# Can **AI** help **MOOCs**?

Jie Tang
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The slides can be downloaded at http://keg.cs.tsinghua.edu.cn/jietang

# Big Data in MOOC

- **149** partners
- 2000+ courses
- **24,000,000** users

- **1,000+** courses
- **8,000,000** users
- **Chinese EDU association**

- **110** partners
- 1,270 courses
- **10,000,000** users
- 10+ MicroMaster

MOOC

網易公开课

- host >1,000 courses
- millions of users

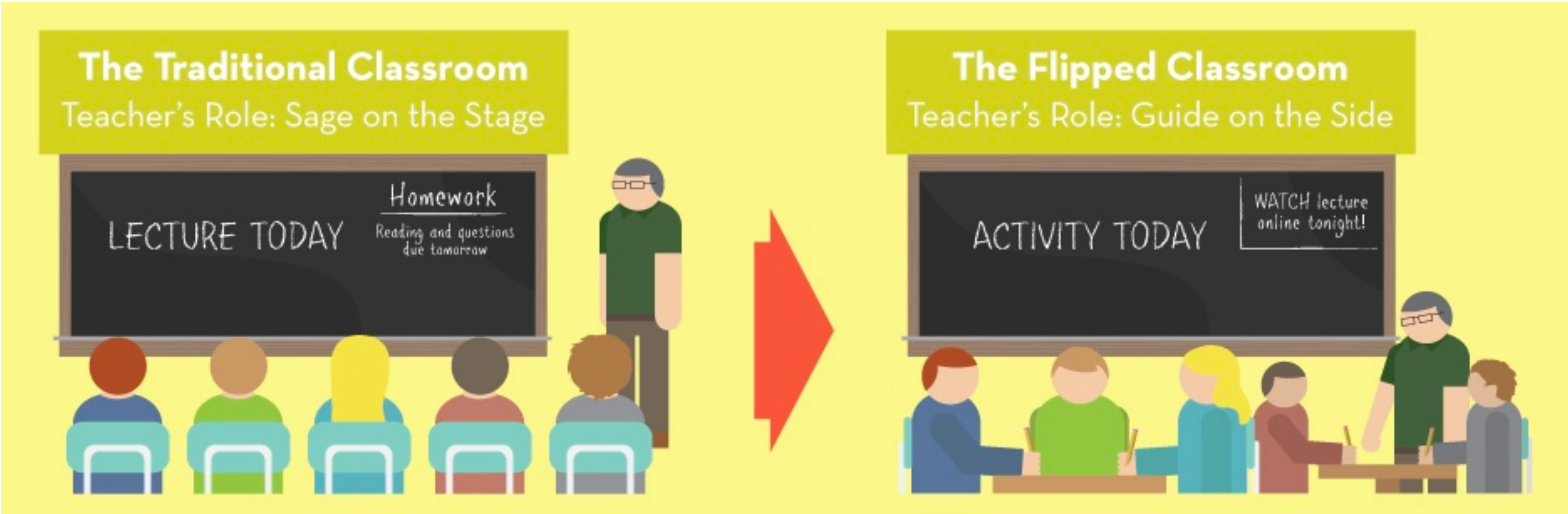
- **~10** partners
- 40+ courses
- **1.6 million** users
- **"nanodegree"**

.......


launched in 2013

# Some exciting data…

- Every day, there are 5,000+ new students
- An MOOC course can reach 100,000+ students
- >35% of the XuetangX users are using mobile
- traditional->flipped classroom->online degree



# Some exciting data…

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- >35% of the XuetangX users are using mobile
- traditional->flipped classroom->online degree
- "**Network+** EDU" (O2O)
  - edX launched 10+ MicroMaster degrees
  - Udacity launched NanoDegree program
  - GIT+Udacity launched the largest online master
  - **Tsinghua+XuetangX** will launch a MicroMaster soon

# However…

- **only ~3% certificate rate**
  - The highest certificate rate is **14.95%**
  - The lowest is only **0.84%**

- Can **AI** help MOOC and how?

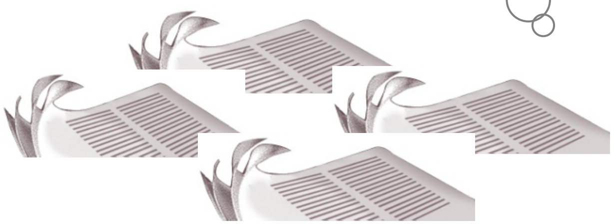
# MOOC user = Student?

How to learn more effectively and more efficiently?

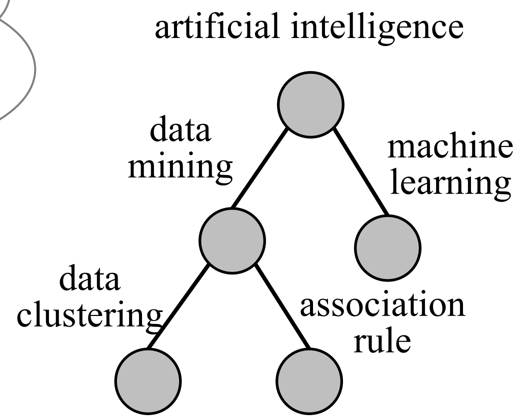
- **Who is who? background, where from?**
- **Why MOOC? motivation? degree?**
- **What is personalization? preference?**

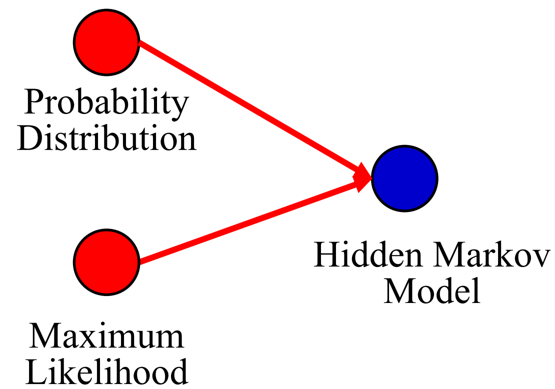
# MOOC course = University course?

How to discover the prerequisite relations between concepts and generate the concept graph automatically?



**Thousands of Courses**



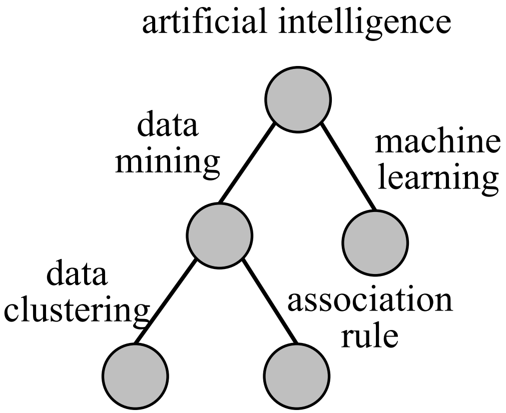

WIKIPEDIA The Free Encyclopedia

Freebase

yago select knowledge

How to leverage the external knowledge?

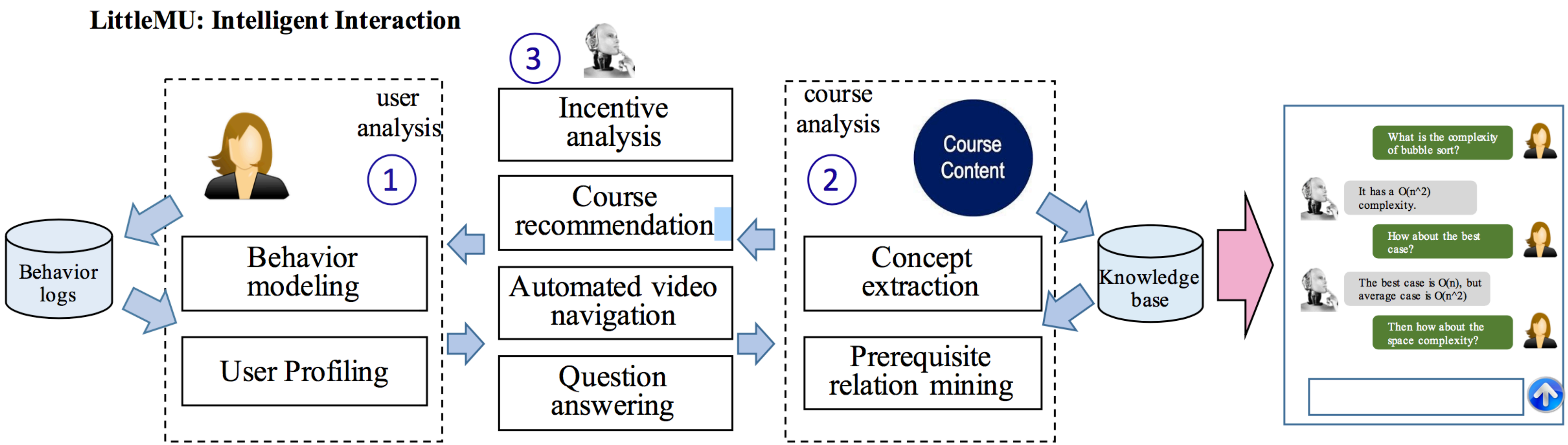
# However to improve the engagement?




User

Knowledge

# LittleMU (小木)



LittleMU: Intelligent Interaction
user analysis
1
Behavior logs
Behavior modeling
User Profiling
3
Incentive analysis
Course recommendation
Automated video navigation
Question answering
course analysis
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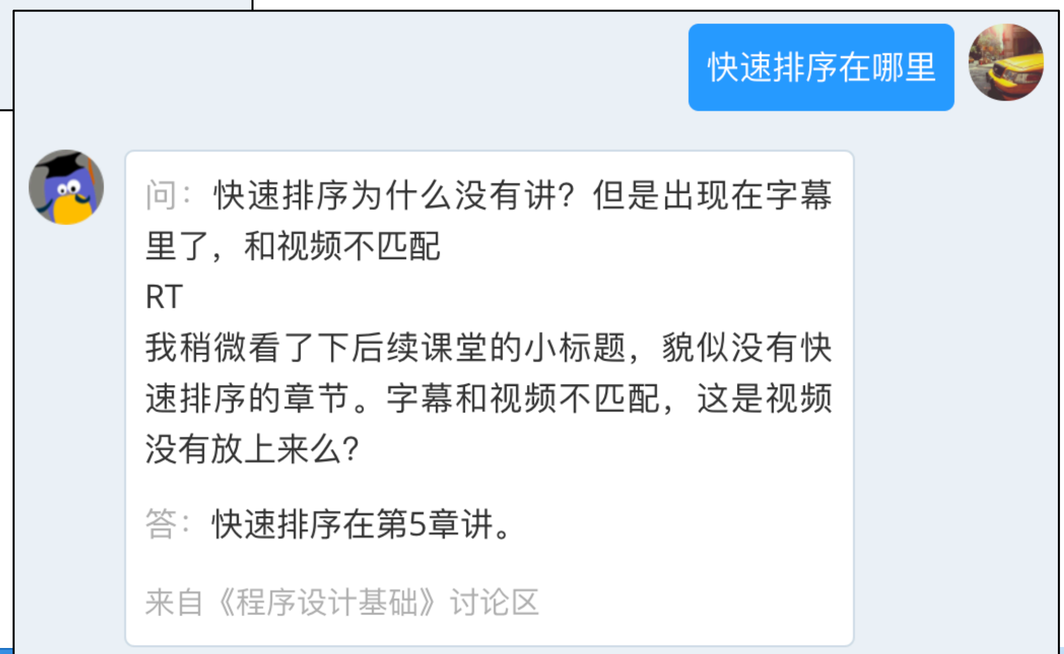
Course Content
Concept extraction
Prerequisite relation mining
Knowledge base
What is the complexity of bubble sort?
It has a O(n^2) complexity.
How about the best case?
The best case is O(n), but average case is O(n^2)
Then how about the space complexity?

# What is LittleMU("小木")

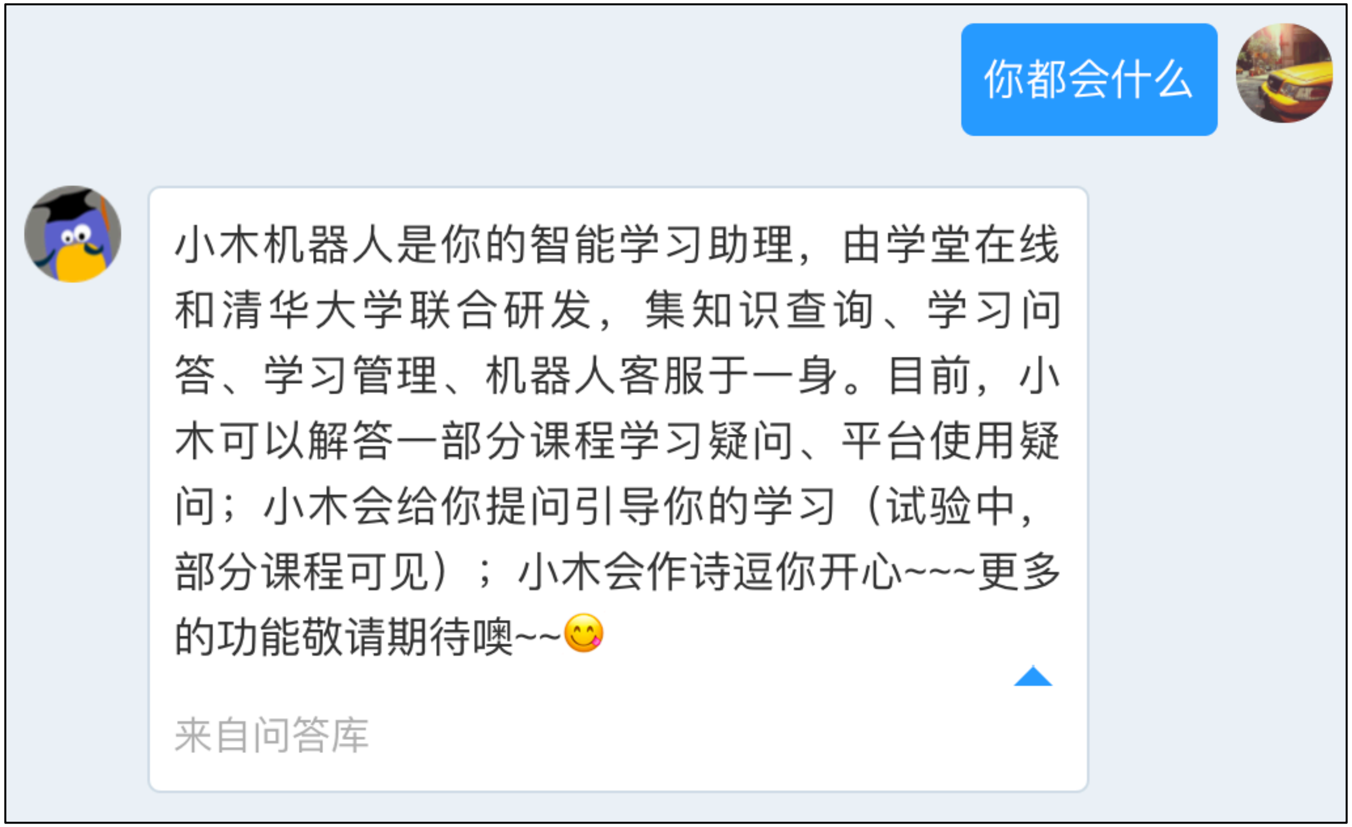
- Not a Chatbot
  – "Good morning", "did you have the breakfast?"—NO
- Not a teacher/TA
  – "Can you explain the equation for me?" —NO

- Instead,"小木" is more like a learning peer
  – Tell you some basic knowledge in her mind
  – Tell you what the other users are thinking/learning
  – Try to understand your intention
  – Teach "小木" what you know

