Relaxed Clustered Hawkes Process for Procrastination Modeling in MOOCs

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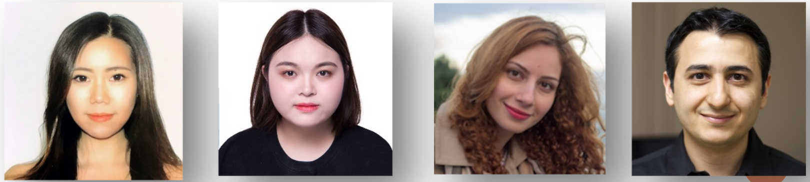

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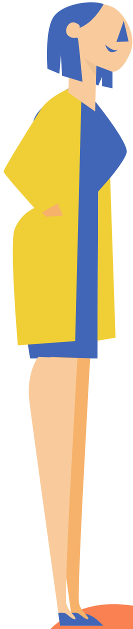


01

Introduction

1.1 procrastination modeling in MOOCs

MOOCs?
= Massive Open Online Courses

Procrastination?
Voluntary delay (≈ cramming behaviors)

Why?
Lack of time management, little self-regulation,…

What?
Characteristic behaviors; clusters

How?
Static measures (e.g. avg. time)

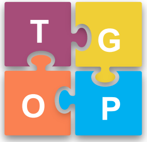
why?
Bad & prevalent
Detect & predict
regulate & prevent

1.2.1 problem

Need a procrastination model that:
- Can model temporal aspects (aot. static)
- Personalized (aot. full set of parameters)

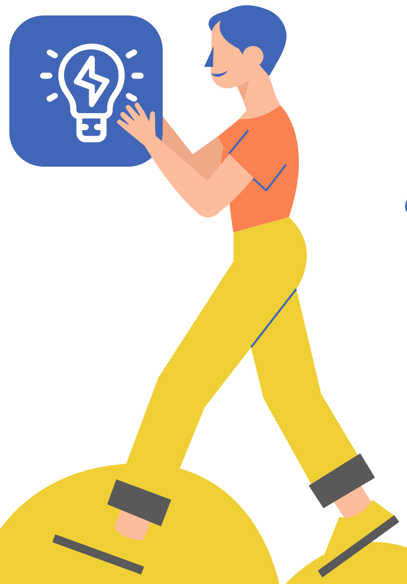
When:
- Observation is sparse
- students' group structure

1.2.2 our solution



A **personalized stochastic model** that discovers **student behavior clusters**, that can predict future activities **with missing and partial data, but without auxiliary features**

