Smart Jump: Automated Navigation Suggestion for Videos in MOOCs

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清華大學
Tsinghua University

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MOOCs

- 808 courses
- 5,900,000 users

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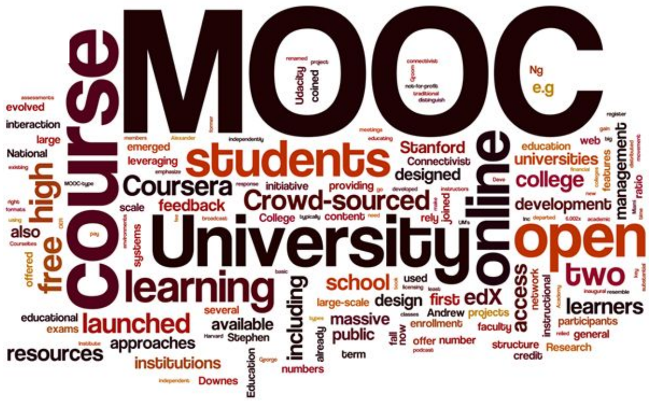
coursera

edX

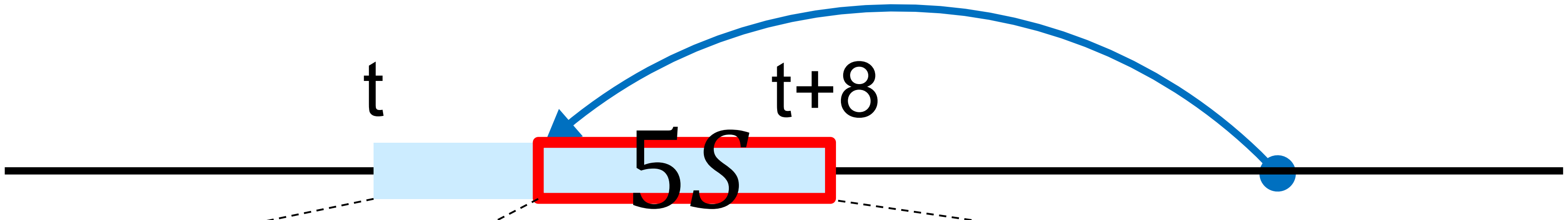


中国大学MOOC

UDACITY

慕课网
imooc.com

Jump Back: How much time, do you know?

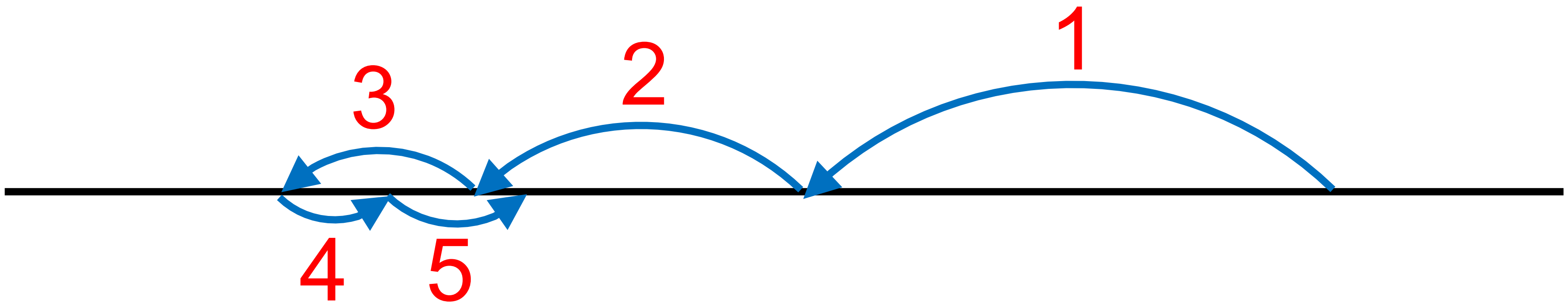


According to what we have discussed we find that the fifth activity belongs to cash outflow of a business activity.