# What is LittleMU(“小木”)

# What is LittleMU(“小木”)

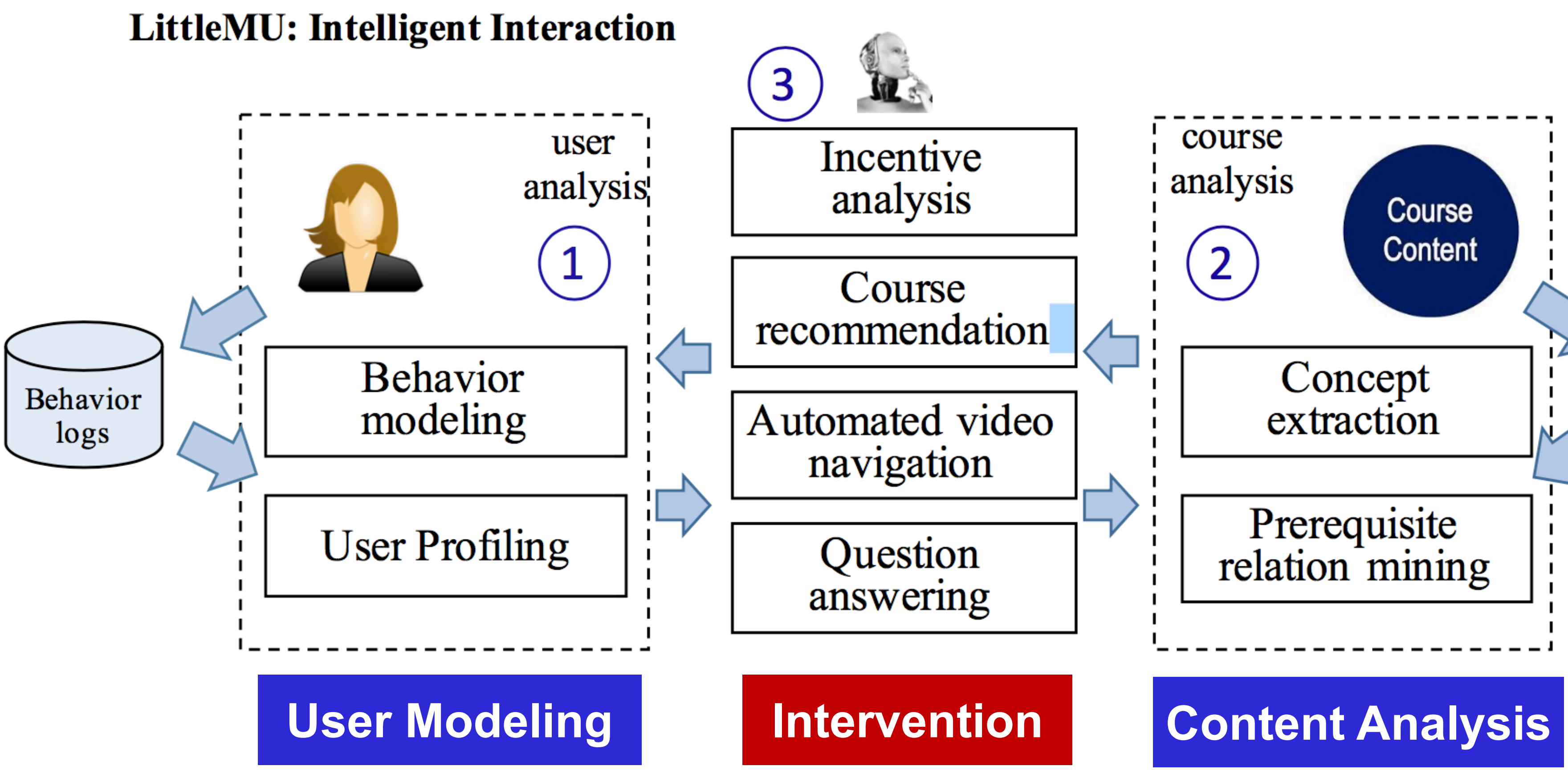


# LittleMU (小木)

学堂小木
如何注册学堂
1、pc端打开http://www.xuetangx.com，右上角点击注册，您可以使用邮箱或手机号进行注册。或者使用第三方账户，比如新浪微 …
来自问答库
二叉树是什么
二叉树：
在计算机科学中，二叉树是每个节点最多有两个子树的树结构。通常子树被称作“左子树”（left subtree）和“右子树”（right subtree）。二叉树常被用于实现二叉查找树和二叉堆。二叉树的每个结点至多只有二棵子树(不存在度大于2的结点)，二叉树的子树有左右之分，次序不能颠倒。二叉树的第i层至多有2^{i-1}个结点；深度为k的二叉树至多有2^k-1个结点；对任何一棵二叉树T，如果其终端结点数为n_0，度为2的结点数为n_2，则n_0=n_2+1。一棵深度为k，且有2^k-1个节点称之为满二叉树；深度为k，有n个节点的二叉树，当且仅当其每一个节点都与深度为k的满二叉树中，序号为1至n的节点对应时，称之为完全二叉树。
另见：
满二叉树
...同学们好，我们这一节介绍树的一种特殊，但又不失代表性的特例。
在这里提问，按enter(回车键)发送
30240184X 数据结构(上)(自主模式)
讨论区
Wiki
课程进度
常见问题
教材
习题解析
05E4-1 次序
小木提问：什么是层次遍历？（2个同学已问过类似问题）
5.二叉树
(e4) 层次遍历
0:16 / 3:34
字幕
高清
1.00x
下载字幕
.txt

# Acrostic Poem: 小木作诗

# LittleMU (小木)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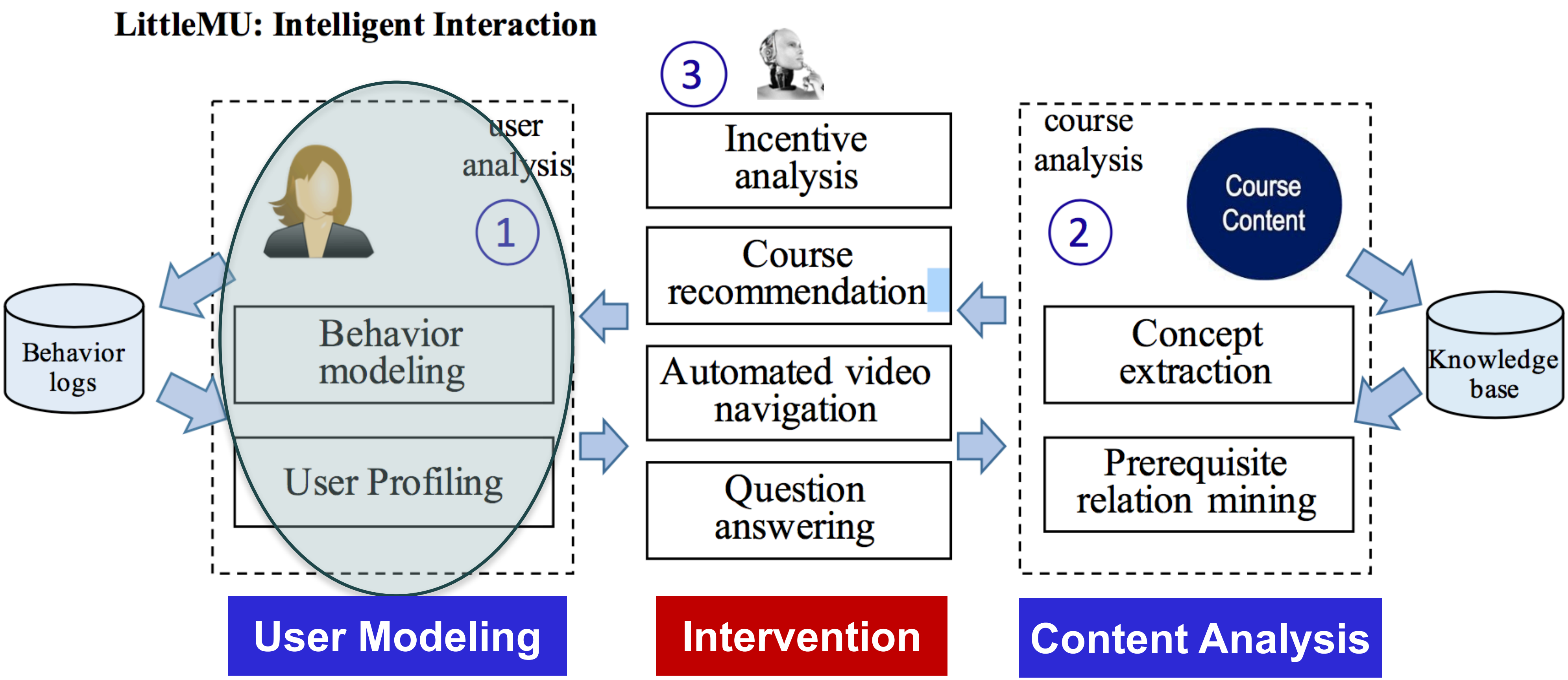

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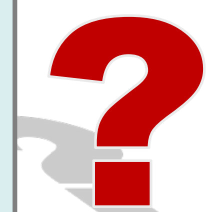
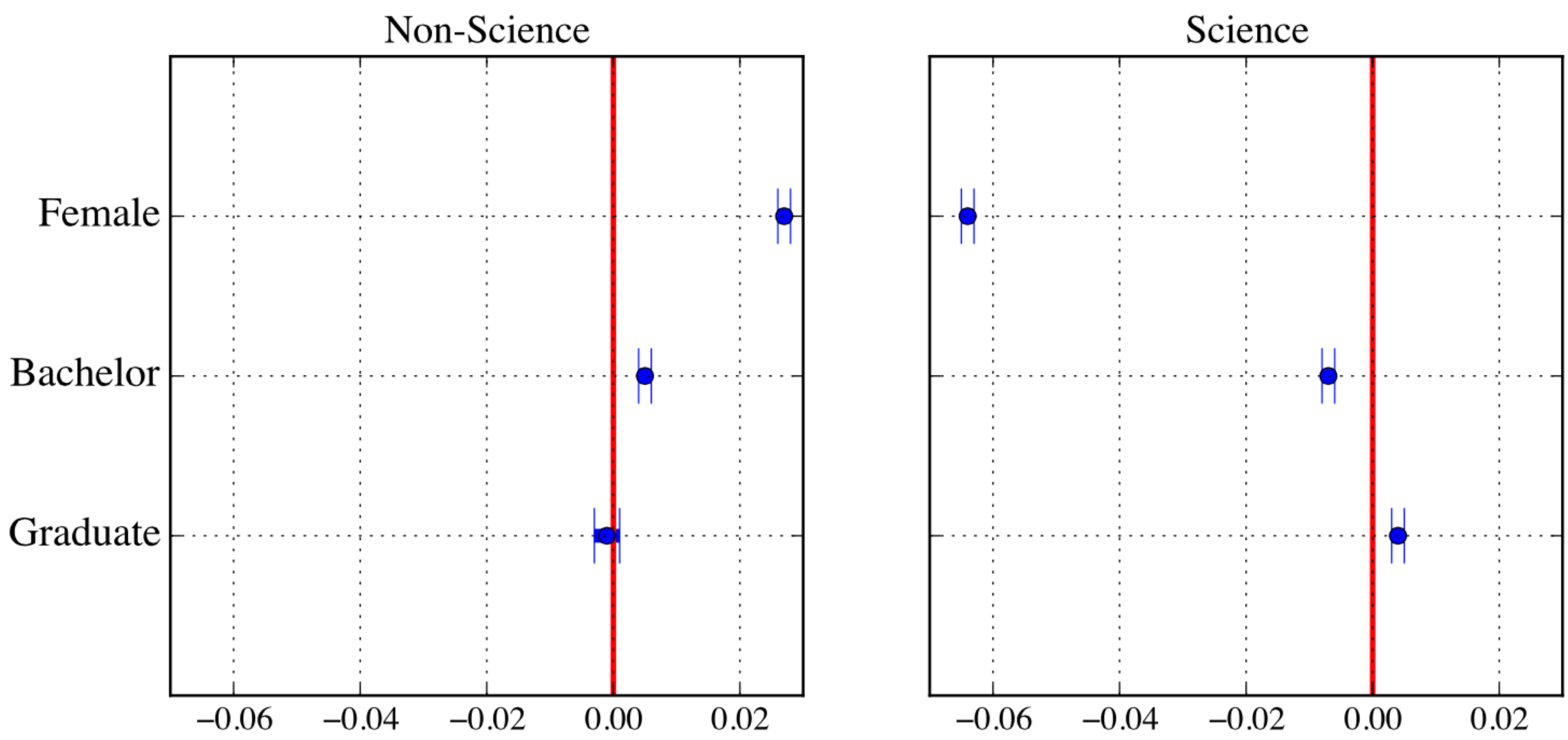
# MOOC user

- Who is who? background, where from?
- Why MOOC? motivation? degree?
- What is personalization? preference?



# Basic Analysis



# Observation 1 – Gender Difference

**Table 4: Regression Analysis for Certificate Rate: All Users**

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Non-Science (1) | Science (2) | Non-Science (3) | Science (4) |
| Female | 0.014*** | -0.003 | 0.002* | 0.001 |
| | (0.002) | (0.002) | (0.001) | (0.002) |
| New Post | — | — | 0.004*** | 0.038*** |
| | | | (0.001) | (0.008) |
| Reply | — | — | 0.004** | 0.001* |
| | | | (0.002) | (0.001) |
| Video | — | — | 0.000*** | -0.000 |
| | | | (0.000) | (0.000) |
| Assignment | — | — | 0.003*** | 0.000*** |
| | | | (0.000) | (0.000) |
| Bachelor | 0.014*** | 0.003* | 0.011*** | -0.001 |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| Graduate | 0.007*** | 0.004 | 0.013*** | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Effort | -0.072*** | | -0.072*** | |
| | (0.003) | | (0.003) | |
| Constant | 0.286*** | 0.018*** | 0.280*** | 0.006 |
| | (0.013) | (0.006) | (0.011) | (0.004) |
| Obs. | 74,480 | 19,269 | 74,480 | 19,269 |
| $R^2$ | 0.024 | 0.001 | 0.462 | 0.363 |

Model 1: Demographics vs Certificate

Model 2: Demographics + Forum activities vs Certificate

- Females are significantly more likely to get the certificate in non-science courses.
- The size of the gender difference decreases significantly after we control for forum activities.