02
Model

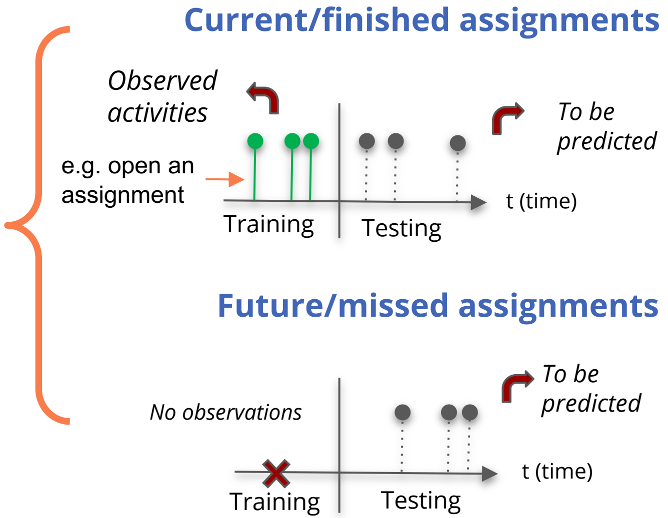


2.1 problem formulation

Consider a MOOC

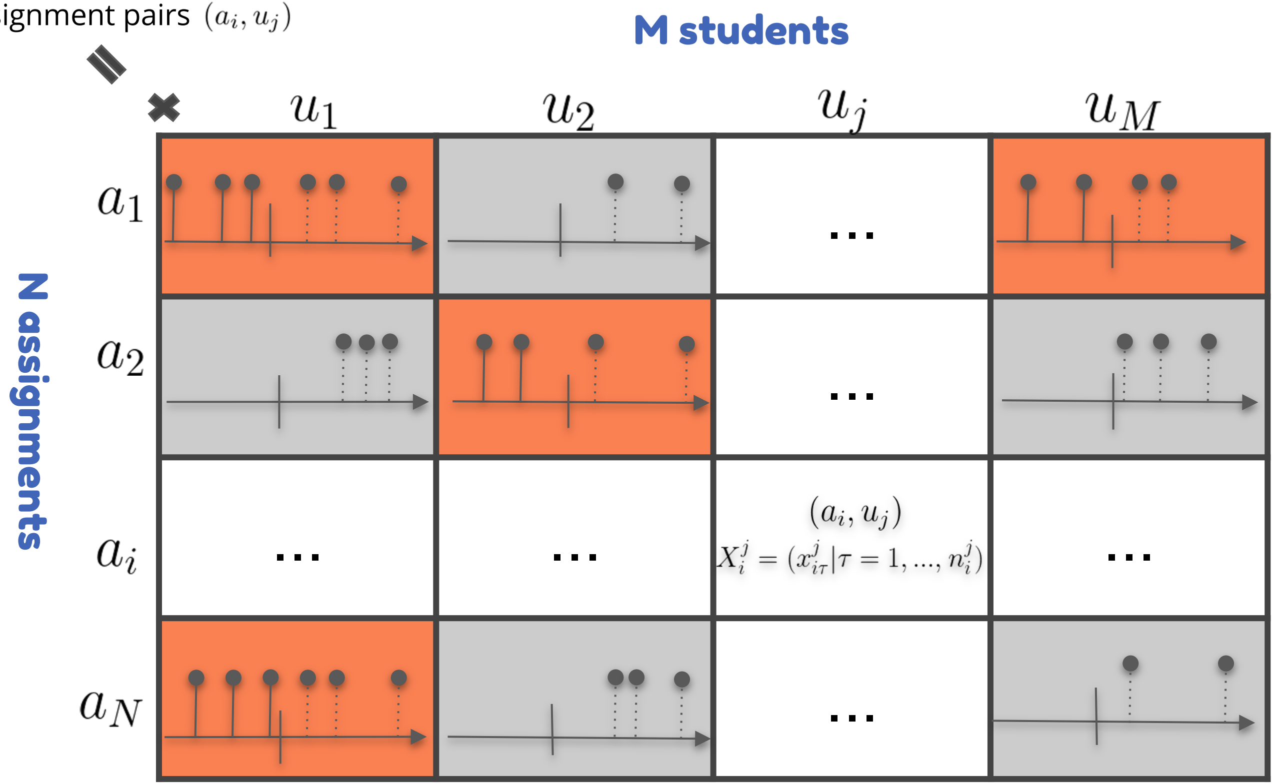
M students

N assignments



2.1 problem formulation (cont.)

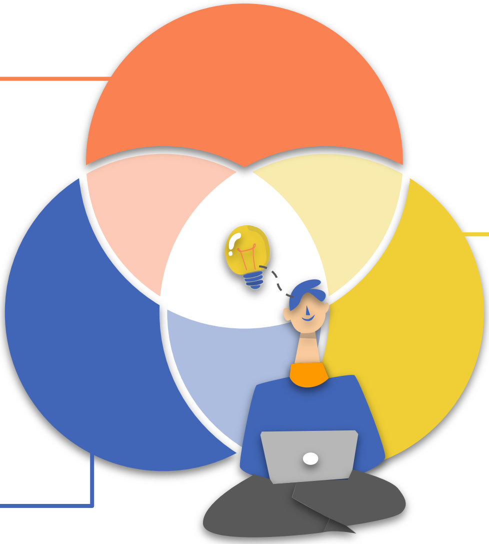
NxM student-assignment pairs (a_i, u_j)



