Paper:
Recomender System for Predicting Student Performance

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2010

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Contexto de SysRec en e-learning

Objetivo	Modelos	Referencia
Predecir la nota de los estudiantes en los próximos cursos.	• Regresión lineal • Factorización matricial • Factorization Machine	[1]
Personalizar el ambiente e-learning mediante la recomendación de recursos.	• Filtrado colaborativo • Filtrado basado en contenido	[4]
Revisión de literatura sobre el panorama de sistemas recomendadores para apoyar el aprendizaje	• Varios, generalmente centrados en filtrado colaborativo. • Se revisan 82 artículos	[5]

Objetivos de la predicción

Table 12.2 Classification of TEL recommenders, according to the Supported Tasks

	Supported tasks
Find good items (61)	[RS1-2000], [RS3-2003], [RS5-2004], [RS7-2005], [RS8-2005], [RS9-2005], [RS11-2006], [RS13-2007], [RS14-2008], [RS17-2008], [RS19-2009], [RS21-2009], [RS22-2009], [RS23-2009], [RS25-2009], [RS26-2009], [RS27-2009], [RS28-2009], [RS29-2010], [RS30-2010], [RS31-2010], [RS32-2010], [RS33-2010], [RS34-2010], [RS35-2010], [RS37-2010], [RS38-2010], [RS39-2010], [RS40-2010], [RS41-2014], [RS42-2010], [RS43-2010], [RS44-2010], [RS45-2010], [RS46-2010], [RS47-2011], [RS48-2011], [RS49-2012], [RS50-2012], [RS52-2012], [RS53-2012], [RS54-2012], [RS55-2012], [RS56-2012], [RS57-2012], [RS58-2012], [RS62-2012], [RS63-2013], [RS64-2013], [RS67-2013], [RS68-2013], [RS70-2013], [RS71-2014], [RS72-2014], [RS73-2014], [RS75-2014], [RS77-2014], [RS78-2010], [RS79-2011], [RS80-2013], [RS81-2013]
Find peers (9)	[RS3-2003], [RS9-2005], [RS37-2010], [RS38-2010], [RS39-2010], [RS47-2011], [RS54-2012], [RS72-2014], [RS77-2014]
Recommend sequence of items (13)	[RS6-2004], [RS12-2007], [RS15-2008], [RS20-2009], [RS34-2010], [RS36-2010], [RS51-2012], [RS57-2012], [RS60-2012], [RS65-2013], [RS71-2014], [RS75-2014], [RS77-2014]
Predict learning performance (1)	[RS59-2012]
Recommend learning activity (4)	[RS66-2013], [RS69-2013], [RS74-2014], [RS82-2014]

[5]

Métodos utilizados

Table 12.5 Classification according to Personalisation characteristics

		Approach: Personalisation
Method	*Collaborative filtering (21)*	[RS3-2003], [RS8-2005], [RS9-2005], [RS1-2000], [RS78–2010], [RS11-2006], [RS5-2004], [RS26-2009], [RS12-2007], [RS44-2010], [RS29-2010], [RS21-2009], [RS37-2010], [RS72-2014], [RS76-2014], [RS73-2014], [RS13-2007], [RS49-2012], [RS63-2013], [RS47-2011], [RS79-2011]
	Content-based (10)	[RS39-2010], [RS38-2010], [RS42-2010], [RS35-2010], [RS21-2009], [RS75-2014], [RS41–2014], [RS70-2013], [RS68-2013], [RS43-2010]
	Hybrid (13)	[RS25-2009], [RS27-2009], [RS56-2012], [RS34-2010], [RS21-2009], [RS46-2010], [RS77-2014], [RS71-2014], [RS48-2011], [RS40-2010], [RS64-2013], [RS14-2008], [RS19-2009]
	Rule-based (22)	[RS6-2004], [RS53-2012], [RS50-2012], [RS52-2012], [RS57-2012], [RS32-2010], [RS31-2010], [RS54-2012], [RS51-2012], [RS55-2012], [RS75-2014], [RS67-2013], [RS70-2013], [RS68-2013], [RS23-2009], [RS28-2009], [RS45-2010], [RS65-2013], [RS22-2009], [RS80-2013], [RS81-2013], [RS82-2014]
	Graph-based (4)	[RS72-2014], [RS76-2014], [RS36-2010], [RS60-2012]
	Knowledge-based (3)	[RS66-2013], [RS69-2013], [RS74-2014]
	Association mining (1)	[RS17-2008]
	Raw retrieval (1)	[RS62-2012]
	Manually selected (1)	[RS52-2012]

[5]

Objetivo de Paper

Objetivo:

Proponer un nuevo método que utiliza técnicas de predicción utilizadas en sistemas recomendadores para predecir el performance de los estudiantes.