# Observation 2 – Ability v.s. Effort

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Model 1: Demographics vs Certificate

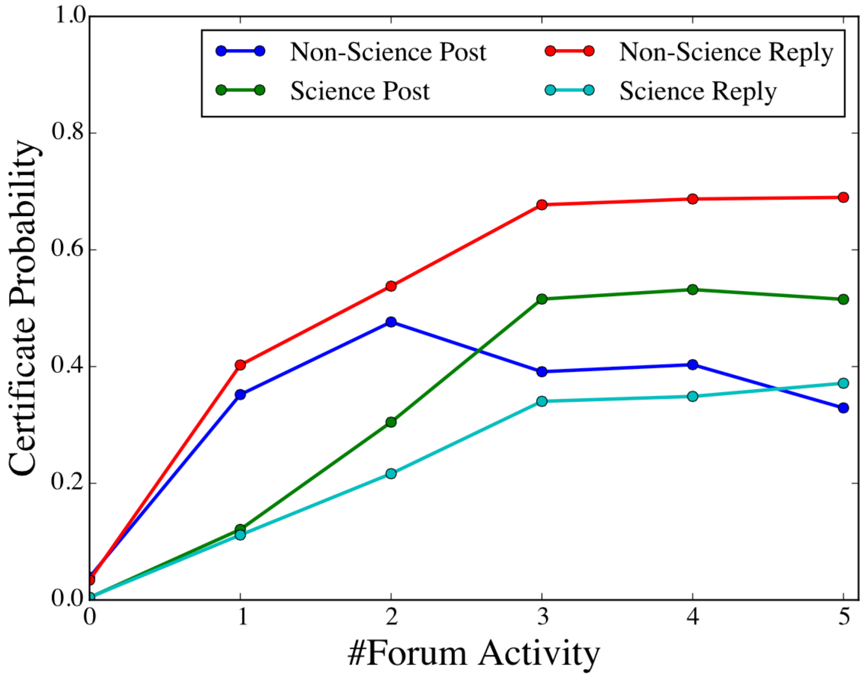
Model 2: Demographics + Forum activities vs Certificate

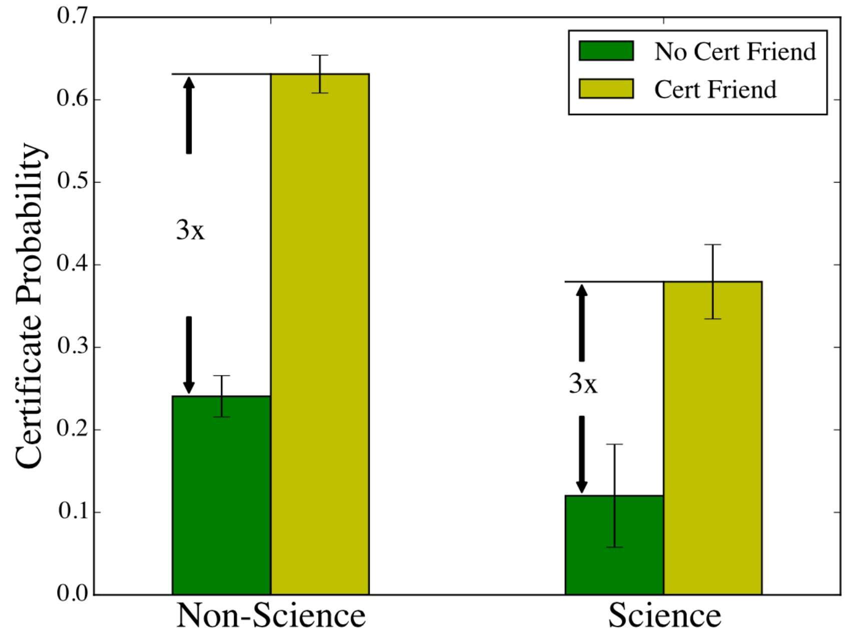
- Bachelors students are significantly more likely to get the certificate in non-science courses.

- Graduate students are more likely to get the certificate in science courses. After controlling for learning activities, the size of the effect is almost doubled.

- Forum activities are good predictors for getting certificates.

# Forum activity vs. Certificate




**Forum activity vs. Certificate**

— It is more important to be presented in forum, while the intensity matters less.

**“近朱者赤” (Homophily)**

– Certificate probability tripled when one is aware that she has certificate friend(s)

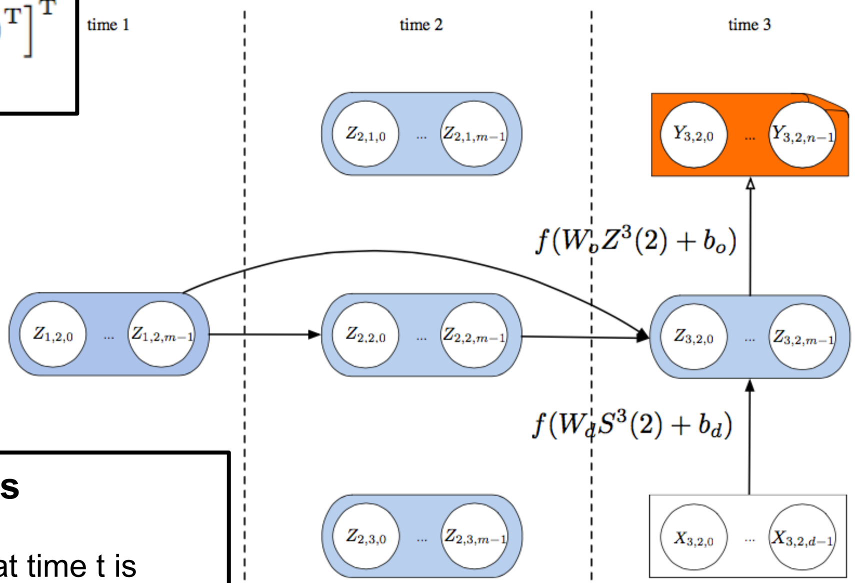
# Dynamic Factor Graph Model

**Model:** incorporating "embedding" and factor graphs

$$Y^t(i)^* = f(W_o Z^t(i) + b_o)$$

$$Z^t(i)^* = f(W_d S^t(i) + b_d)$$

$$S^t(i) = \left[\mathbf{Z}_{t-p}^{t-1}(i)^{\mathrm{T}}, X^t(i)^{\mathrm{T}}\right]^{\mathrm{T}}$$




**Prediction labels:**
Activities we are interested in, e.g., assignments performance and getting certificates.

$$Y^t(i) = [Y_{t,i,0}, Y_{t,i,1}, \ldots, Y_{t,i,n-1}]^{\mathrm{T}}$$

**Latent learning states**

Every student's status in at time t is associated with a vector representation

$$Z^t(i) = [Z_{t,i,0}, Z_{t,i,1}, \ldots, Z_{t,i,m-1}]^{\mathrm{T}}$$

**All features:** time-varying attributes:
1.Demographics
2.Forum Activities
3. Learning Behaviors

$$X^t(i) = [X_{t,i,0}, X_{t,i,1}, \ldots, X_{t,i,d-1}]^{\mathrm{T}}$$


[1] Jiezhong Qiu, Jie Tang, Tracy Xiao Liu, Jie Gong, Chenhui Zhang, Qian Zhang, and Yufei Xue. Modeling and Predicting Learning Behavior in MOOCs. **WSDM'16**, pages 93-102.

# Certificate Prediction

| Category | Method | AUC | Precision | Recall | F1-score |
|---|---|---|---|---|---|
| Science | LRC | 92.13 | **83.33** | 46.51 | 59.70 |
| | SVM | 92.67 | 52.17 | 83.72 | 64.29 |
| | FM | 94.48 | 61.54 | 74.42 | 67.37 |
| | LadFG | **95.73** | 73.91 | **79.07** | **76.40** |
| Non-Science | LRC | 94.16 | 76.93 | 89.20 | 82.57 |
| | SVM | 93.94 | 76.96 | 88.60 | 82.37 |
| | FM | 94.87 | **80.22** | 86.23 | 83.07 |
| | LadFG | **95.54** | 79.76 | **89.01** | **84.10** |

- LRC, SVM, and FM are different baseline models
- LadFG is our proposed model

# Predicting more

- Dropout
  - KDDCUP 2015, 1,000+ teams worldwide
- Demographics
  - Gender, education, etc.
- User interests
  - computer science, mathematics, psychology, etc.
- …

# User Tagging

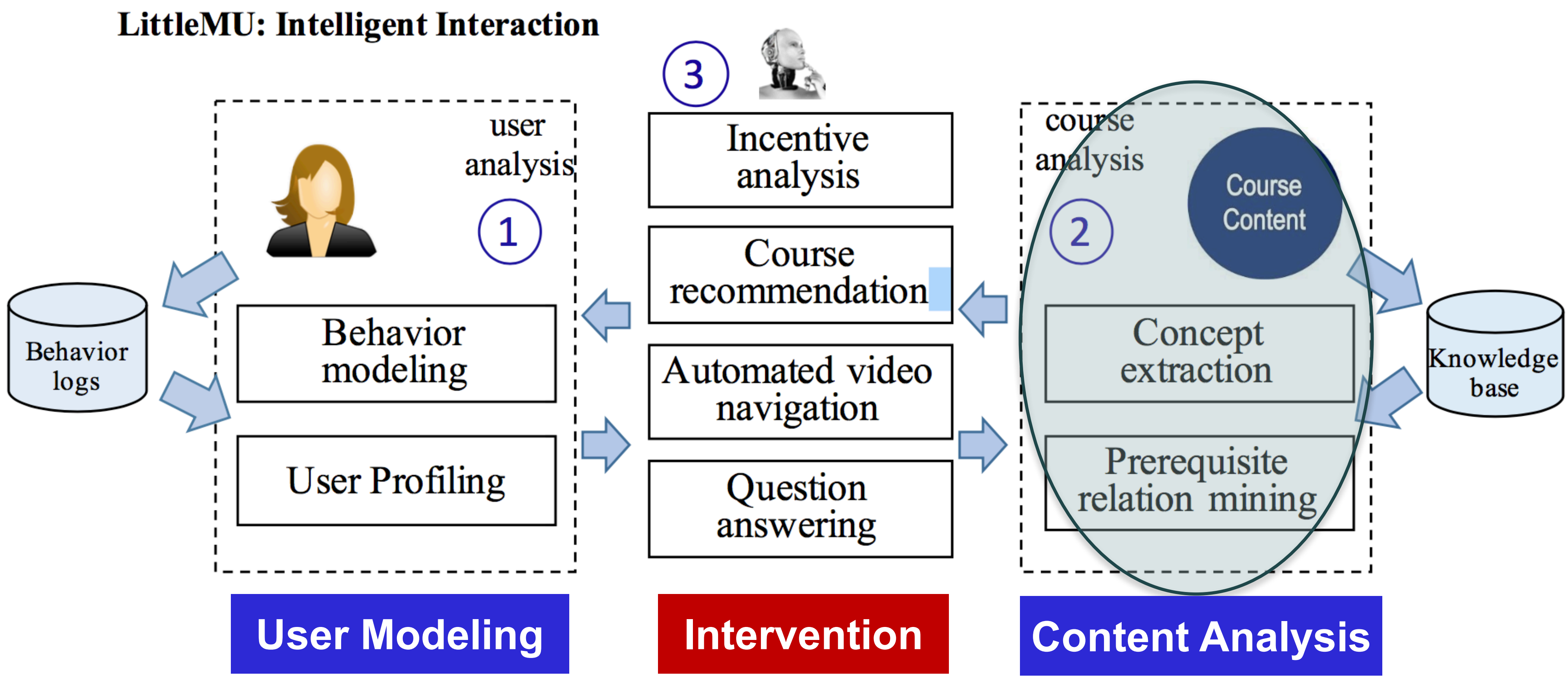
- Observation: With probability 43.91%, a user will enroll in a course in the same category as the last course (s)he enrolled in.
- Method: Use course categories to tag users who enroll in courses under this category to aid course recommendation.

# Random Walk with Restart

- Use RWR on the user-tag bipartite with # of enrolled courses in the tag (category) as edge weight to generate tag preference of users.
- Offline test in course recommendation

| | top1 | top3 | top5 | top10 |
|---|---|---|---|---|
| Original | 0.0071 | 0.0247 | 0.0416 | 0.0890 |
| +Tag | 0.0185 | 0.0573 | 0.1022 | 0.2198 |

# LittleMU (小木)



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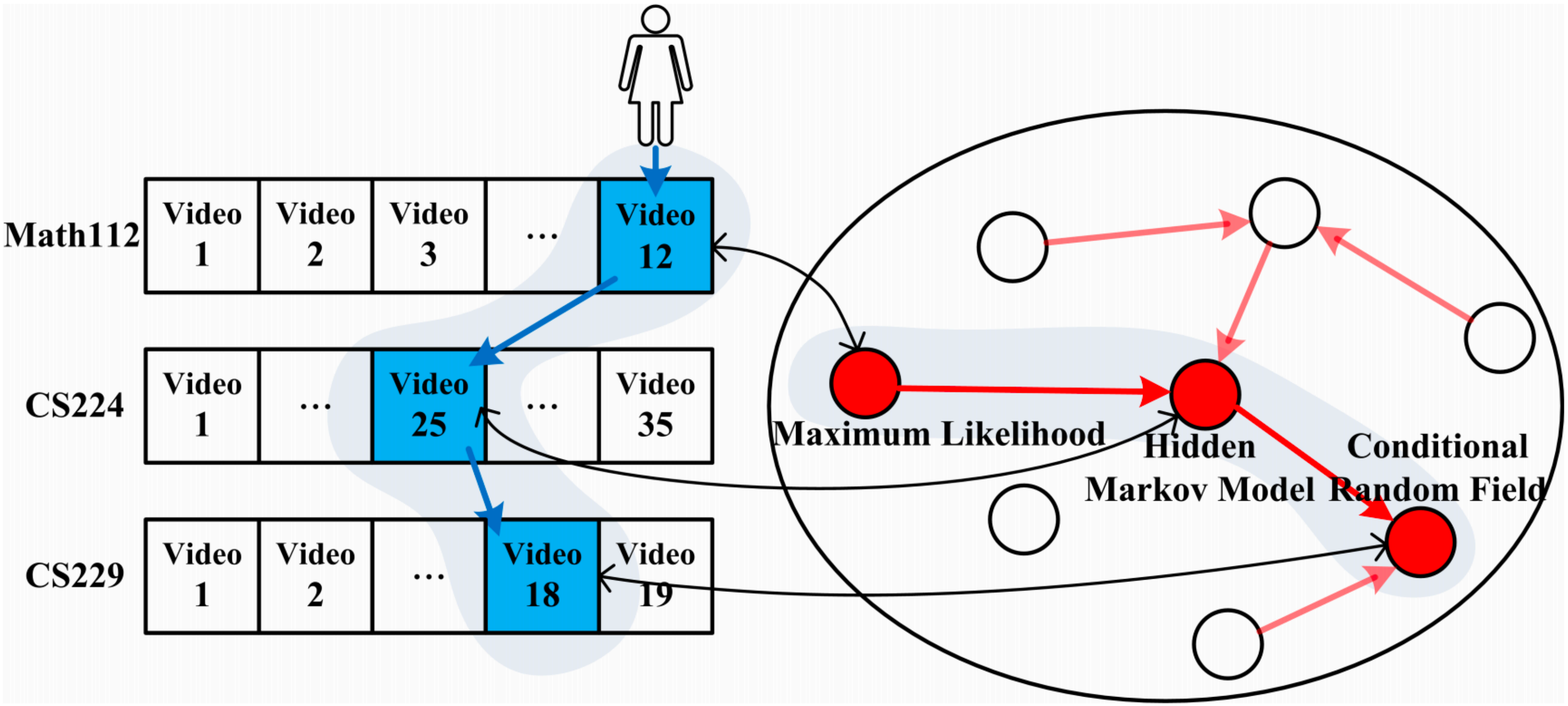
# Knowledge Graph




- How to extract concepts from course scripts?
- How to recognize (prerequisite) relationships between concepts?

[1] Liangming Pan, Chengjiang Li, Juanzi Li, and Jie Tang. Prerequisite Relation Learning for Concepts in MOOCs. **ACL'17.**

# Concept Extraction

Candidate Concept Extraction → Semantic Representation Learning → Graph-based Ranking

In this course, we will teach some basic knowledge about data mining and its application in business intelligence.