2.2 RCHawkes-Gamma

2.2.1 Hawkes model

T *model temporal aspects*



2.2.3 Mixture Gamma

Robustness ✓ *interpretability* ✓

2.2.2 Joint relaxed Clustering

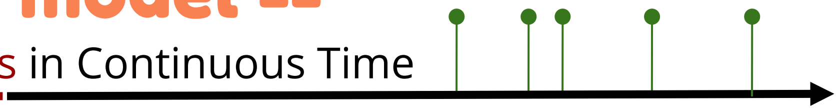
P *Personalized*

O *Observation is sparse*

G *students' group structure*

2.2.1 Hawkes model --

Model Discrete Events in Continuous Time

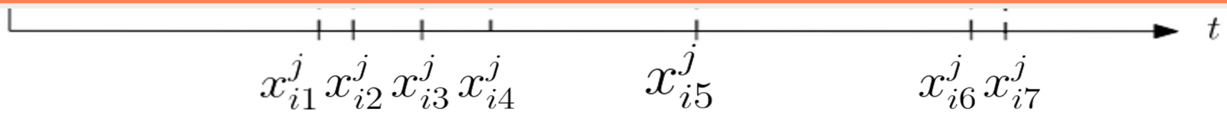


model temporal aspects

For (a_i, u_j), observe its time sequence: $X_i^j = (x_{i\tau}^j | \tau = 1, \ldots, n_i^j)$

Define its intensity function $\lambda(t)_{ij} = U_{ij} + A_{ij}\beta \sum^{n_{ij}} \exp(-\beta(t - x_{i,\tau}^j))$

But what if there is no observed activity for a sequence? And how to model more than one sequences?



2.2.2 Joint relaxed Clustering

P *Personalized*

O *Observation is sparse*

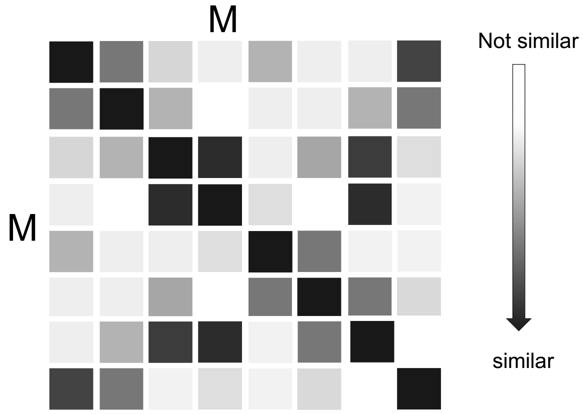
G *students' group structure*

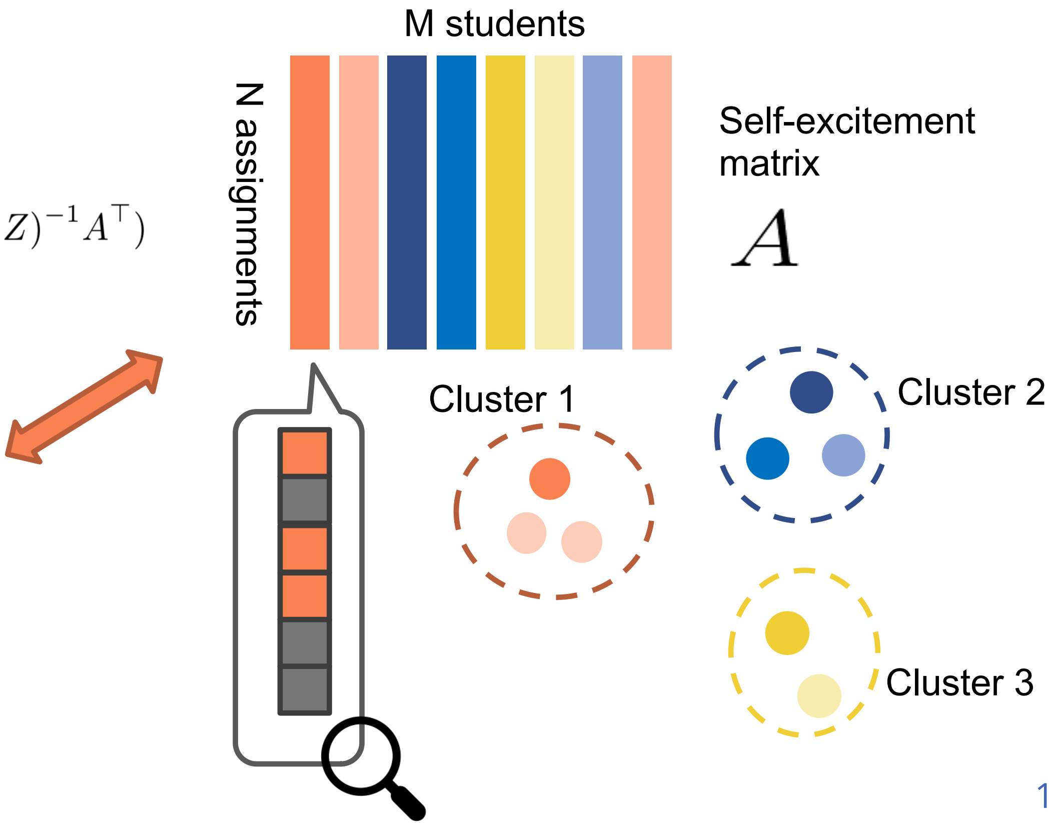
Convex relaxation:

$$\min \mathcal{L}_c(A, Z) = \min \frac{\rho_2(\rho_2 + \rho_1)}{\rho_1} tr(A(\frac{\rho_1}{\rho_2} I + Z)^{-1} A^\top)$$

$$\text{s.t. } tr(Z) = k, Z \preceq I, Z \in S_+^M.$$

Learnable Z





2.2.3 Mixture Gamma prior

Robustness ☑

interpretability ☑

The prior when student i is in m-th cluster

$$p(A_{ij};\Theta_m) = \frac{1}{\Gamma(s_m)\theta_m^{s_m}} A_{ij}^{s_m-1} \exp(-\frac{A_{ij}}{\theta_m^{s_m}})$$

$$\Theta_m = (s_m, k_m)$$

Shape
(pesudo base rate)

Scale
(pesudo #. Events
triggered internally)

Loss:

$$\mathcal{L}_g = \log p(A;\Theta_1,..,\Theta_k)$$

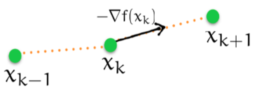
$$= \sum_{X_i^j \in \mathcal{O}} \left[\log \sum_{m=1}^{k} \frac{1}{k} \frac{1}{\Gamma(s_m)\theta_m^{s_m}} A_{ij}^{s_m-1} \exp(-\frac{A_{ij}}{\theta_m^{k_m}})\right]$$

2.2.4 Optimization

$$\begin{aligned}\min_{A_z,U_z,Z_z} \; & -L_{mle} - L_c - L_g \\ & + \|A_z - A_s\|_F^2 + \|U_z - U_s\|_F^2 + \|Z_z - Z_s\|_F^2, \\ \text{s.t. } & tr(Z_z) = k, tr(A_z) \leq c, A_z \geq 0, U_z \geq 0, \\ & Z_z \leq I, Z_z \in S_+^M\end{aligned}$$

Gradient Descent

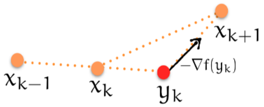
$$x_{k+1} = x_k - \epsilon \nabla f(x_k)$$



Accelerated GD

$$x_{k+1} = y_k - \epsilon \nabla f(y_k)$$

$$y_k = x_k + \frac{k-1}{k+2}(x_k - x_{k-1})$$



when $\|\nabla^2 f\| \leq \frac{1}{\epsilon}$

$O\left(\frac{1}{\epsilon k}\right) \xrightarrow{\text{accelerated!}} O\left(\frac{1}{\epsilon k^2}\right)$ optimal rate Proof

source

03

Experiments

3. Experiments

3.1 Datasets

3.2 Baselines

3.3 Evaluation

3.4 Student Procrastination Analysis

3.1 datasets

- **Synthetic**
  - **5400 s-a pairs**
  - **~810 K activities**
    - 10% missing
    - 30% missing
    - 50% missing
    - 70% missing
- **real-world**
  - **CANVAS**
    - 471 students, 6 assignments, ~740K activities
  - **MORF**
    - 675 students, 8 assignments, ~102K activities