$$5S \times 5000000 = {\color{red}6944} hours$$

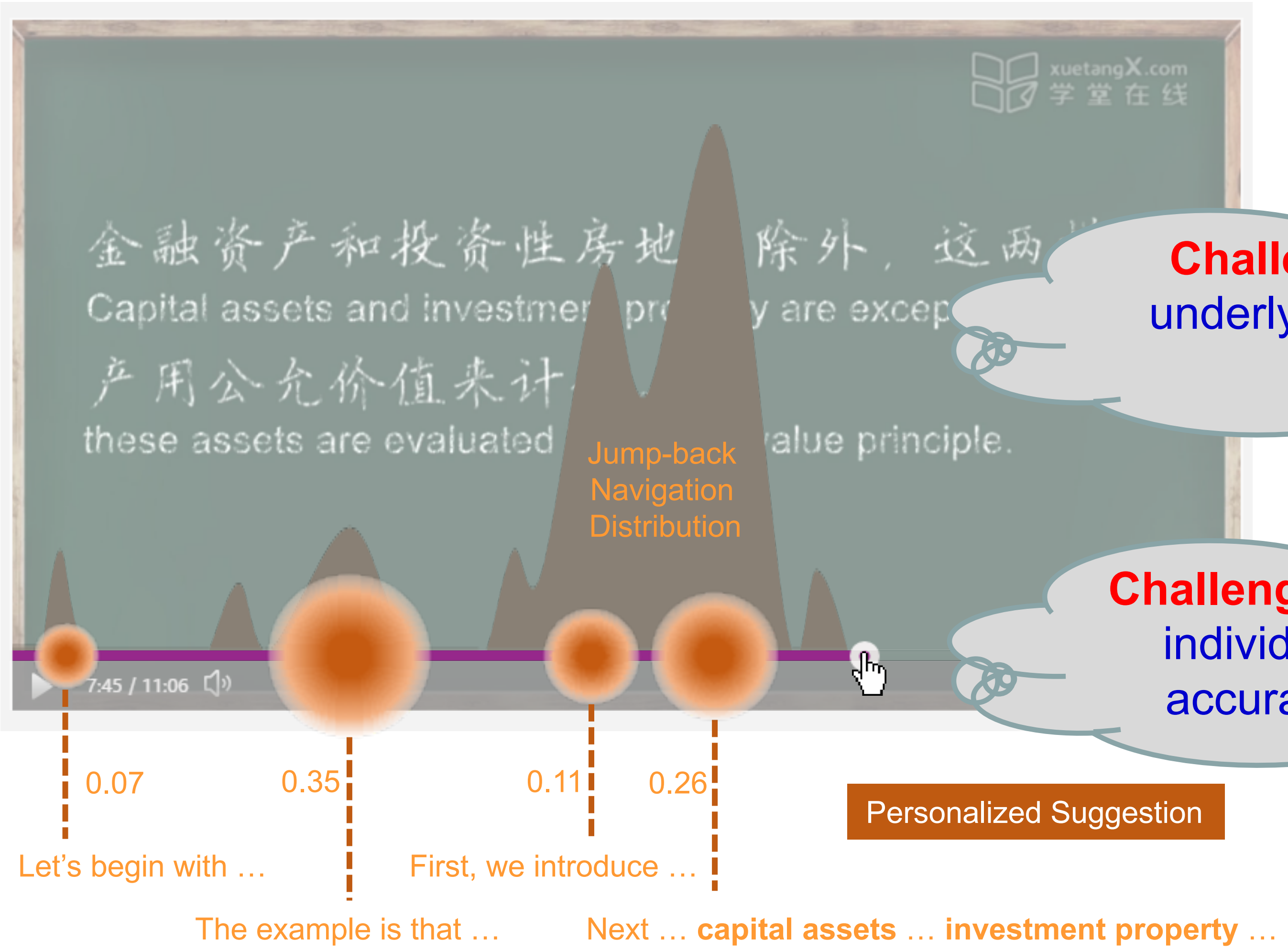
(Users)

Multiple Jumping



2.6 clicks on average for a complete jumping back

Problem: Smart Jump

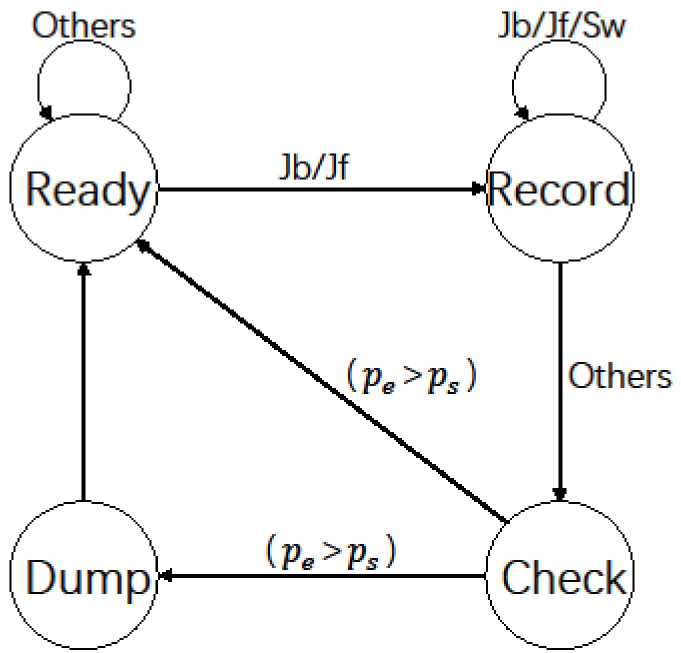


Challenge 1: What are the underlying factors behind the jump?