Video script

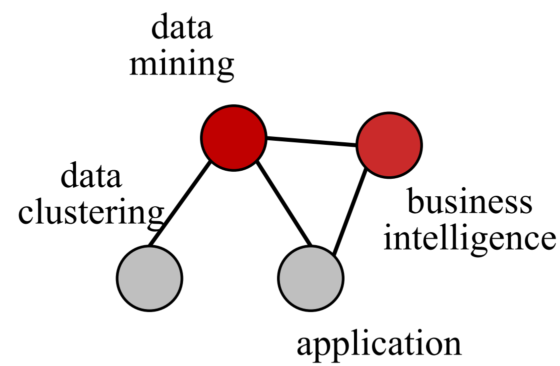
data mining

| | | | | | |
|---|---|---|---|---|---|
| 0.8 | 0.2 | 0.3 | … | 0.0 | 0.0 |

business intelligence

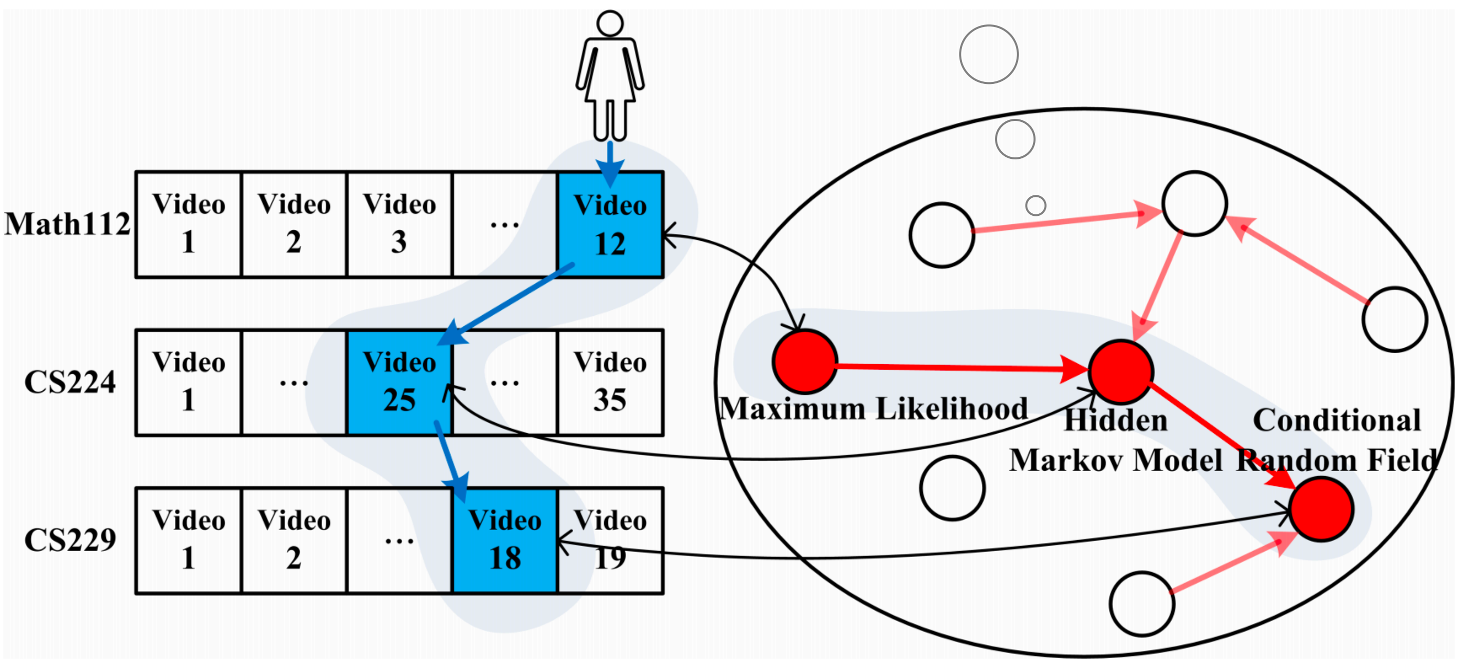
| | | | | | |
|---|---|---|---|---|---|
| 0.1 | 0.1 | 0.2 | … | 0.8 | 0.7 |

Vector representation
Learned via embedding or deep learning



# Prerequisite Relationship

How to extract the prerequisite relationship?

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# Prerequisite Relationship Extraction

- Step 1： First extract important concepts
- Step 2： Use Word2Vec to learn representations of concepts

data mining

| | | | | | |
|---|---|---|---|---|---|
| 0.8 | 0.2 | 0.3 | … | 0.0 | 0.0 |

business intelligence

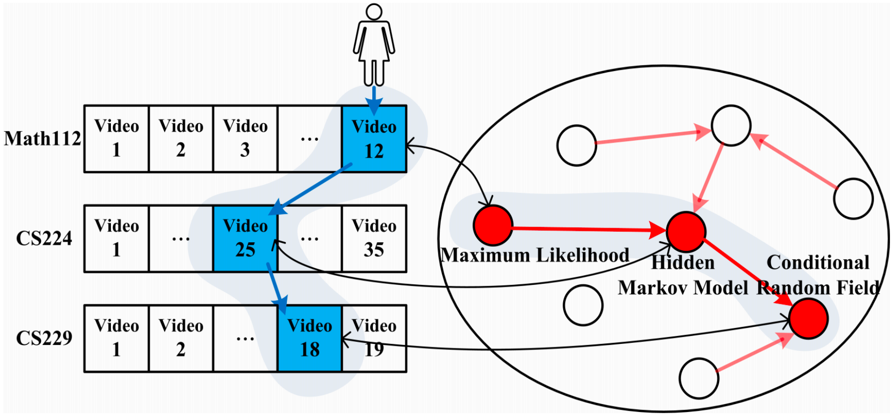
| | | | | | |
|---|---|---|---|---|---|
| 0.1 | 0.1 | 0.2 | … | 0.8 | 0.7 |

Vector representation

Learned via embedding or deep learning

# Prerequisite Relationship Extraction

- Step 1：First extract important concepts
- Step 2：Use Word2Vec to learn representations of concepts
- Step 3：Distance functions
  - Semantic Relatedness
  - Video Reference Distance
  - Sentence Reference Distance
  - Wikipedia Reference Distance
  - Average Position Distance
  - Distributional Asymmetry Distance
  - Complexity Level Distance



# Result of Prerequisite Relationship

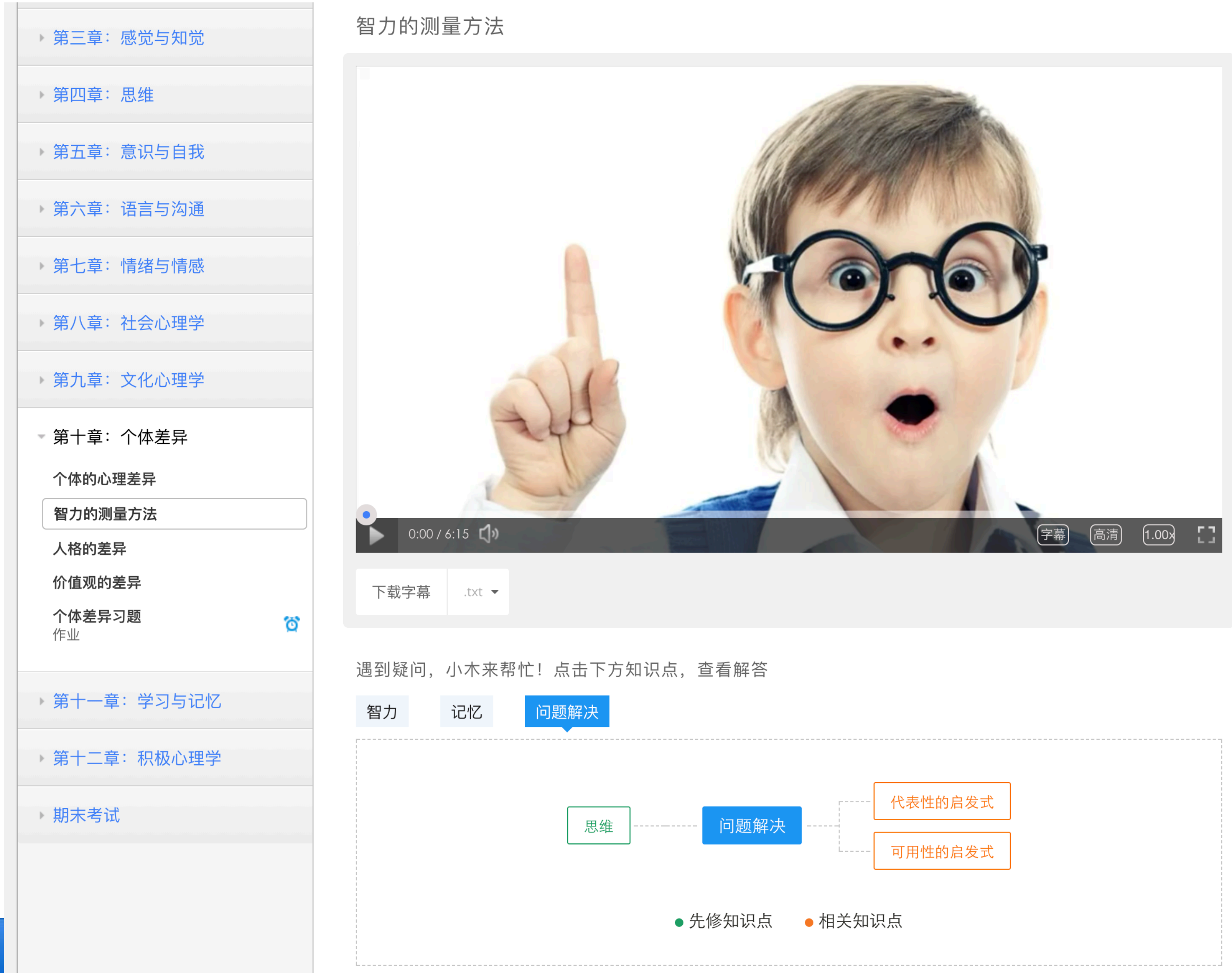
| Classifier | | ML | | DSA | | CAL | |
|---|---|---|---|---|---|---|---|
| | $M$ | 1 | 10 | 1 | 10 | 1 | 10 |
| SVM | $P$ | 63.2 | 60.1 | 60.7 | 62.3 | 61.1 | 61.9 |
| | $R$ | 68.5 | 72.4 | **69.3** | 67.5 | **67.9** | 68.3 |
| | $F_1$ | 65.8 | 65.7 | 64.7 | 64.8 | 64.3 | 64.9 |
| NB | $P$ | 58.0 | 58.2 | 62.9 | 62.6 | 60.1 | 60.6 |
| | $R$ | 58.1 | 60.5 | 62.3 | 61.8 | 61.2 | 62.1 |
| | $F_1$ | 58.1 | 59.4 | 62.6 | 62.2 | 60.6 | 61.3 |
| LR | $P$ | 66.8 | 67.6 | 63.1 | 62.0 | 62.7 | 63.3 |
| | $R$ | 60.8 | 61.0 | 64.8 | 66.8 | 63.6 | 64.1 |
| | $F_1$ | 63.7 | 64.2 | 63.9 | 64.3 | 61.6 | 62.9 |
| RF | $P$ | **68.1** | **71.4** | **69.1** | **72.7** | **67.3** | **70.3** |
| | $R$ | **70.0** | **73.8** | 68.4 | **72.3** | 67.8 | **71.9** |
| | $F_1$ | **69.1** | **72.6** | **68.7** | **72.5** | **67.5** | **71.1** |

Table 2: Classification results of the proposed method(%).

- SVM, NB, LR, and RF are different classification models
- It seems that with the defined distance functions, RF achieves the best

[1] Liangming Pan, Chengjiang Li, Juanzi Li, and Jie Tang. Prerequisite Relation Learning for Concepts in MOOCs. **ACL'17.**

# System Deployed



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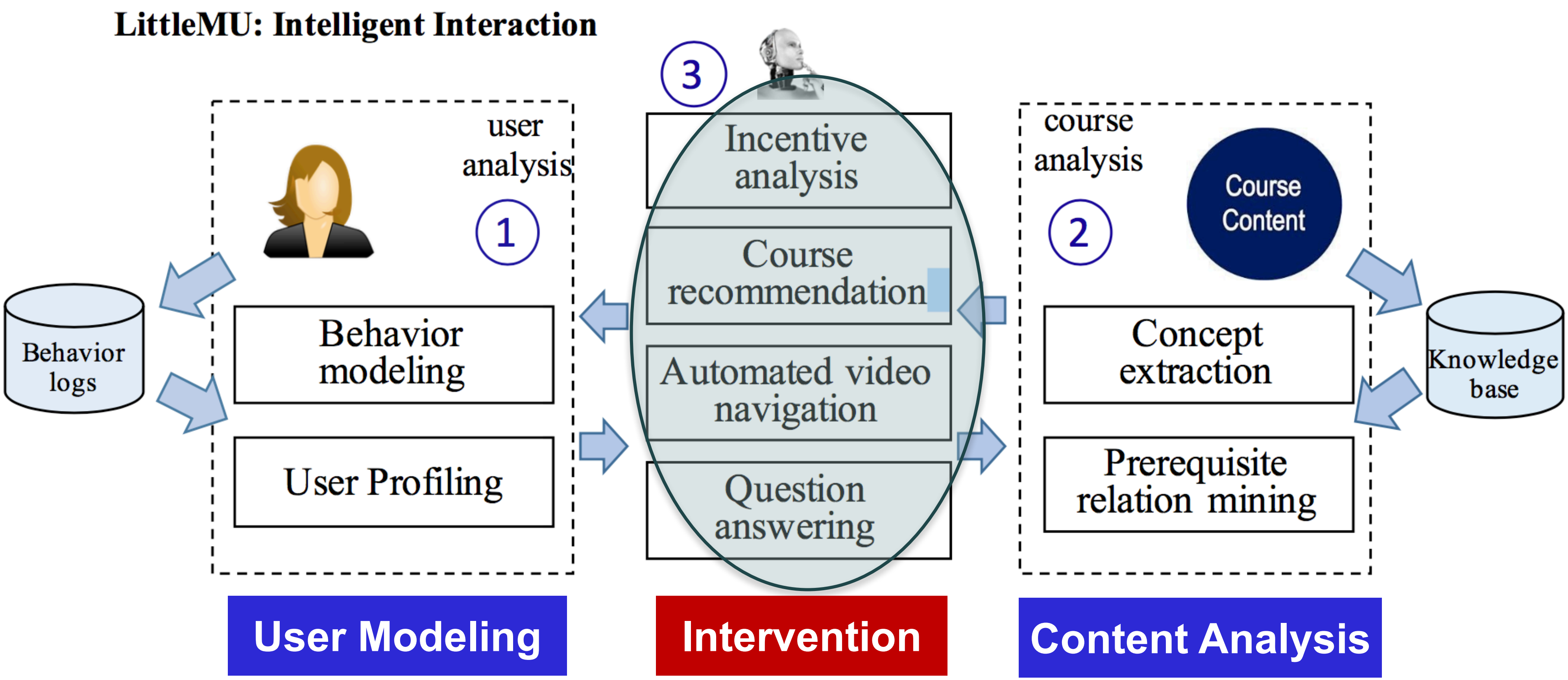

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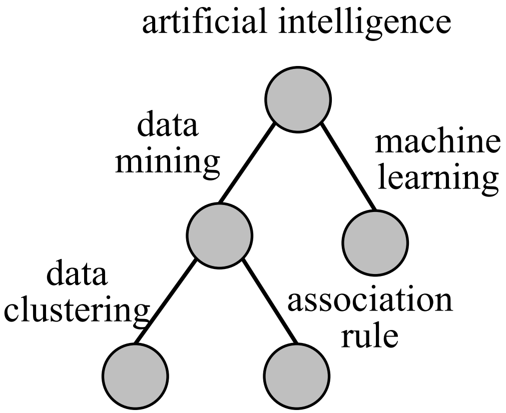
# What we can do?