3.2 baseline approaches

Application	Model	Infer future of unseen Data	Require No External Features	Capture Temporal dependency
EDM	RCHawkes-Gamma	✓	✓	✓
EDM	RCHawkes	✓	✓	✓
EDM	EdMHP (Yao et al, 2020)	x	x	✓
Rec-Sys	HPLR (Du et al, 2015)	✓	✓	✓
ATM	ERPP (Xiao et al, 2017)	x	x	✓
Rec-Sys	HRPF (Hosseini, 2017)	✓	✓	x
Rec-Sys	DRPF (Hosseini, 2017)	✓	✓	x
Others	RMTPP (Du et al, 2016)	x	x	✓

3.3. Evaluation

Parameter Estimation

RMSE of estimated parameters

The lower the better

Synthetic ✓ real-world ✗

Time prediction

RMSE of predicted next arrival time

The lower the better

Synthetic ✓ real-world ✓

Cluster recovery

Recovered correlation matrix

The higher the within-group correlation and the lower the between-group correlation the better

Synthetic ✓ real-world ✗

Parameter Estimation

Synthetic ✓ real-world ✗

Infer unseen data ✓

Table 2: RMSE (±standard deviation) of $\hat{A}$ and $\hat{U}$ on seen and unseen data, with various missing data ratios (r)

	Model	r = 0.1		r = 0.3		r = 0.5		r = 0.7	
		seen	unseen	seen	unseen	seen	unseen	seen	unseen
RMSE for A	RCHawkes-Gamma	**0.094±0.024**	**0.102±0.037**	0.121±0.017	**0.114±0.056**	0.141±0.033	0.139±0.033	**0.136±0.077**	**0.137±0.052**
	RCHawkes	0.108±0.017	0.108±0.054	**0.115±0.024**	0.116±0.039	**0.126±0.033**	**0.136±0.033**	0.180±0.072	0.170±0.048
	HPLR	0.631±0.110	0.663±0.331	0.645±0.141	0.607±0.216	0.635±0.133	0.633±0.133	0.634±0.304	0.634±0.204
	HRPF	0.664±0.769	0.664±0.769	0.664±0.770	0.664±0.770	0.663±0.769	0.663±0.770	0.664±0.769	0.664±0.767
	DRPF	0.474±0.461	0.474±0.461	0.479±0.465	0.479±0.465	0.473±0.462	0.473±0.462	0.474±0.463	0.474±0.463
RMSE for U	RCHawkes-Gamma	0.075±0.022	0.085±0.036	**0.069±0.017**	**0.060±0.050**	**0.062±0.030**	**0.064±0.030**	0.071±0.039	0.075±0.026
	RCHawkes	0.074±0.020	0.089±0.061	0.074±0.020	0.075±0.032	0.077±0.030	0.079±0.030	**0.069±0.026**	**0.062±0.017**
	HPLR	0.110±0.082	**0.078±0.047**	0.081±0.060	0.078±0.094	0.091±0.035	0.091±0.035	0.090±0.096	0.095±0.065
	HRPF	0.105±0.055	0.311±0.055	0.119±0.068	0.183±0.068	0.141±0.071	0.142±0.071	0.179±0.068	0.120±0.070
	DRPF	**0.062±0.052**	0.300±0.035	0.088±0.049	0.165±0.045	0.121±0.051	0.121±0.050	0.167±0.053	0.102±0.054