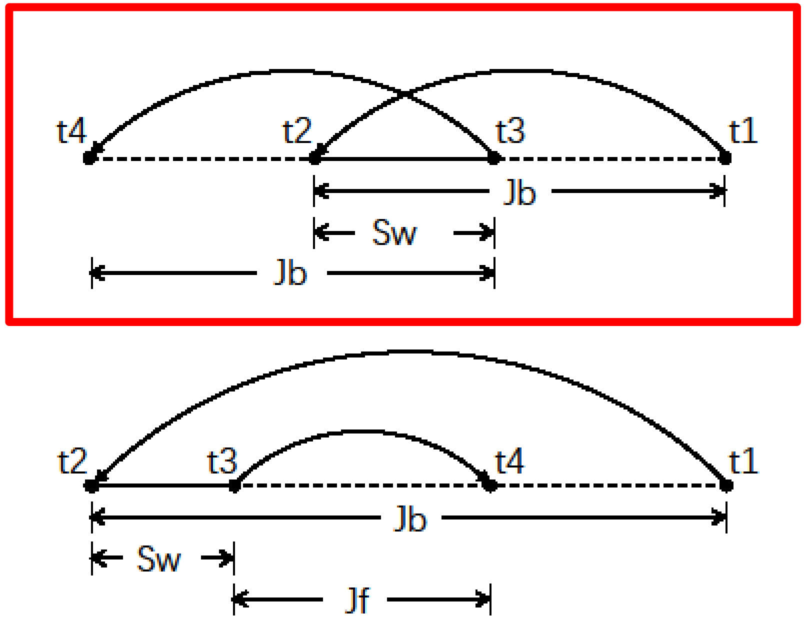
Challenge 2: How to incorporate individual information for an accurate recommendation?

