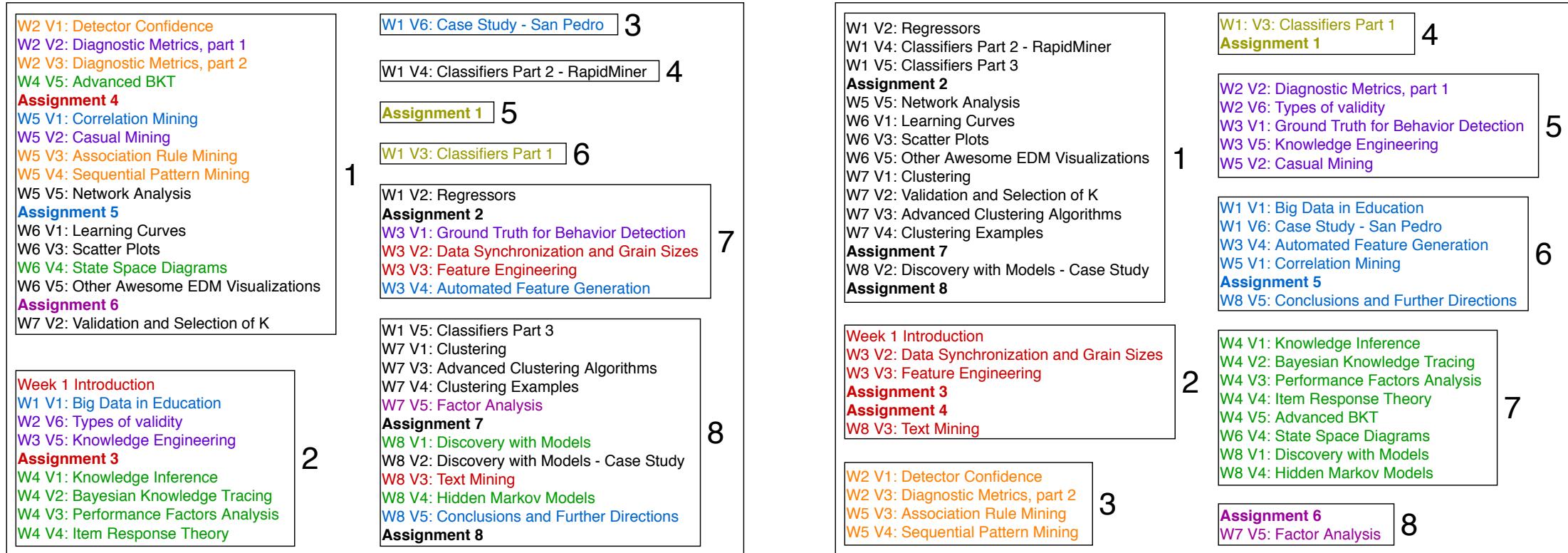


Clusters discovered by using LDA topics



Between-Type Concept Evaluation

Assignments are grouped with the upcoming lecture



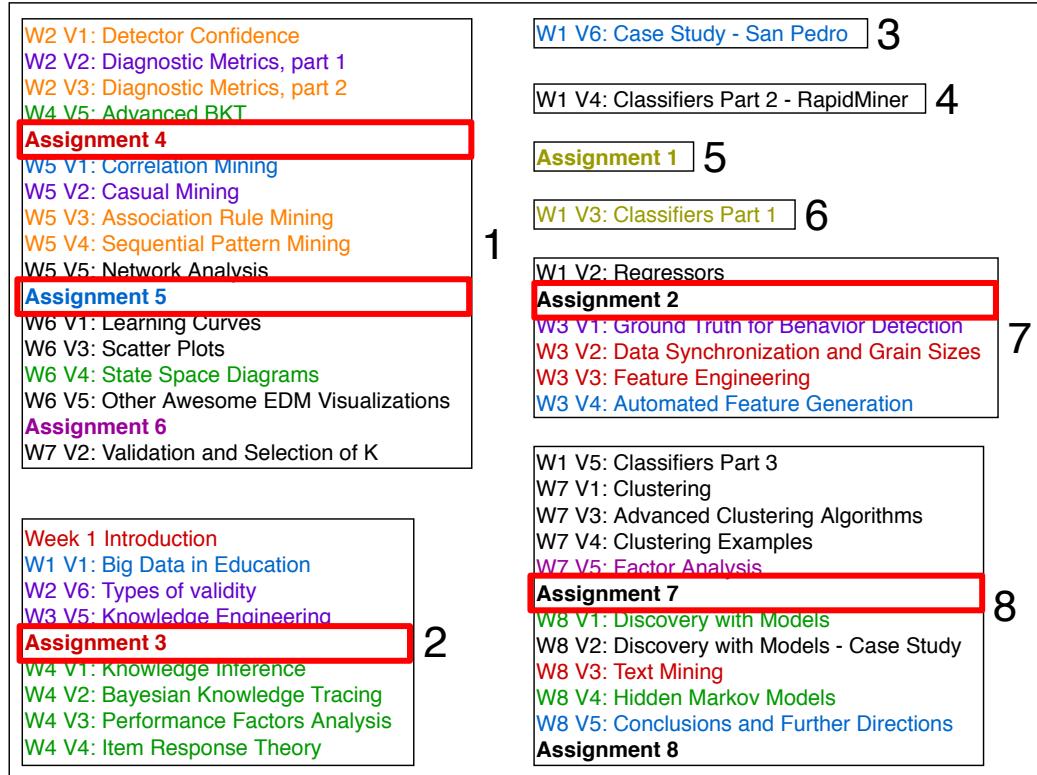
Clusters that were discovered by using MVKM