- Lower RMSE
- Less sensitive to miss ratio

Cluster recovery

Synthetic

real-world

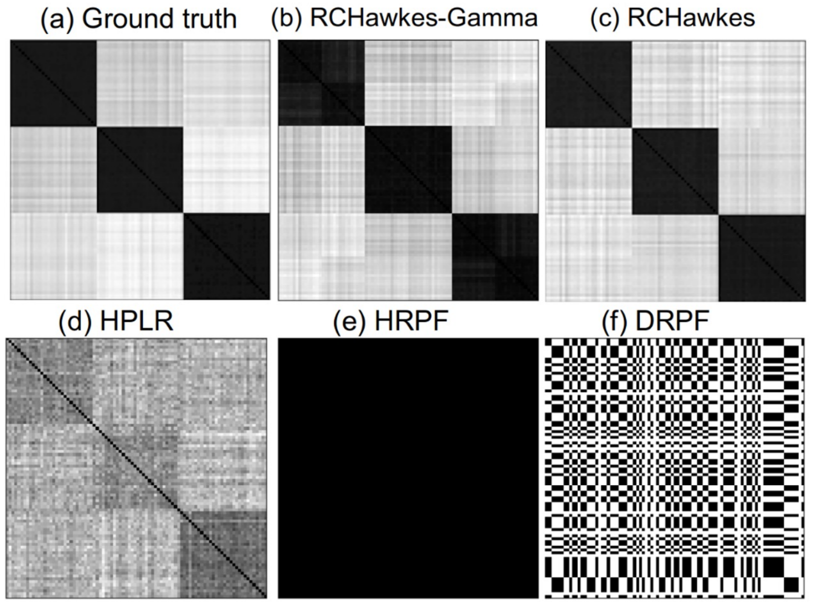


Figure 3: The ground truth of A's correlation matrix (a), and the estimated $\hat{A}$'s correlation matrix learned by each model.

- Successfully recover correlation matrix
- The closest to ground truth

Time prediction

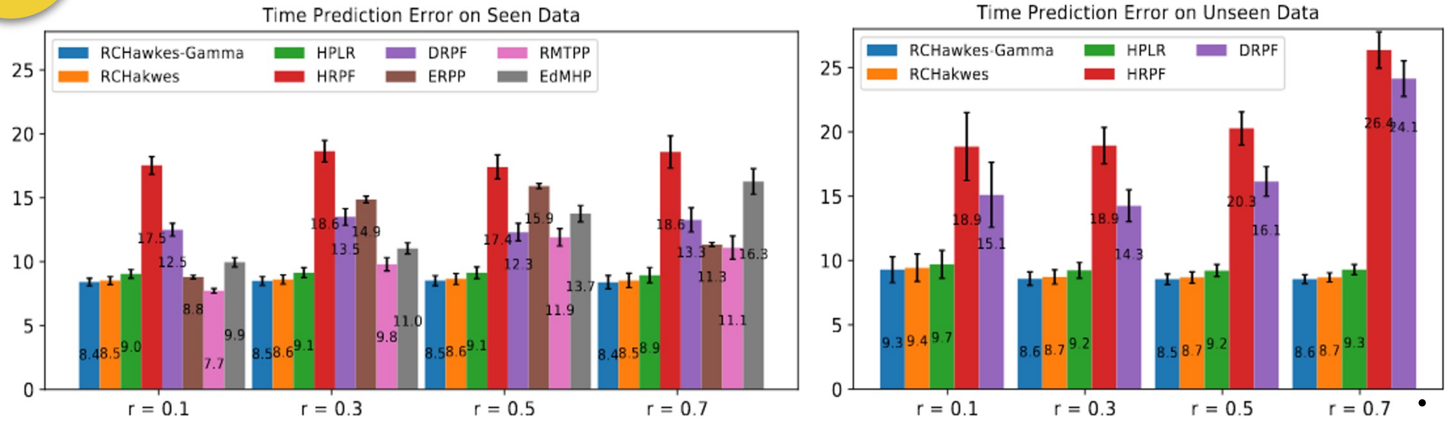


Figure 1: Time prediction error and 95% confidence interval on synthetic datasets with varying data missing ratios (r)