Automated suggestion for video navigation

Complete-jump

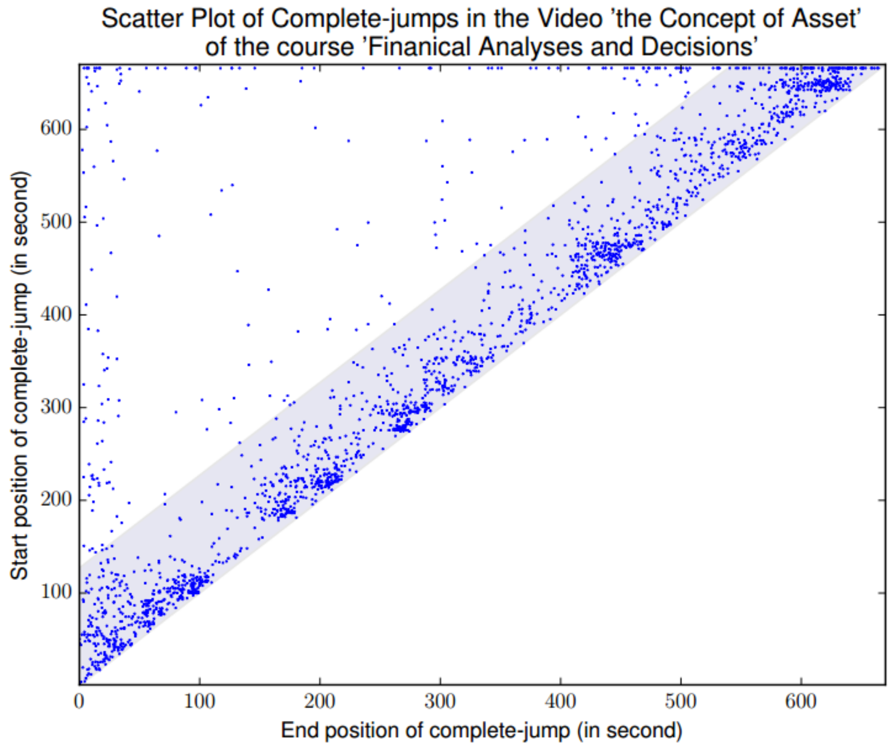


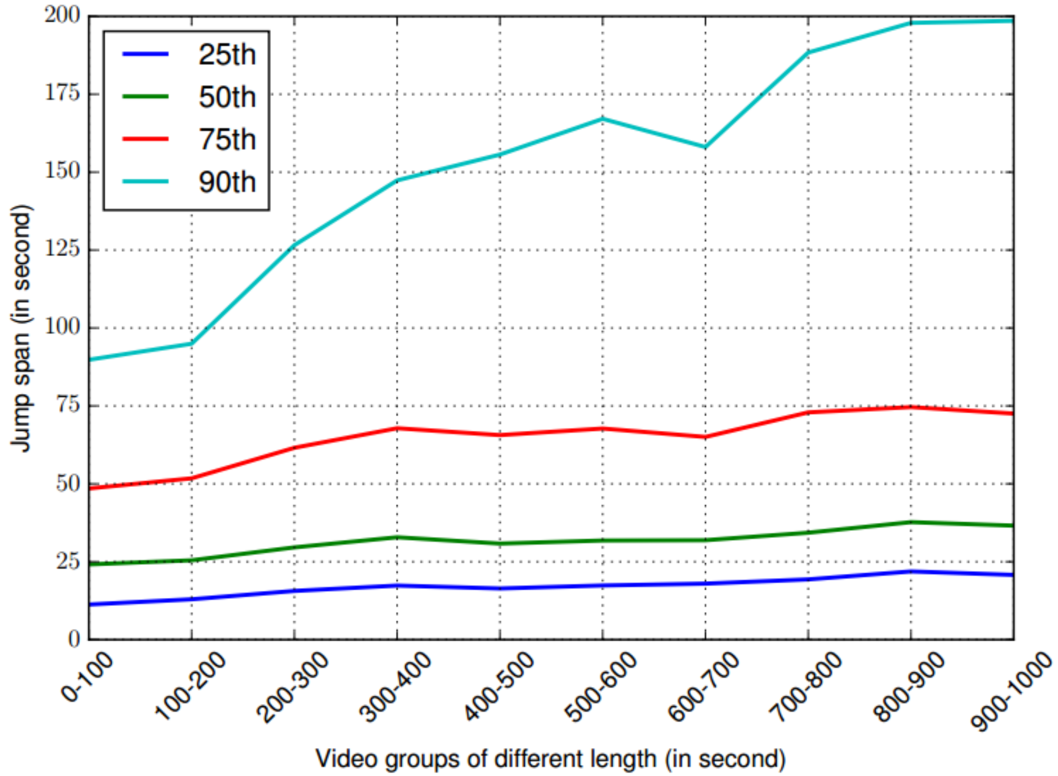
Complete-jump construction base on DFA



Two basic complete-jump patterns

Observations – Video Related

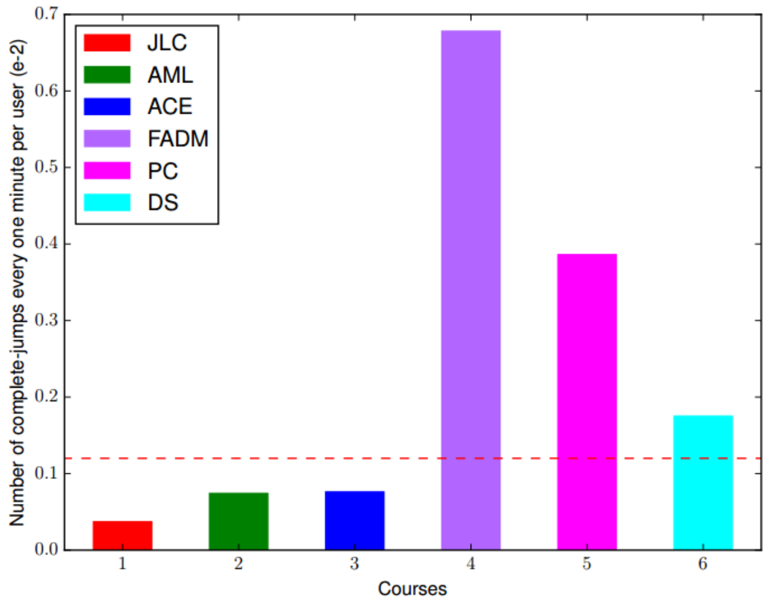