Métodos de regresión tradicional

VS

Técnicas de sistemas recomendadores

El problema

Problema de predecir el performance de un estudiante

Sistemas de tutoría apoyados por computadores

Predecir el performance de un estudiante para algunos ejercicios

Recomendación

Recomendaciones basadas en la predicción del performance

Seleccionando el grupo correcto de ejercicios

Seleccionando el nivel apropiado de dificultad

Seleccionando posibles intervenciones, como sugerencias

Log de eventos
time, student, context, action

Escenario de predicción de performance

Problema: Predecir el performance para cada paso en un problema

Logfile
step no, student, context, actions, duration, correct

- S = a set of studens IDs
- T = a set of task IDs
- f $\subseteq$ $\mathbb{R}$ = performance measure

$\Rightarrow$

- D $\subseteq$ (S x T x f)

- f (correct [1], incorrect [0])
- s $\in$ S
- t $\in$ T

- f = rating
- $s = user$
- $t = item$

Algoritmos y evaluación

Factorización Matricial

$$\hat{r}_{ui} = \sum_{k=1}^{K} w_{uk} h_{ik} = (WH^T)_{u,i}$$

RMSE

$$RMSE = \sqrt{\frac{\sum_{ui}(r_{ui} - \hat{r}_{ui})^2}{n}}$$

- Regresión Logística/lineal
- Gloval average
- UserKNN
- Rules-based

Data Set

Knowledge Discovery and Data Mining (KDD) Challenge 2010

Table 1: KDD Challenge 2010 Data sets

Data sets	Size	#Attributes	#Instances
Algebra 2008-2009 train	3.1 Gb	23	8,918,054
Algebra 2008-2009 test	124 Mb	23	508,912
Bridge to Algebra 2008-2009 train	5.5 Gb	21	20,012,498
Bridge to Algebra 2008-2009 test	135 Mb	21	756,386

Conceptos claves

Problema

Un problema es una tarea que un estudiante debe llevar a cabo que típicamente involucra varios pasos

Knowledge Component (KC)

Un componente de conocimiento es una pieza de información que se puede utilizar para realizar tareas

Paso

Un paso es una parte observable de la solución a un problema

Conteo de oportunidades

Una oportunidad es una oportunidad para que un estudiante demuestre si él o ella ha aprendido un componente de conocimiento dado

Data Set

Table 1. Data from the "Making Cans" example, aggregated by student-step

Row	Student	Problem	Step	Incorrects	Hints	Error Rate	Knowledge component	Opportunity Count
1	S01	WATERING_VEGGIES	(WATERED-AREA Q1)	0	0	0	Circle-Area	1
2	S01	WATERING_VEGGIES	(TOTAL-GARDEN Q1)	2	1	1	Rectangle-Area	1
3	S01	WATERING_VEGGIES	(UNWATERED-AREA Q1)	0	0	0	Compose-Areas	1
4	S01	WATERING_VEGGIES	DONE	0	0	0	Determine-Done	1
5	S01	MAKING-CANS	(POG-RADIUS Q1)	0	0	0	Enter-Given	1
6	S01	MAKING-CANS	(SQUARE-BASE Q1)	0	0	0	Enter-Given	2
7	S01	MAKING-CANS	(SQUARE-AREA Q1)	0	0	0	Square-Area	1
8	S01	MAKING-CANS	(POG-AREA Q1)	0	0	0	Circle-Area	2
9	S01	MAKING-CANS	(SCRAP-METAL-AREA Q1)	2	0	1	Compose-Areas	2

https://pslcdatashop.web.cmu.edu/KDDCup/rules_data_format.jsp [3]

Mapeo de datos para el sistema recomendador

Predecir si el estudiante tendrá éxito en el primer intento para realizar un paso