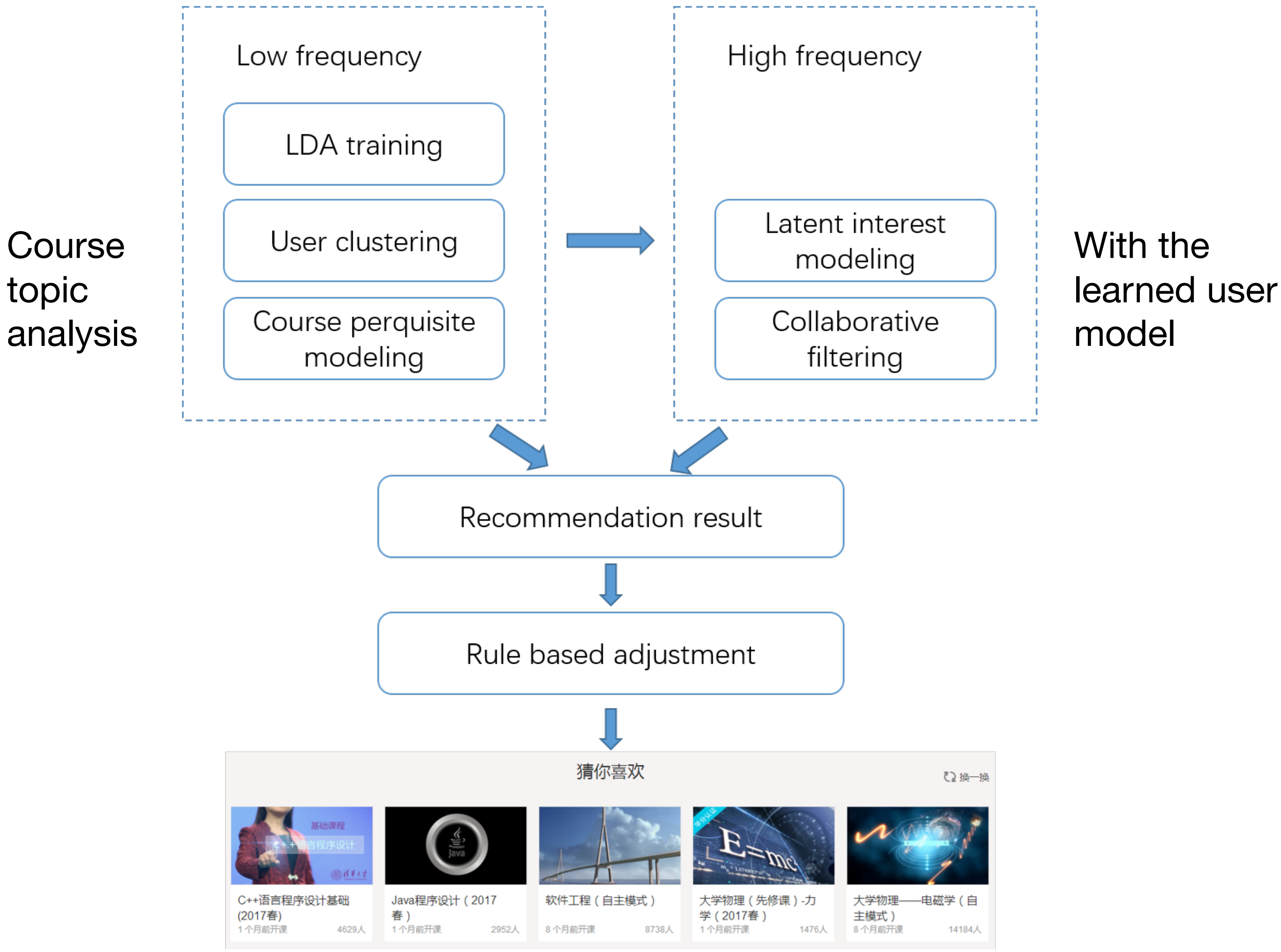
User modeling




Knowledge

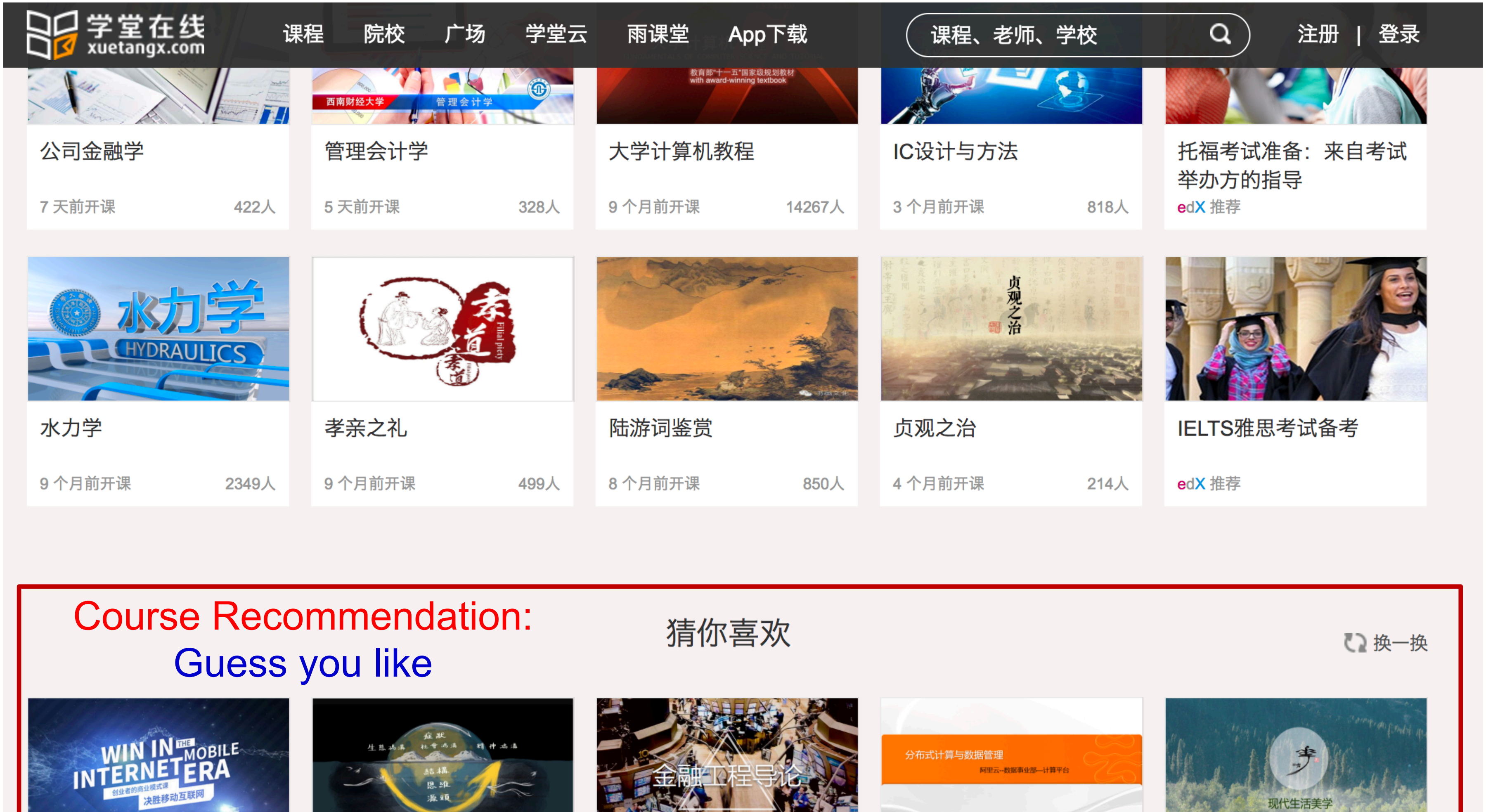
- Let start with a simple case
  - Course recommendation based on user interest

# Course Recommendation



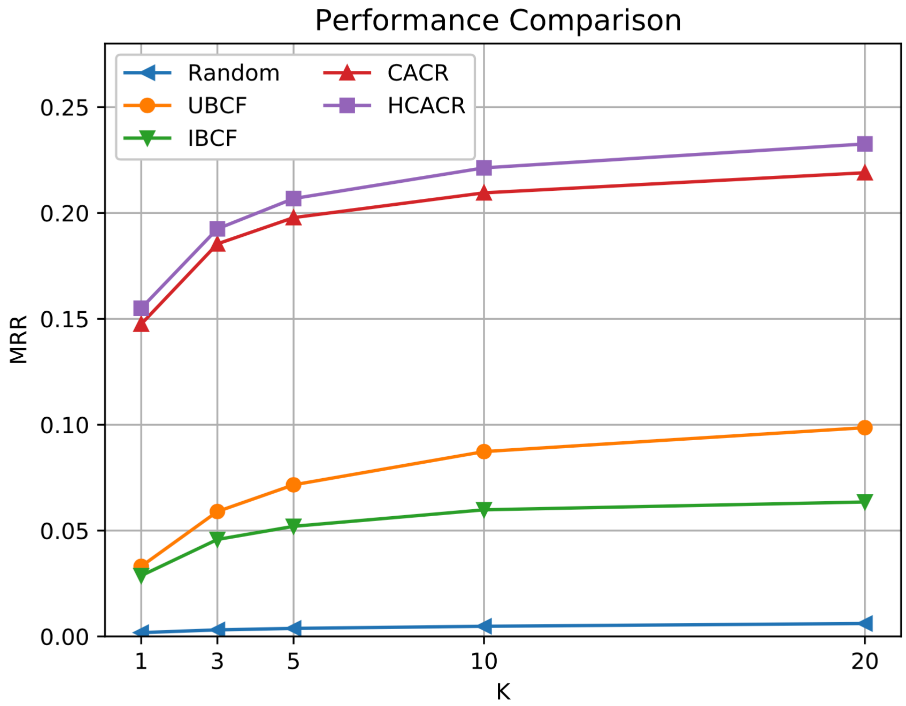

[1] Xia Jing, Jie Tang, Wenguang Chen, Maosong Sun, and Zhengyang Song. Guess You Like: Course Recommendation in MOOCs. **WI'17.**

# Course Recommendation




Course Recommendation:
Guess you like

# Online A/B Test




Top-k recommendation accuracy (MRR)

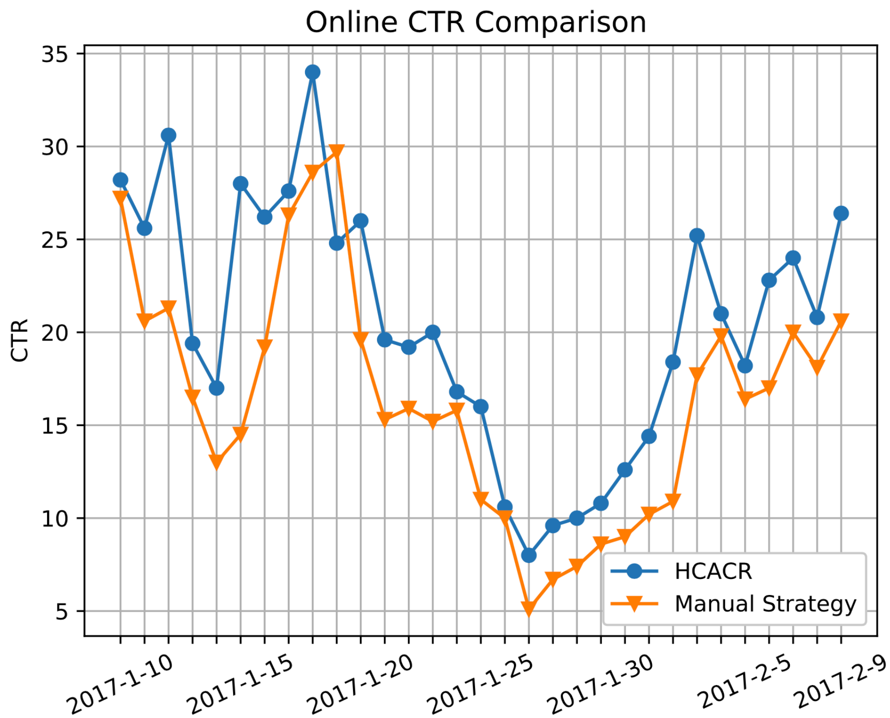
Comparison methods:

HCACR – Hybrid Content-Aware Course Recommendation

CACR – Content-Aware Course Recommendation

IBCF – Item-Based Collaborative Filtering

UBCF – User-Based Collaborative Filtering



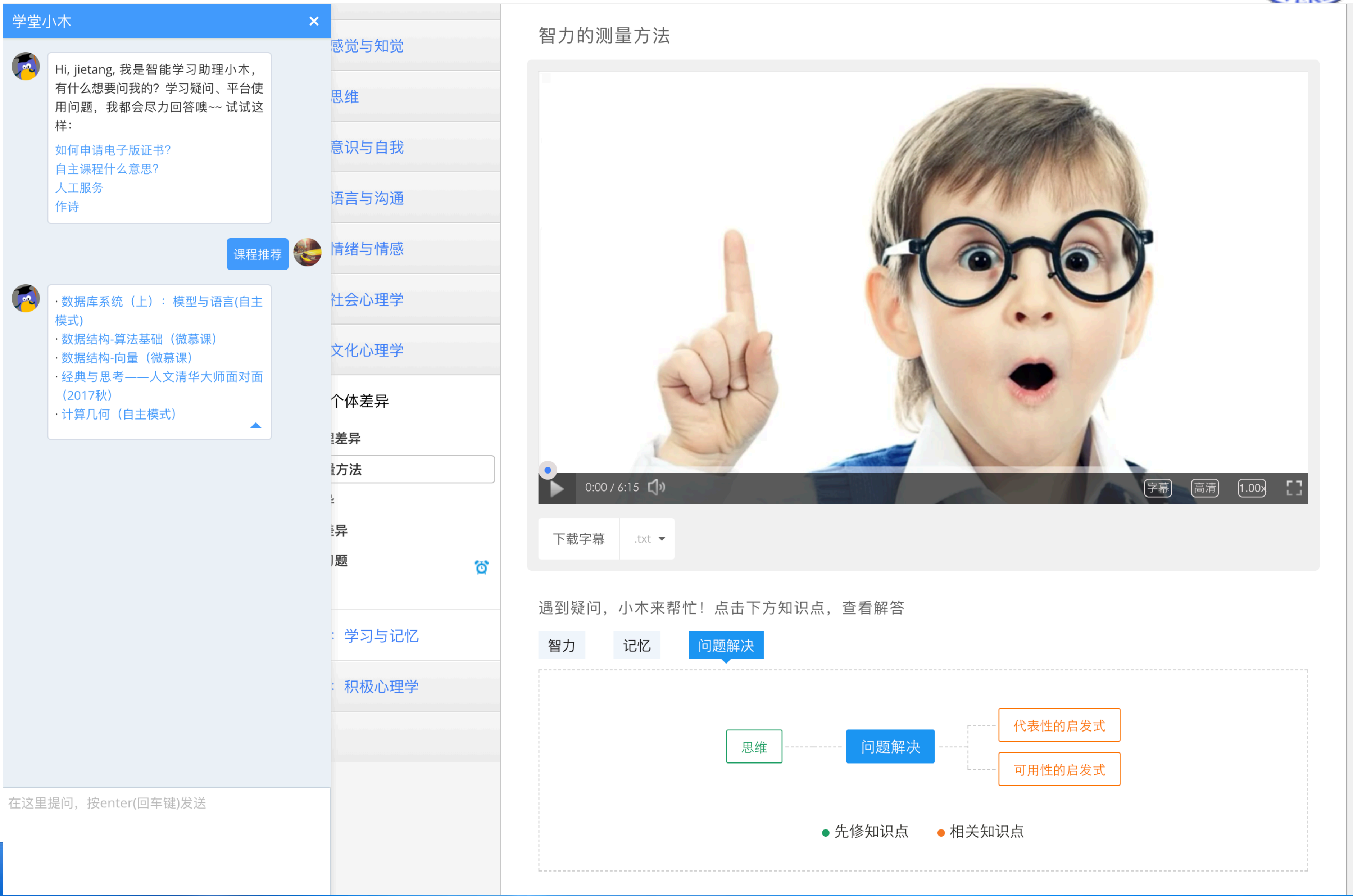

Online Click-through Rate

Comparison methods:

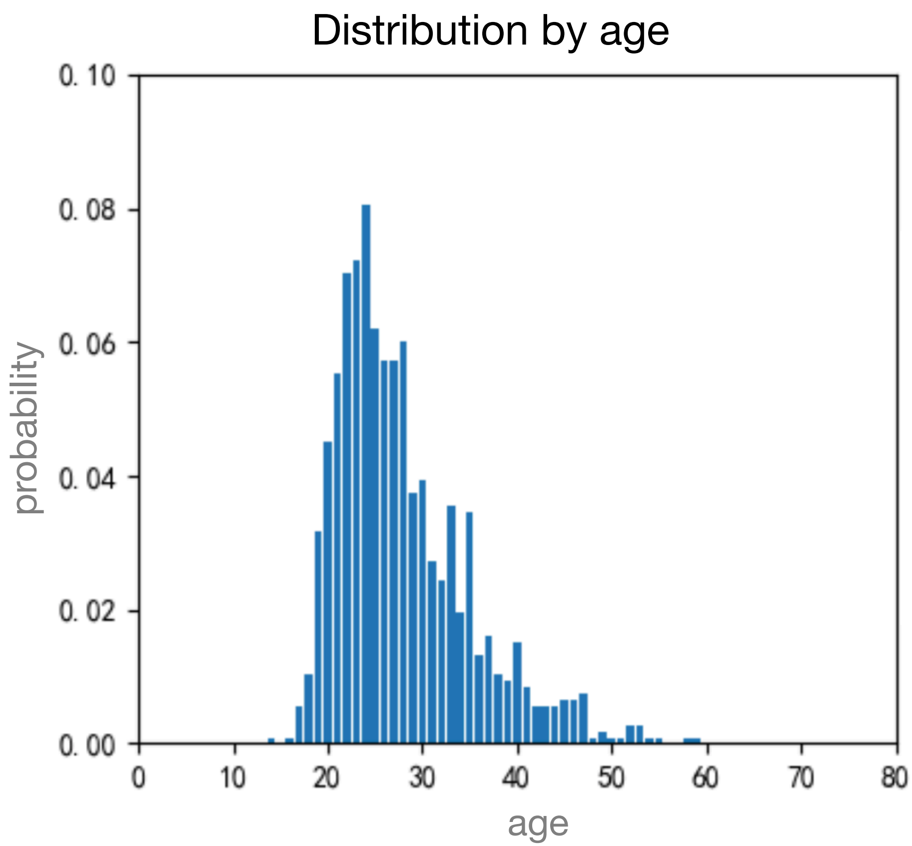
HCACR – Our method

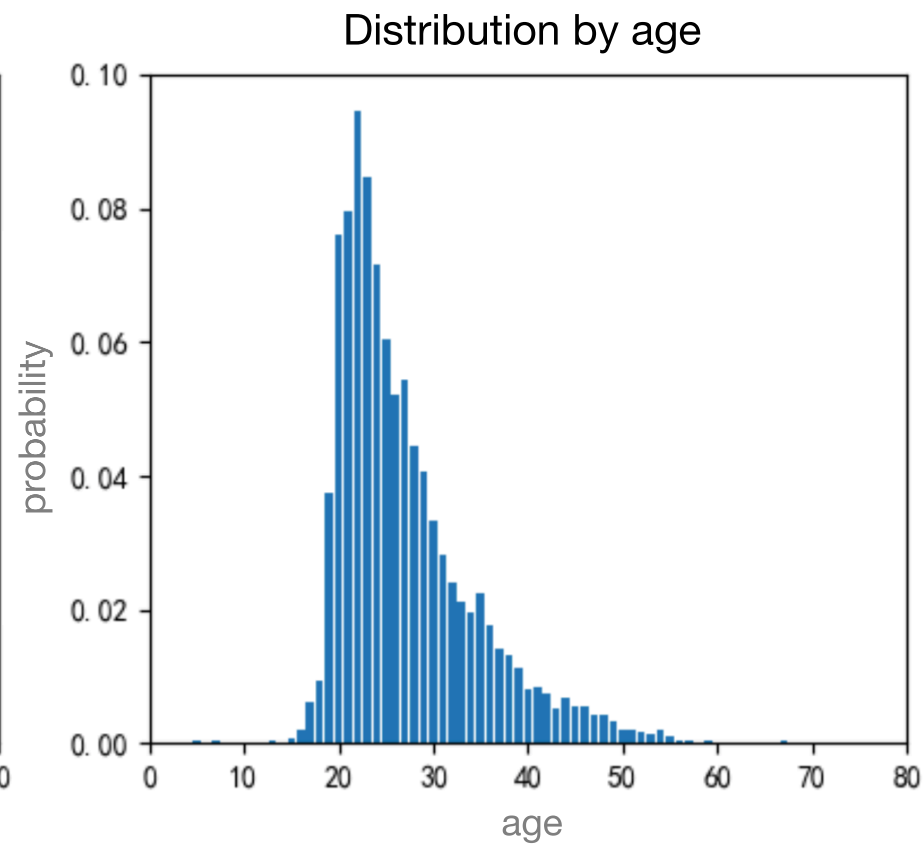
Manual strategy

# Context based Recommendation



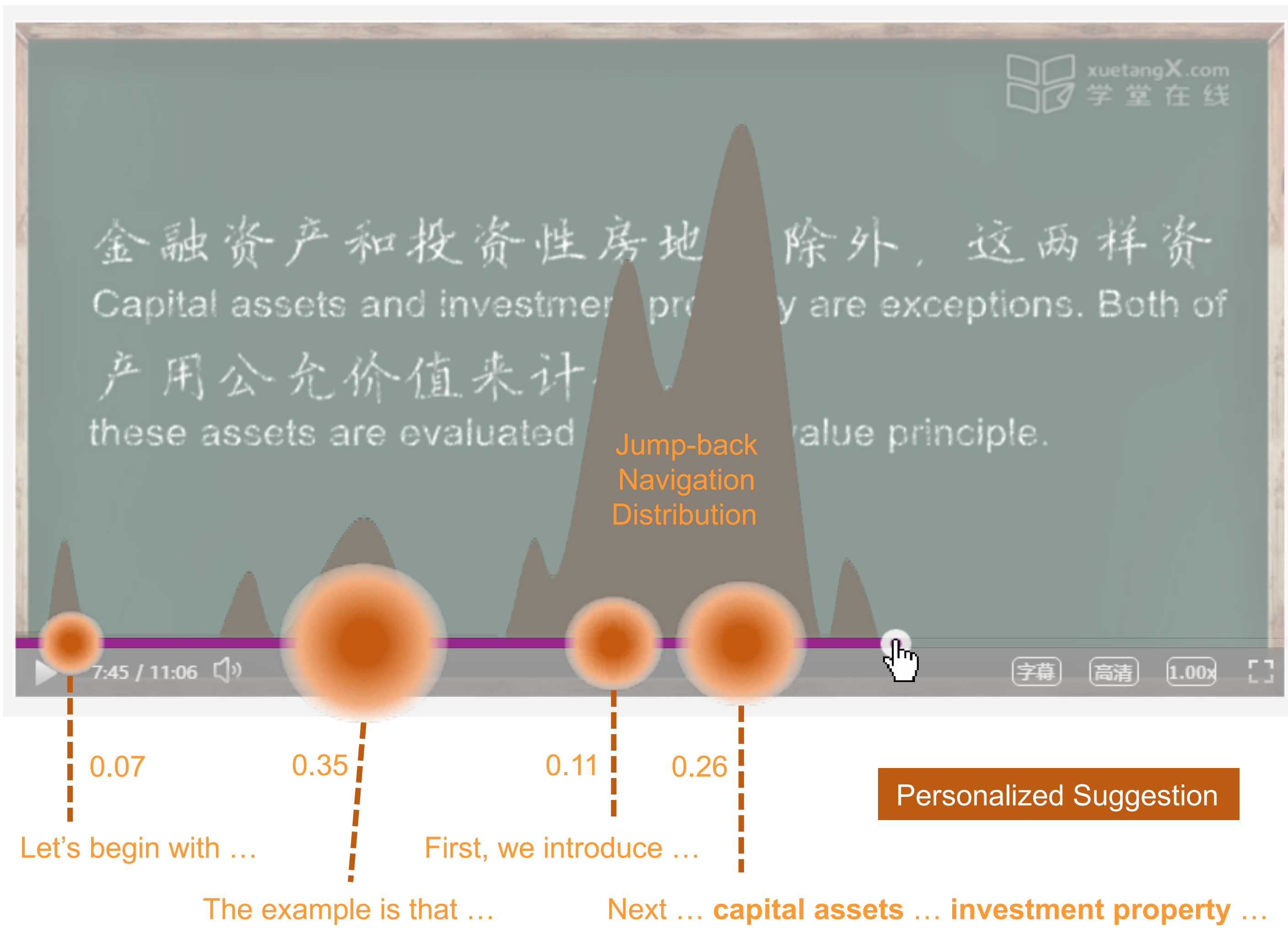
# More Analysis



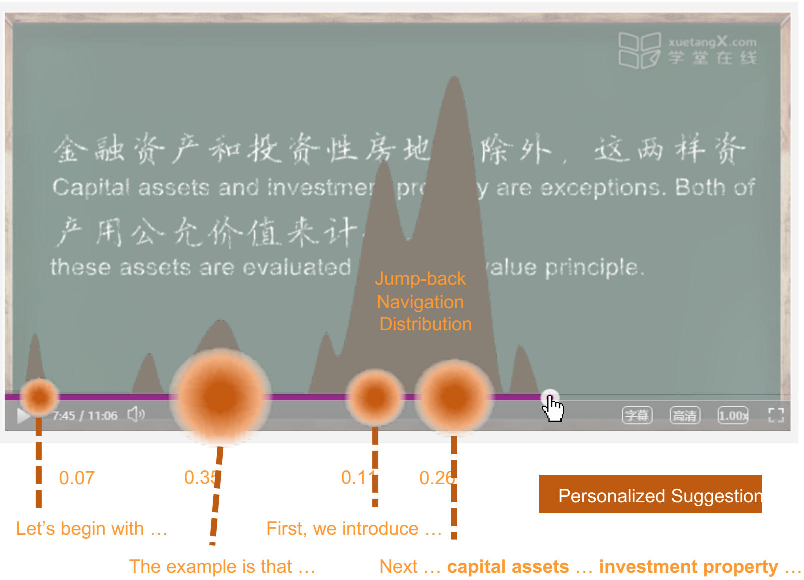



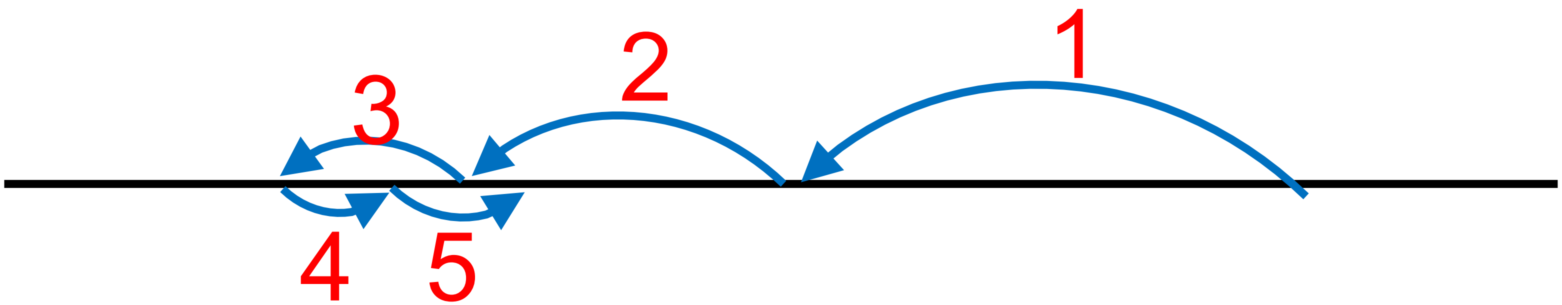
- Let start the simplest case
  - Course recommendation based on user interest
- What can we else?
  - Interaction when watching video?

# Smart Jump
## —Automated suggestion for video navigation



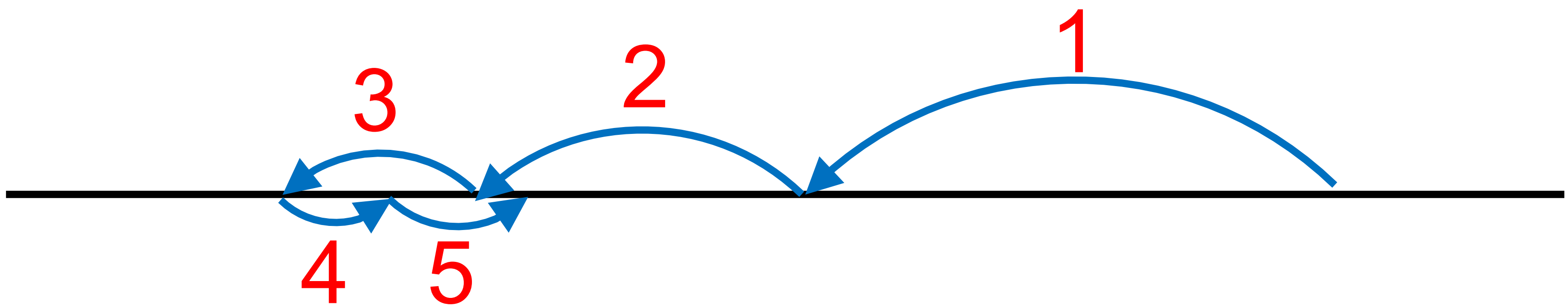
# Average Jump



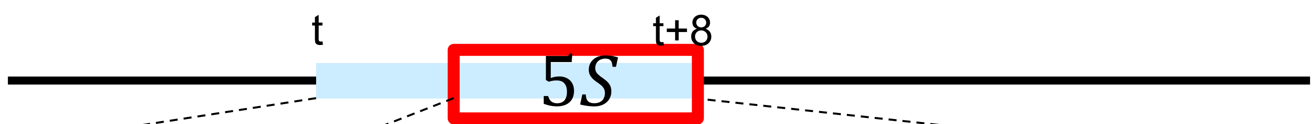




On Average: 2.6 Clicks = 5 seconds

# Two Numbers



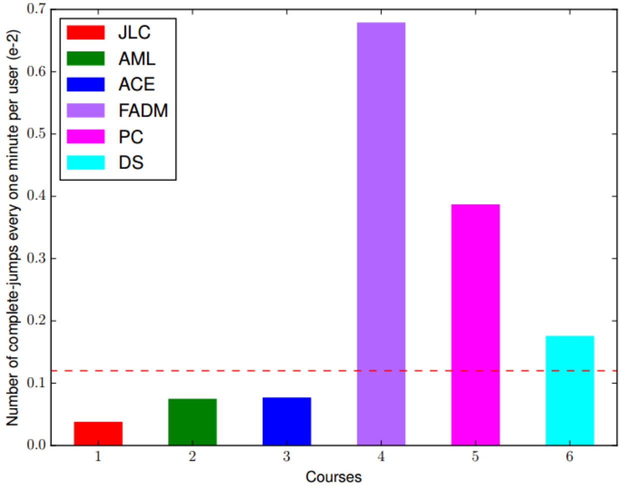

**On Average: 2.6 Clicks = 5 seconds**

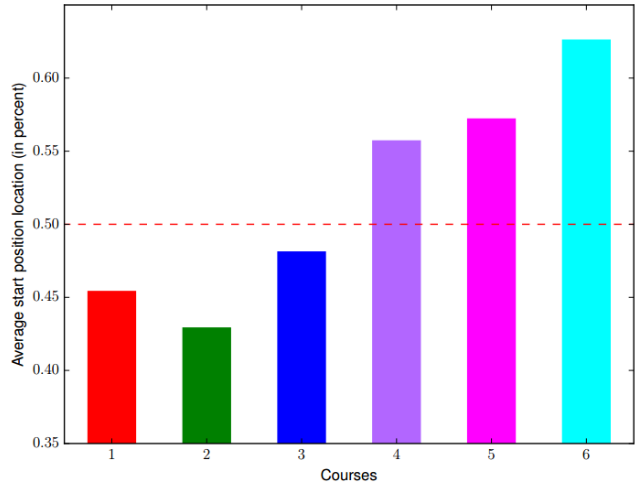


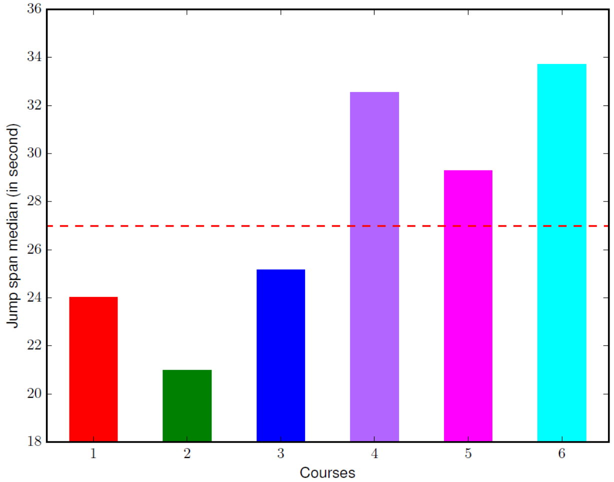

According to what we have discussed we find that the fifth activity belongs to cash outflow of a business activity.