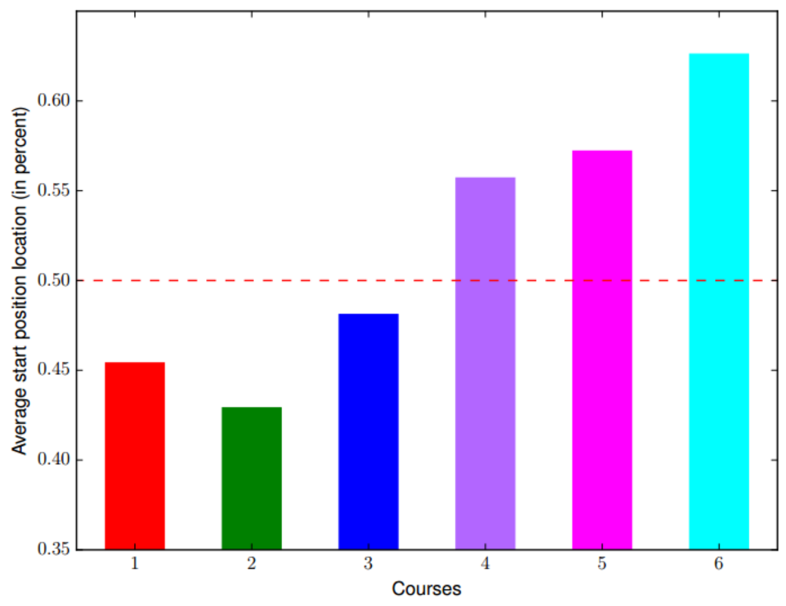


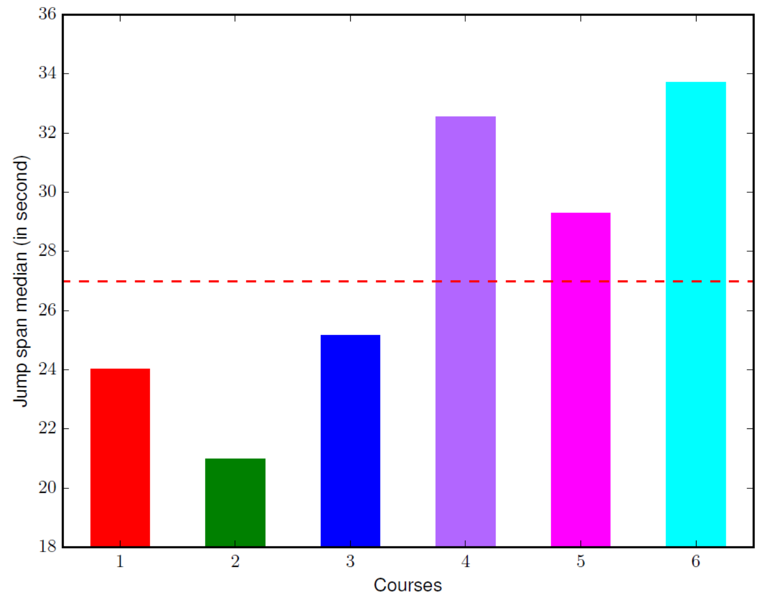
Most jumps are close to the diagonal (~90% locate in the light blue area)

- Jump span is positively correlated with the length of videos.
- Complete-jumps with longer jump span are more easily to be affected by video length