Estudiante $\Rightarrow$ user

Correct First Attempt (CFA) $\Rightarrow$ rating

Mapeo de datos para el sistema recomendador

Item ⇒

Table 2: Mapping educational data to User/Item in recommender systems

Algebra		Bridge	
User	**#User**	**User**	**#User**
Student	3,310	Student	6,043
Item	**#Item**	**Item**	**#Item**
PH, PN, SN	1,309,038	PH, PN, SN	593,369
PH, PG, SN	848,218	PH, PG, SN	188,001
PG, SN	776,155	PG, SN	155,808
PN, SN	1,254,897	PN, SN	566,843
SN	695,674	SN	126,560
PN(*)	188,368	PN(*)	52,754
PG(*)	185,918	PG(*)	52,189
PH, PN	206,596	PH, PN	61,848
PH, PG	1,000	PH, PG	1,343
PH	165	PH	186
PH, PN, SN, PV(*)	1,416,473	PH, PN, SN, PV(*)	887,740
PH, PN, PV	220,045	PH, PN, PV	101,707
PH, PG, PV	3,203	PH, PG, PV	5,537
PH, PV	780	PH, PV	1,526
KC-rules(*)	2,979	KC-rules	-

(*) combinations used for the recommender systems experiments. PH: problem hierarchy; PN: problem name (converted to id); SN: step name (converted to id); PV: problem view; KC: knowledge components

Mapeo de datos para el modelo de regresión

Regresión lineal y logística

$$D_{s,t} := \{(s', t', f) \in D \mid s' = s, t' = t\}$$

Entrada modelo de regression (promedio)

$$\frac{\sum_{(s,t,f) \in D_{s,t}} f}{|D_{s,t}|}$$

Mapeo de datos para el modelo de regresión

A = (Student-Average, Step-Average)

B = (Student-PV-Average, Step-PV-Average)

C = (PG-Average, PN-Average, Student-PG-PV-Average).

Protocolo

1. Se hizo un mapeo de los dataset al context educacional
2. Se utilizó como baseline method el global average
3. Ejecutar los algoritmos con las combinaciones de datos definidas

Resultados

Table 3: Root mean squared error (RMSE) for different methods using different sets of attributes as items

Technique	**Item**	**Algebra**	**Bridge**	**Average**
Global Average	-	0.34316	0.33199	0.33757
User Average	-	0.33892	0.32843	0.33367
Logistic Regression	A	0.32226	0.30456	0.31341
Logistic Regression	B	0.32444	0.30589	0.31517
Logistic Regression	A + B	0.32354	0.30498	0.31426
Logistic Regression	A + B + C	0.31988	0.30583	0.31286
Matrix Factorization	PN	0.33752	0.31515	0.32633
Matrix Factorization	PG	0.34316	0.33199	0.33757
User-Item Collaborative Filtering	PH, PN, SN, PV	0.32240	0.29817	0.31029
Matrix Factorization + Global Average	PH, PN, SN, PV	0.31817	0.29825	0.30821
Matrix Factorization + User Average	PH, PN, SN, PV	0.31812	0.29865	0.30837
Matrix Factorization + User-Item Collaborative Filtering	PH, PN, SN, PV	0.31787	0.29804	0.30796
Matrix Factorization + User-Item Collaborative Filtering	KC-rules	*0.30228*	0.29804	**0.30016**

The best result is bold faced. A: (Student-Average, Step-Average); B: (Student-PV-Average, Step-PV-Average); C: (PG-Average, PN-Average, Student-PG-PV-Average)

Conclusiones y trabajo futuro

- El modelo propuesto mejora los resultados de predicción con respecto a los modelos de regresión lineal.
- Utilizar otros métodos para abordar el problema de cold-start usando factorización matricial.
- Utilizar factorización de tensores para mejorar los resultados

Comparación

TABLE 1. Next-term grade prediction results on George Mason University transcript data.

Method	Root-mean-square error (RMSE)	Mean absolute error (MAE)
Factorization machine (FM)	0.7423	0.52 ± 0.53
Personalized linear multi-regression (PLMR)	0.7886	0.57 ± 0.55
Random forest (RF)	0.7936	0.58 ± 0.54
Mean of means	0.8643	0.64 ± 0.58
Uniform random guessing	1.8667	1.54 ± 1.06

Resultados de [2], 2016

User-Item Collaborative Filtering	PH, PN, SN, PV	0.32240	0.29817	0.31029
Matrix Factorization + Global Average	PH, PN, SN, PV	0.31817	0.29825	0.30821
Matrix Factorization + User Average	PH, PN, SN, PV	0.31812	0.29865	0.30837
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Matrix Factorization + User-Item Collaborative Filtering	KC-rules	*0.30228*	0.29804	**0.30016**

Resultados de [1], 2010

Referencias

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