Clusters discovered by using LDA topics

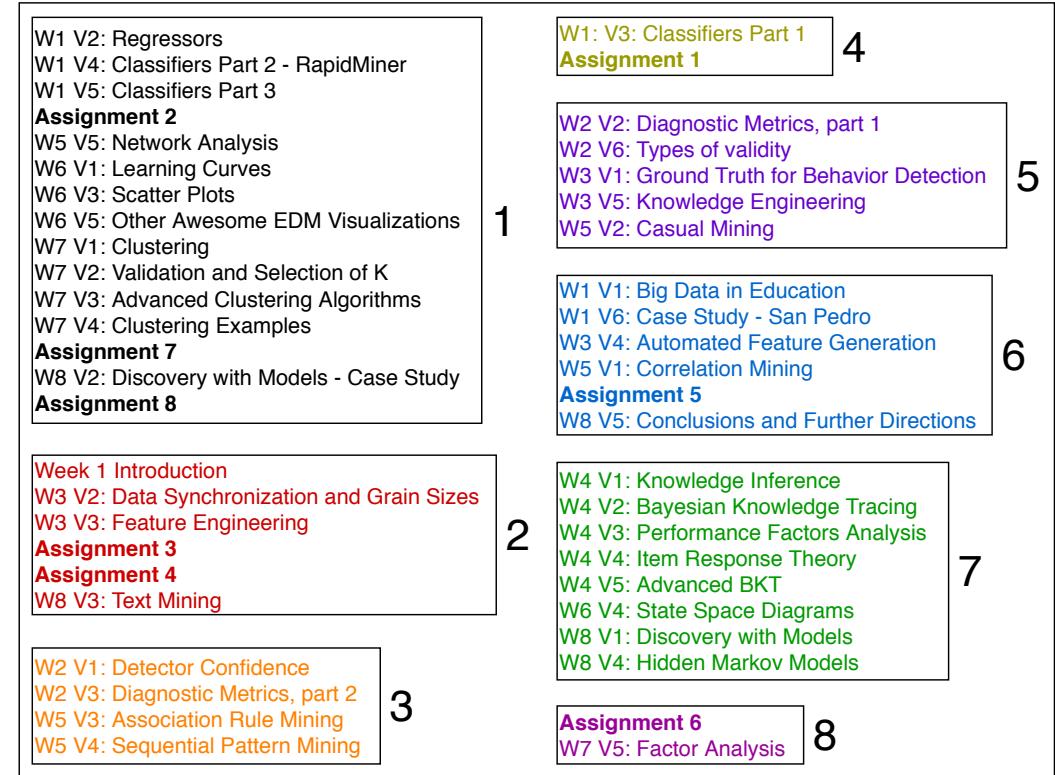


Between-Type Concept Evaluation

Assignments are grouped with the upcoming lecture



Clusters that were discovered by using MVKM



Clusters discovered by using LDA topics



Conclusions

- We proposed a novel Multi-View Knowledge Model (MVKM)
 -  • MVKM outperforms other baselines in the task of student performance prediction
 -  • Can model students' knowledge gain from different learning materials types
 -  • Can effectively capture students' knowledge growth,
 - Represent similarities between different learning material types



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Thank you! Q & A

Our code are available at GitHub:
<https://github.com/sz612866/MVKM-Multiview-Tensor>



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