Observations – Course Related





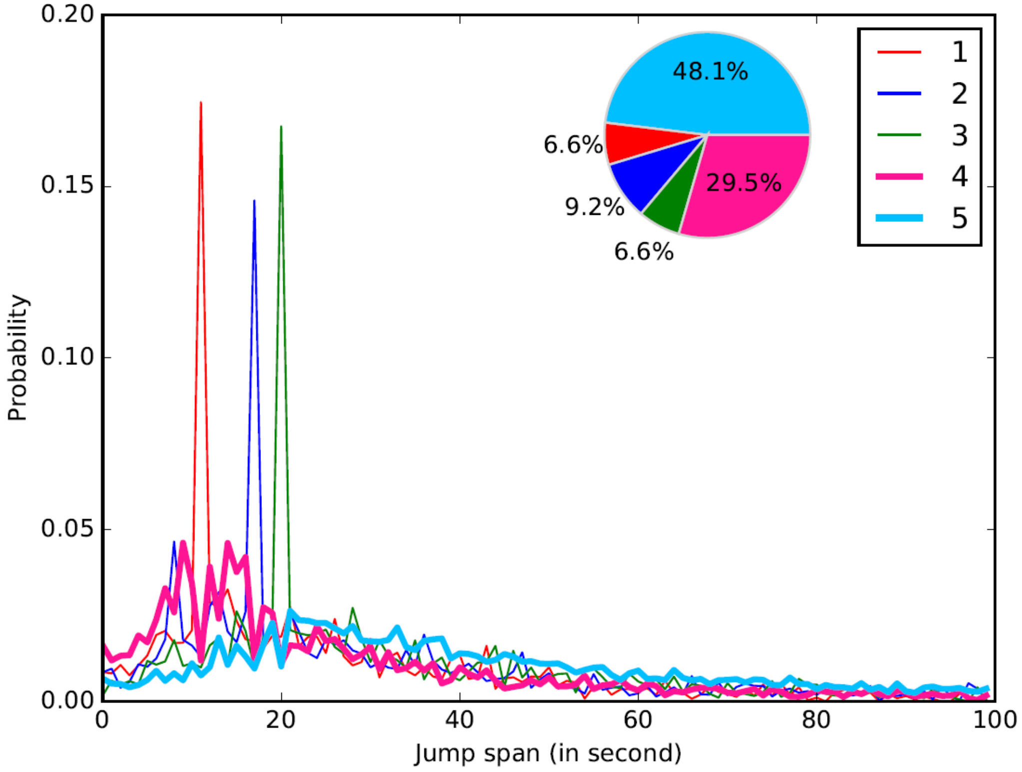


Science courses contain much more frequent jump-backs than non-science courses.

Users in non-science courses jump back earlier than users in science courses.

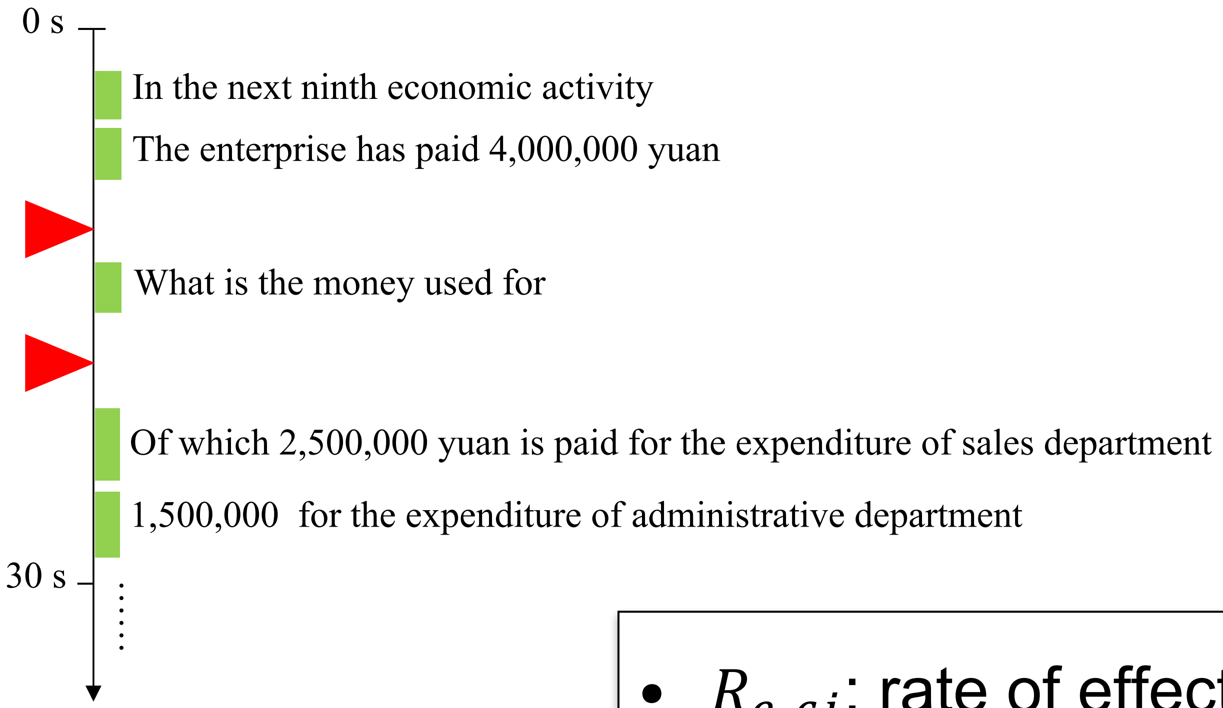
Users in science courses are likely to rewind farther than users in non-science courses.