$$5S \times 8{,}000{,}000\ users = 1.3\ years$$

# Observations – Course Related



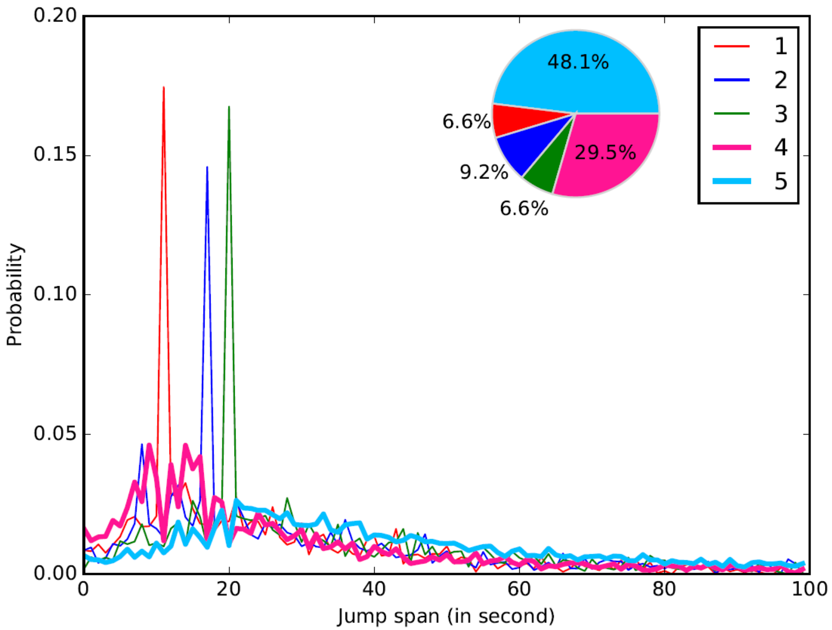




Science courses contain much more frequent jump-backs than non-science courses.

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

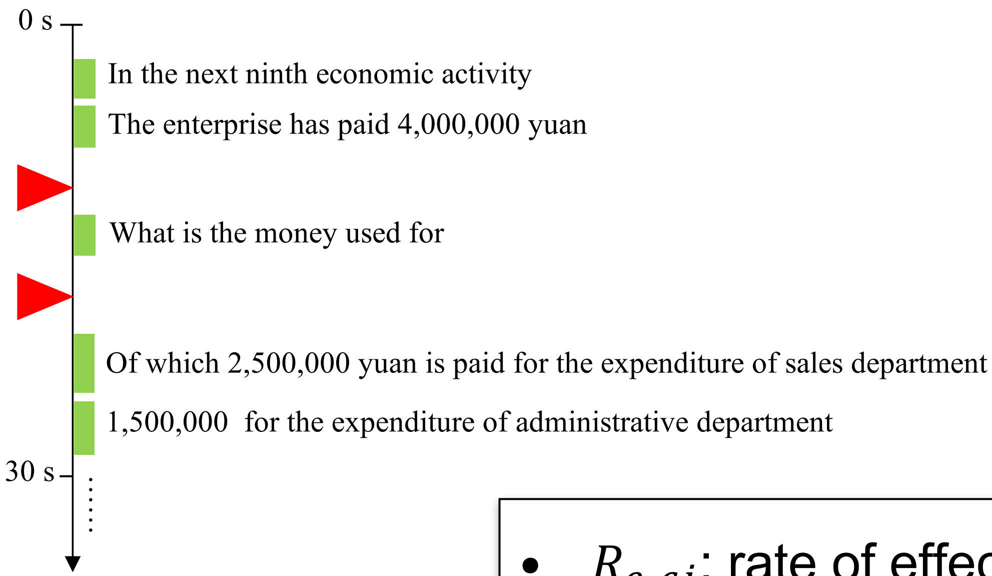
Users in science courses are likely to rewind farther than users in non-science courses.

# Observations – User Related




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

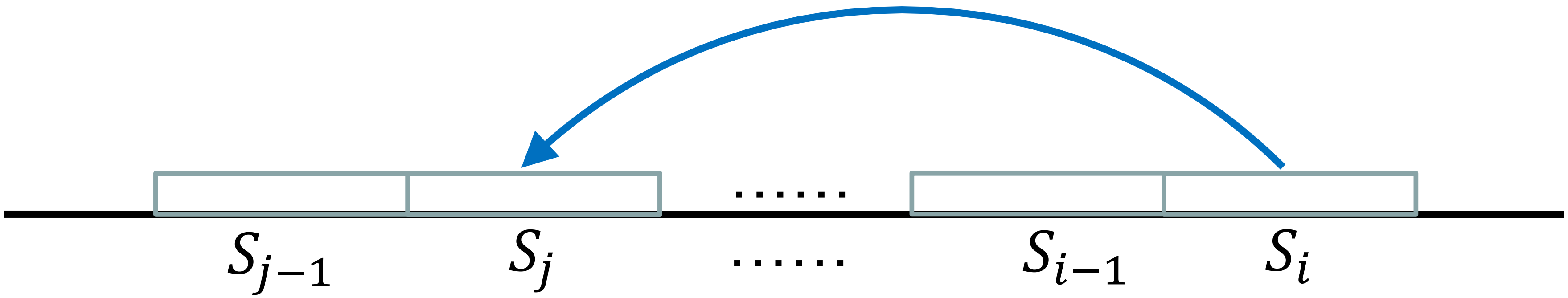
# Video Segmentation




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

- $R_{e\_cj}$: 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




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

[1] Han Zhang, Maosong Sun, Xiaochen Wang, Zhengyang Song, Jie Tang, and Jimeng Sun. Smart Jump: Automated Navigation Suggestion for Videos in MOOCs. **WWW'17**, pages 331-339.

# Prediction Results

| Course | Model | AUC | P@1 | P@3 | P@5 |
|---|---|---|---|---|---|
| **Science** | **LRC** | 72.46 | 35.95 | 65.54 | 80.13 |
| | **SVM** | 71.92 | 35.45 | 66.15 | 81.99 |
| | **FM** | 74.02 | 37.61 | **76.04** | **89.59** |
| **Non-science** | **LRC** | 72.59 | 69.23 | 73.23 | 89.32 |
| | **SVM** | 73.52 | 68.39 | 76.64 | 91.30 |
| | **FM** | 73.57 | 67.56 | **88.43** | **96.05** |

- LRC, SVM, and FM are different models
- FM is defined as follows

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

# Data statistics

| 类别 | 统计量 | 7.15-8.15 | 8.16-10.09 |
|---|---|---|---|
| 用户数量 | 总共用户数量 | 14875 | 20043 |
| | 触发了回看事件的用户数量 | 781 | 1025 |
| 视频数量 | 总共视频数量 | 235 | 235 |
| | 触发了回看事件的视频数量 | 234 | 235 |
| | 总的回看次数 | 7772 | 10369 |
| 回看路径不包含推荐点的回看 | 回看次数 | 3809 | 5325 |
| | 平均回跳次数 | 1.657653 | 1.722441 |
| 回看路径包含但未点击推荐点的回看 | 回看次数 | 3408 | 4333 |
| | 平均回跳次数 | 1.784918 | 1.803831 |
| 点击推荐点开始看视频的回看 | 回看次数 | 196 | 297 |
| | 平均回跳次数 | 1.882653 | 1.845118 |
| 点击推荐点后继续跳转的回看 | 回看次数 | 359 | 414 |
| | 平均回跳次数 | 2.788301 | 3.135266 |

# Data statistics

## 效果好的统计量：

点击推荐点后开始看视频的回看比例有所上升：35.3% -> 41.7%

点击推荐点后开始看视频的回看的平均回跳次数：1.882653 -> 1.845118

## 效果不好的统计量：

回看路径不包含推荐点的回看

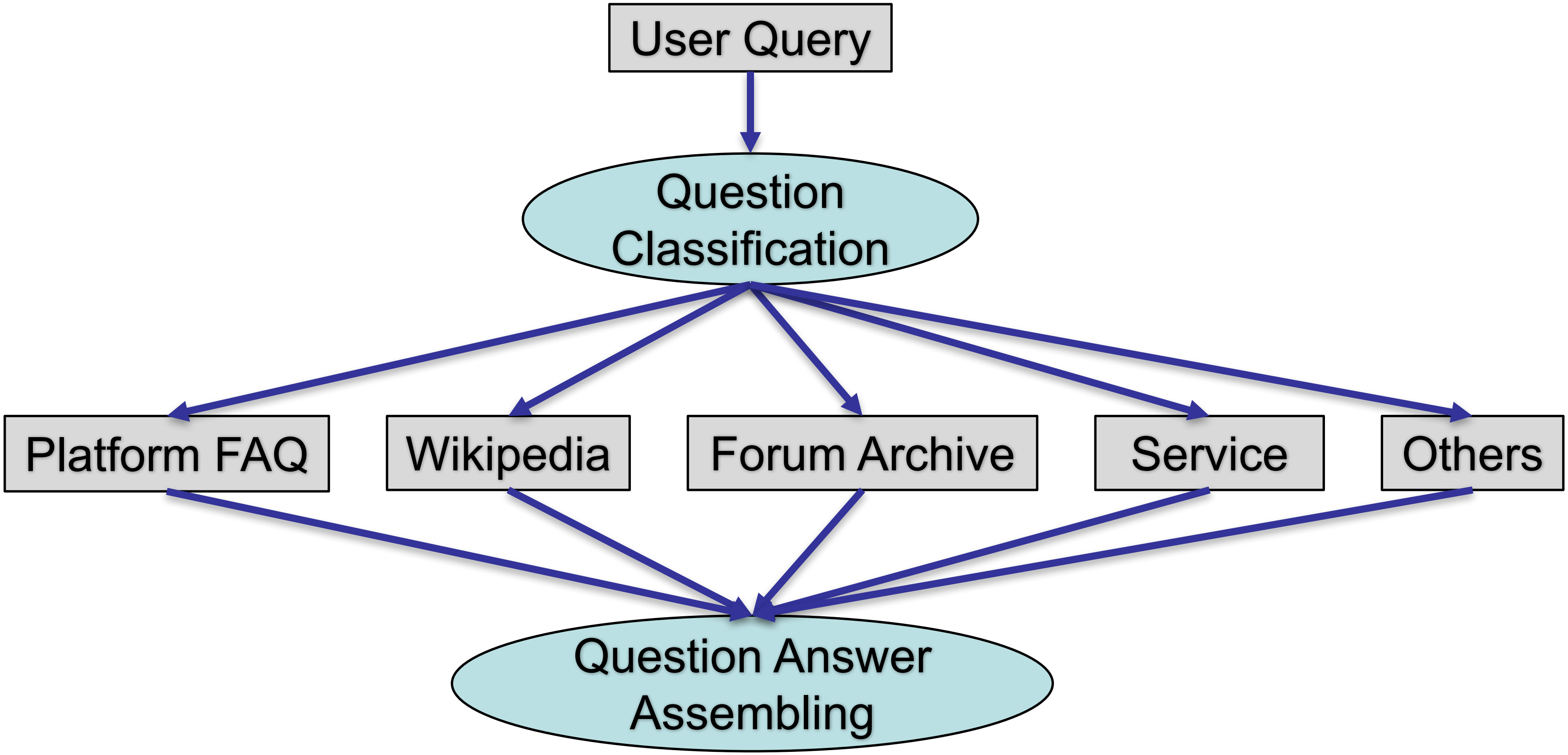
回看路径包含但未点击推荐点的回看

点击推荐点后继续跳转的回看

# More

- Let start the simplest case
  - Course recommendation based on user interest
- What can we else?
  - Interaction when watching video?
  - What kind of questions did the users ask?

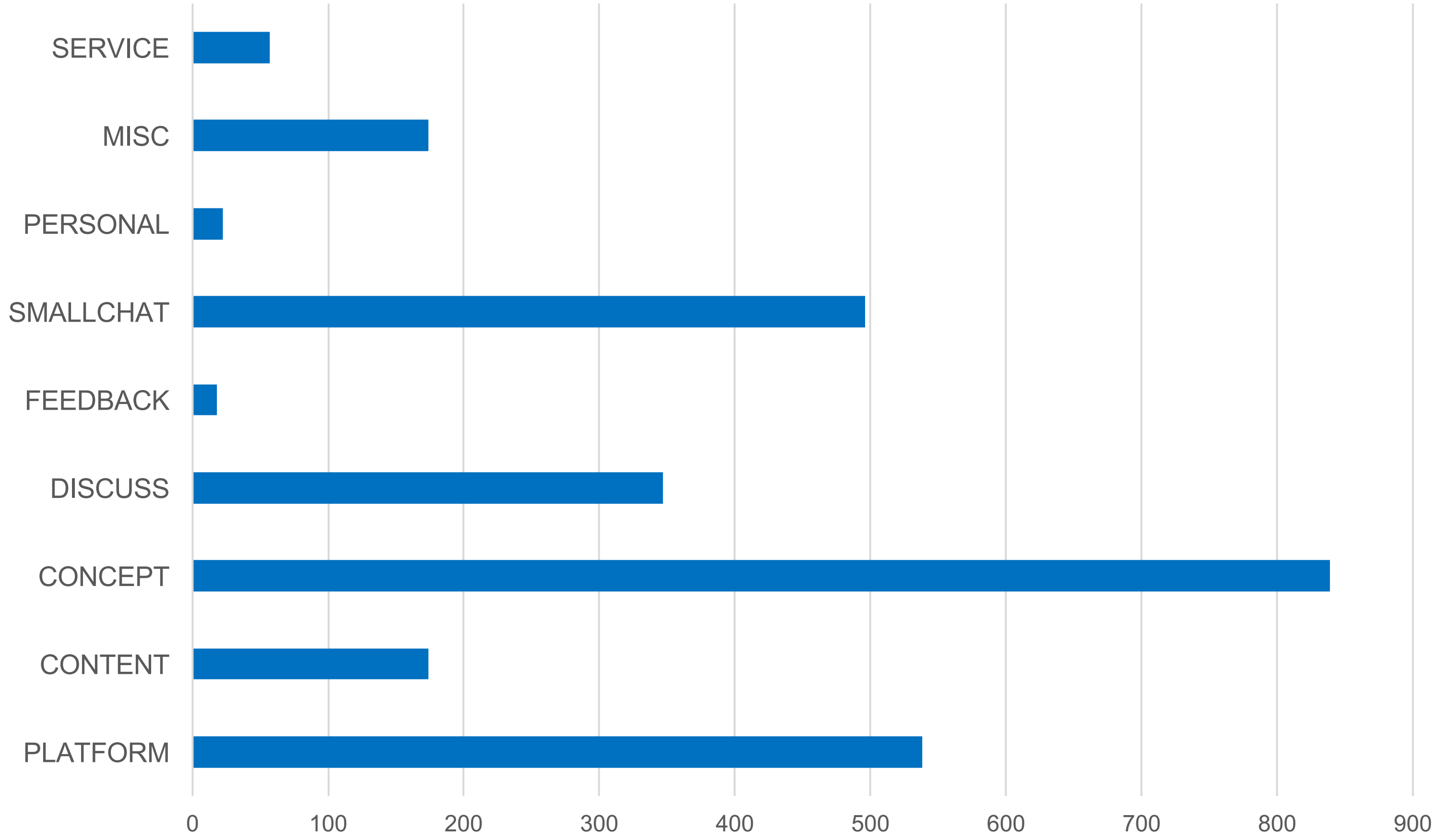
# Question Answering



# Query Categories

- PLATFORM: XuetangX platform
- CONTENT: enrollments, courses, teachers
- CONCEPT: simple knowledge point
- DISCUSS: general discussion, comparison
- FEEDBACK: suggestions, complains
- SMALLCHAT: small chat
- CUSTOMER: personal questions (e.g., account)
- MISC: meaningless questions (e.g., asjedkjqw)
- SERVICE: poem, recommendation