- Smaller RMSE in all settings
- More robust to large miss ratio

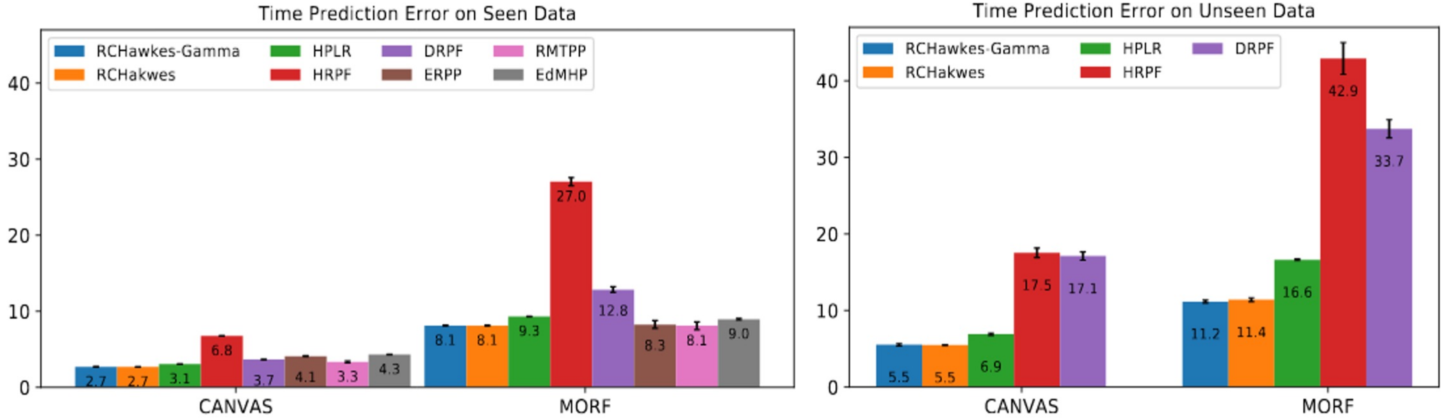


Figure 2: Time prediction error on seen and unseen data with 95% confidence interval on real-world datasets

3.4 Student Procrastination Analysis

Correlation Analysis

		A	U	delay
CANVAS	A	1		
	U	0.284***	1	
	delay	0.345***	0.144***	1
MORF	A	1		
	U	0.243***	1	
	delay	0.264***	0.412***	1

- All correlations are statistically significant with p-value<0.05
- All correlations are positive (e.g. higher delay and higher self-excitement)

3.4 Student Procrastination Analysis

Clustering Analysis - CANVAS

Assign. #.	cluster 1	cluster 2	cluster 3	cluster 4	p-value
size	81	144	207	39	-
1	0.3335	0.4583	0.6108	0.9064	1.34E-16***
2	0.6245	0.5788	0.8476	1.0854	3.59E-09***
3	0.6911	0.7143	0.8633	0.9655	4.36E-05***
4	0.6050	0.6958	0.8515	1.0717	0.0008***
5	0.5969	0.7080	0.9084	1.1217	0.0195*
6	0.5351	0.7647	0.9002	1.0970	0.0149*

Cluster 1: small, increasing then decreasing delay
Cluster 2: higher, increasing delay
Cluster 3: high, increasing delay
Cluster 4: high, consistent delay

Clustering Analysis - MORF

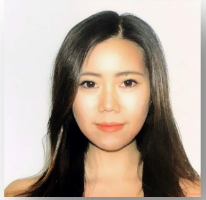
Assign. #.	cluster 1	cluster 2	cluster 3	p-value
size	573	34	68	-
1	0.4991	0.6710	0.4477	2.30E-09***
2	0.5120	0.7288	0.4855	1.90E-08***
3	0.5570	0.6904	0.6105	7.50E-05***
4	0.4699	0.6122	0.5360	0.0004***
5	0.5626	0.6358	0.6308	0.0070***
6	0.5329	0.6236	0.6642	8.56E-06***
7	0.4325	0.5598	0.7672	2.12E-20***
8	0.3974	0.5172	0.7629	3.84E-27***

Cluster 1: small, consistent delay
Cluster 2: higher, decreasing delay
Cluster 3: small, increasing delay

4. Conclusion

1. Provide our solution to the problem of modeling procrastination in MOOCs.
2. Proposed a student procrastination model: **personalized** ; capture group structure, predict future for unseen, without auxiliary features.
3. Provide a novel framework for Hawkes process modeling that jointly learn all sequences.
4. Achieve a better performance than state-of-the-art in synthetic and real datasets
5. Demonstrate the identified clusters are meaningful representations of procrastination.

Thanks!

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Questions?