Observations – User Related



- 6.6% users prefer 10 seconds
- 9.2% users prefer 17 seconds
- 6.6% users prefer 20 seconds

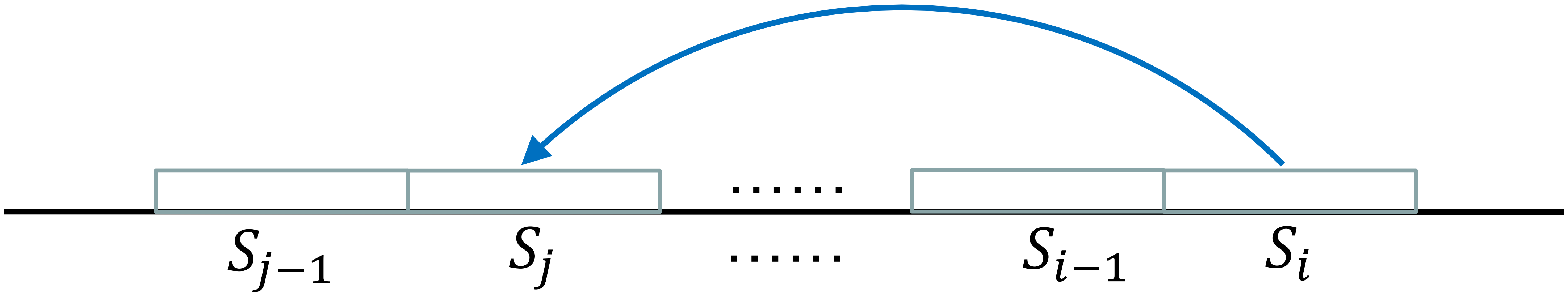
Video Segmentation



$$\underset{\Delta t}{\operatorname{argmax}}\ 2\frac{\boxed{R_{e\_cj}} \cdot \boxed{R_{n\_s}}}{R_{e\_cj} + R_{n\_s}}$$

- R_{e_cj}: rate of effective complete-jumps (start position and end position located in different segments).
- R_{n_s}: rate of non-empty segments (contains at least one start position or end position of some complete-jumps).

Problem Formulation



$$\underset{\Theta}{\operatorname{argmax}}\; P(s_j \mid u, v, s_i; \Theta)$$

Data Set

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- Science: Financial Analysis and Decision Making,
  Data Structure
  Principle of Circuits.
- Non-science: Japanese Language and Culture
  the Aesthetics of Modern Life,
  Chinese Ancient Civilization Etiquette

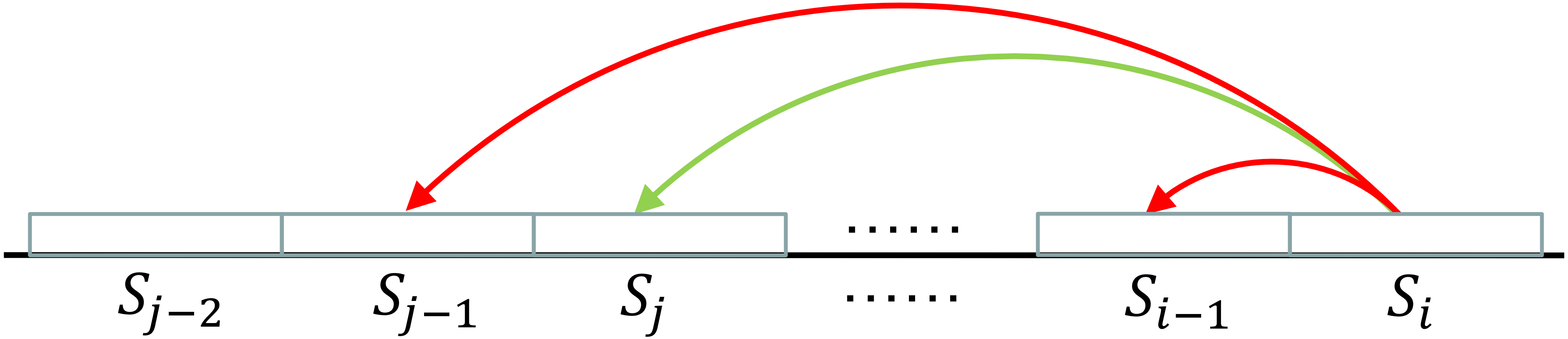
Table 1: the Description of the Dataset

Course	Category	Type	Number
Science	Video	Total #	791
		Avg. length	303.71
	User	Total #	26,487
		Max #users/course	12,989
		Min #users/course	7,590
	Complete-jump	Total #	112,854
		Max #Cjs/course	52,939
		Min #Cjs/course	27,316
Non-science	Video	Total #	438
		Avg. length	635.28
	User	Total #	8,598
		Max #users/course	5,126
		Min #users/course	1,540
	Complete-jump	Total #	7,569
		Max #Cjs/course	2,802
		Min #Cjs/course	2,012

Features

Basic features	One-hot representation of user id
	Start and end position of complete-jump
Video	Length of video in second
	Kth percentile of jump span in the video, K = 25, 50, 75, 90
Start position	Number of complete-jumps start from the position
	Entropy of jump span
User	Number of complete-jumps of the user
	User category generated by k-means clustering

Experimental set – Negative Sample Construction



We randomly select **m (tunable parameter)** **end positions as negative samples**

End Position Prediction

Course	Model	AUC	Recall	Precision	F1-score
Science	**LRC**	72.46	64.28	25.95	37.37
	SVM	71.92	64.06	25.45	36.42
	FM	**74.02**	**68.36**	**27.61**	**39.28**
Non-science	**LRC**	72.59	72.96	**69.23**	70.69
	SVM	73.52	79.03	68.39	**73.28**
	FM	**73.57**	**79.82**	67.56	72.88

$$\hat{y}(\mathbf{x}_i) = w_0 + \sum_{j=1}^{d} w_j x_{i,j} + \boxed{\sum_{j=1}^{d-1} \sum_{j'=j+1}^{d} x_{i,j} x_{i,j'} \langle \mathbf{p}_j, \mathbf{p}_{j'} \rangle}$$

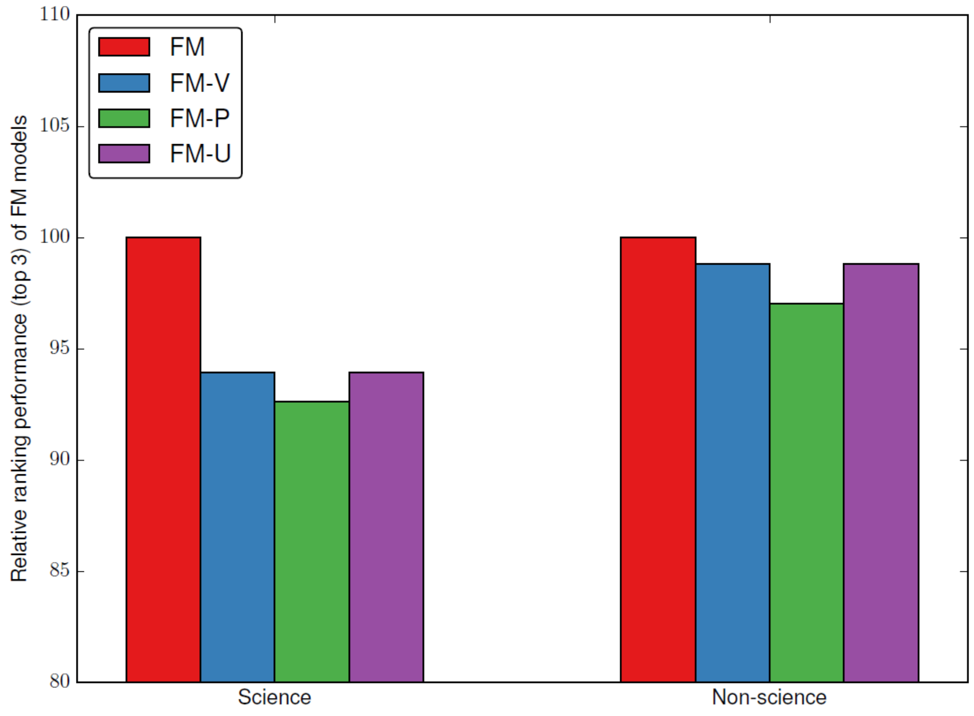
End Position Ranking

Course	Method	n = 1	n = 2	n = 3	n = 5
Science	**Baseline**	33.21	53.21	66.15	81.99
	FM	**37.05**	**60.40**	**76.04**	**89.59**
Non-science	**Baseline**	39.26	62.61	76.64	91.30
	FM	**42.25**	**72.42**	**88.43**	**96.05**

- Hits@n to evaluate the ranking performance
- Baseline method is based on navigation distribution of all users
- Our method based on FM outperforms baseline over ~10%

Feature Contribution

Ignoring each category of features



- Each category of features contributes improvement in the performance
- Our method works well by combining different features

Summary

- We formally define an interesting problem of automated navigation suggestion in MOOCs, and systematically study the problem on a real large MOOC dataset.

- We reveal several interesting phenomena about jump-back behaviors.

- We propose a method to predict users' jump-back behaviors.

Future Research

- Explore more factors that have influence on video navigation, like user location, visual information, etc.

- Take account of dynamic information, like the behaviors just before a jump-back.

- Design a better predictive model with higher accuracy

Thank you！

Collaborators:

Jie Tang, Maosong Sun, Xiaochen Wang, Zhengyang Song (**THU**)

Jimeng Sun (**Gatech**)