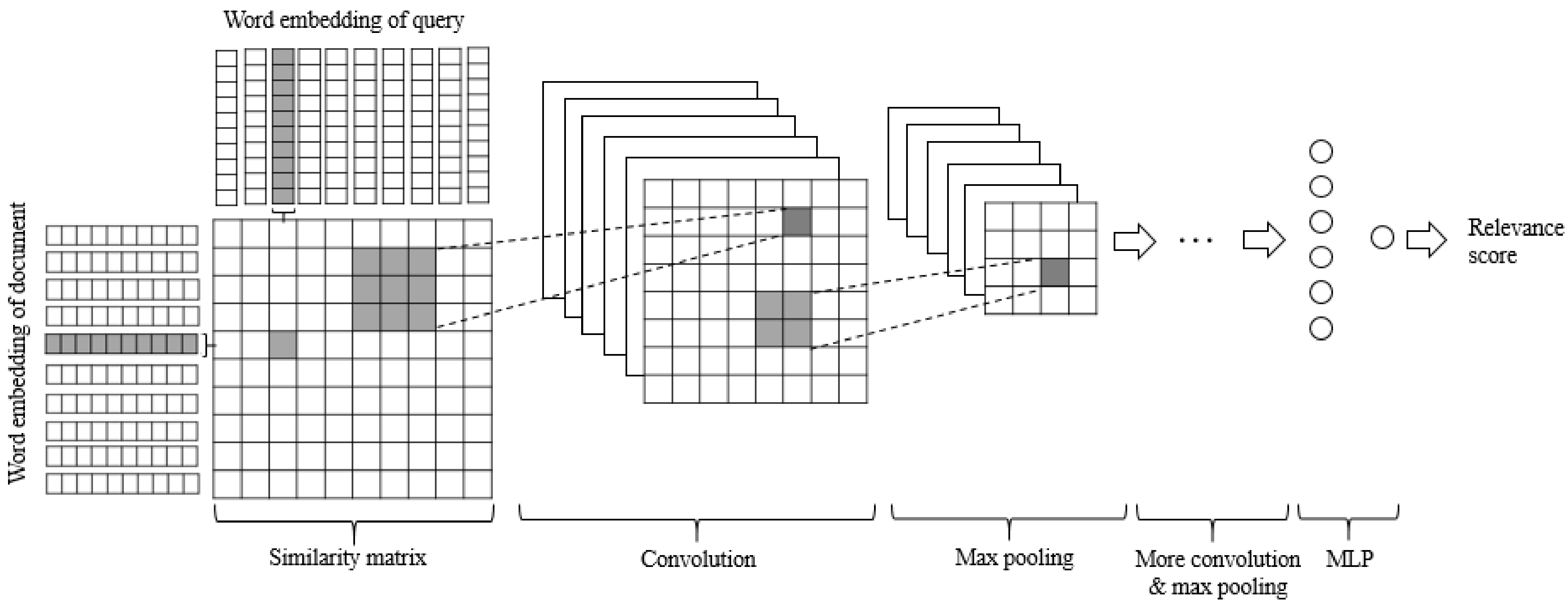
# Category Distribution



# Candidate Dataset

- Wikipedia: 892,185
- Forum Archive: 65,001
- Platform FAQ: 137
- Zhihu: 1,000+
- CSDN: 670
- Course Structure: 8 types

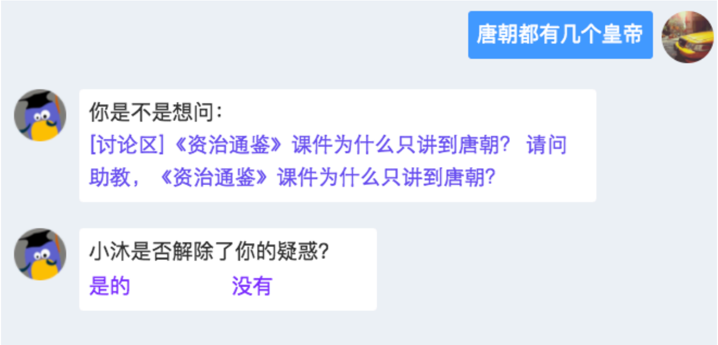
# Question Classification




- #Training (March 2017 – August 2017): 2162
- #Test (September 2017): 499

    Precision: 0.77, Recall: 0.78

# Online Result




| | #Questions |
|---|---|
| Total_request | 20604 |
| feedback | 470 |
| Feedback_ratio | 0.023 |
| User-thumb_up | 245 |
| User-thumb_down | 225 |
| Thumb_ratio | 0.52 |

# Question Retrieval

- Queries in PLATFORM category:  538
- Q-A pairs in Candidate Set: 77

| | MRR | Hit @ 1 | Hit @ 3 | Hit @5 |
|---|---|---|---|---|
| ES (TF-IDF) | 0.617 | 0.558 | 0.698 | 0.748 |
| Word2vec + WMD | 0.695 | 0.602 | 0.745 | 0.817 |
| Word2vec + Cosine | 0.653 | 0.577 | 0.685 | 0.726 |
| 1.0*WMD+1.5*ES | 0.728 | 0.640 | 0.781 | 0.845 |

# More

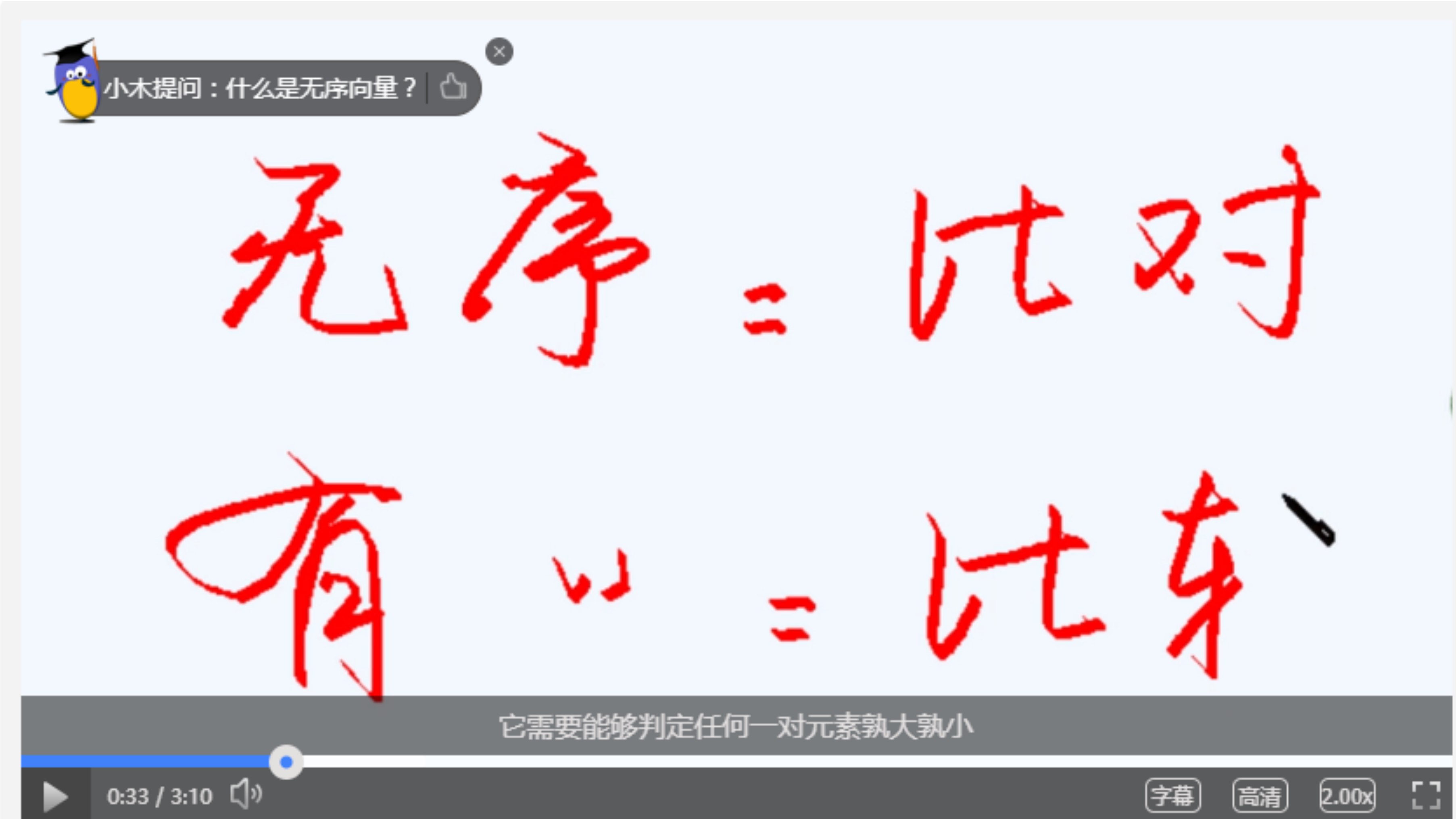
- Let start the simplest case
  - Course recommendation based on user interest
- What can we else?
  - Interaction when watching video?
  - What kind of questions did the users ask?
  - Interaction->intervention

# Active Question

Question: What is **time complexity?**

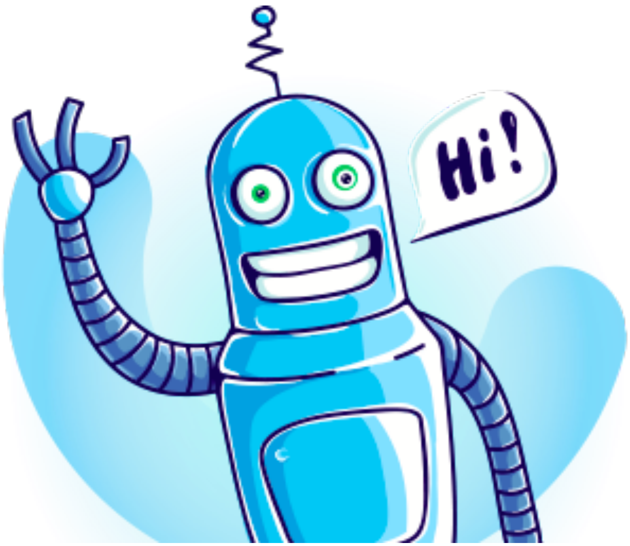
# Active Question

## Question: What is **Random Vector?**



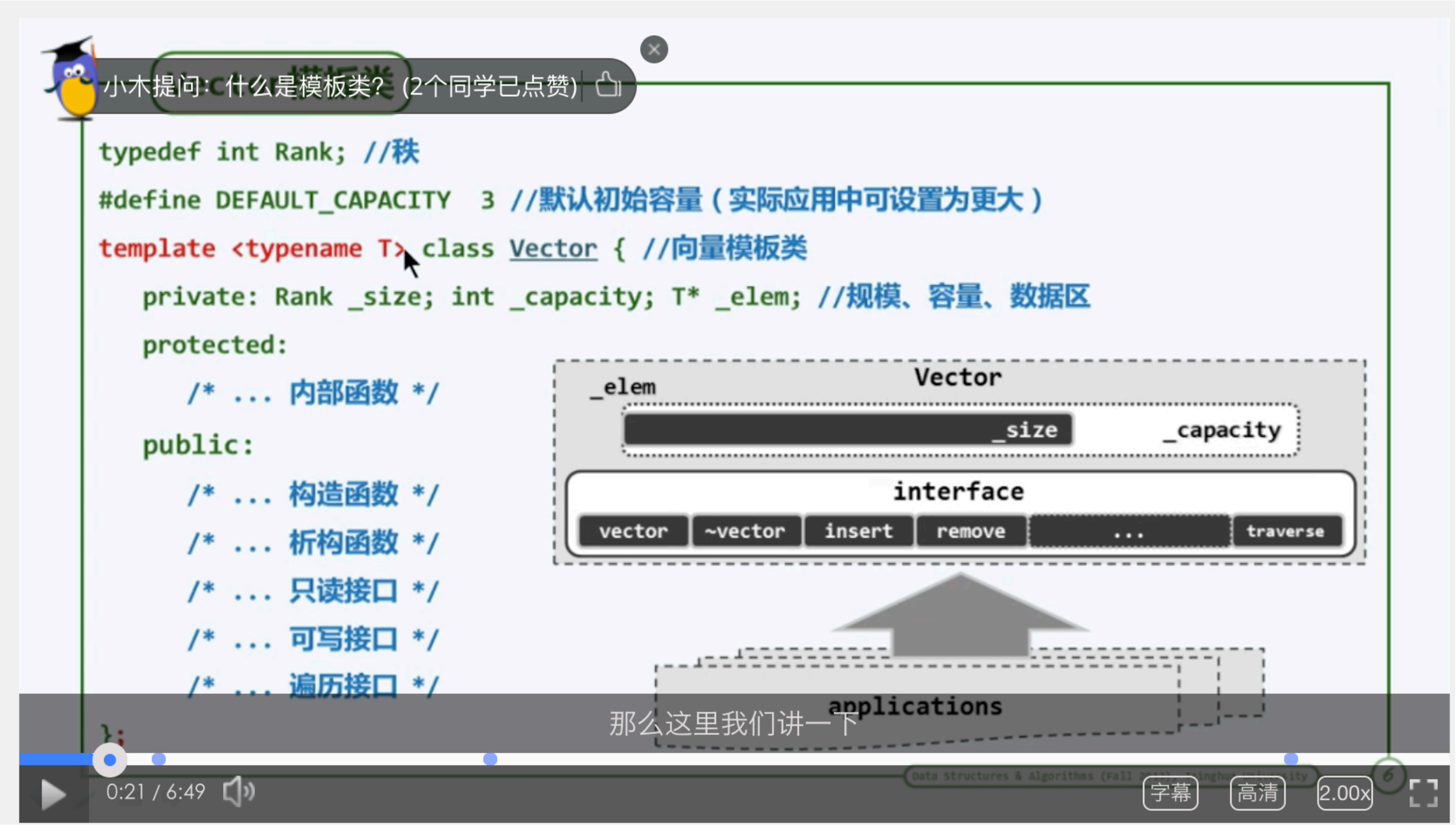
# Bot->Mindsets

- are those interventions really useful?
  - not enough…



# Active Question with Social Pressure

Example: Thumb_up Class (with #thumbup)



# Active Question

## On-line experiment Setting:

| Time | Classified Type | Total user count | User Count per Class | | |
|---|---|---|---|---|---|
| 9/14 – 9/17 | On/Off | 266 | On | | Off |
| | | | 137 | | 129 |
| 9/23 – 9/30 | Social/Thumb_up/None | 1150 | Social | Thumb_up | None |
| | | | 365 | 414 | 371 |

1. Each question lasts for 10 seconds;
2. Displaying time is notated manually to ensure strong connection with the on-going content;

# Active Question

## Positive Direct Feedback:

| Time | Classfied Type | Feedback ratio(at least once) | Thumb_up Ratio |
|---|---|---|---|
| 0914 -- 0917 | On/Off | 12.4%(17/134) | 31.2%(10/32) |
| 0923 -- 0930 | Social/Thumb_up/None | 17.5%(151/864) | 47.1%(113/240) |

1. Each question lasts for 10 seconds;
2. Appearing time is notated manually to ensure strong connection with the on-going content;

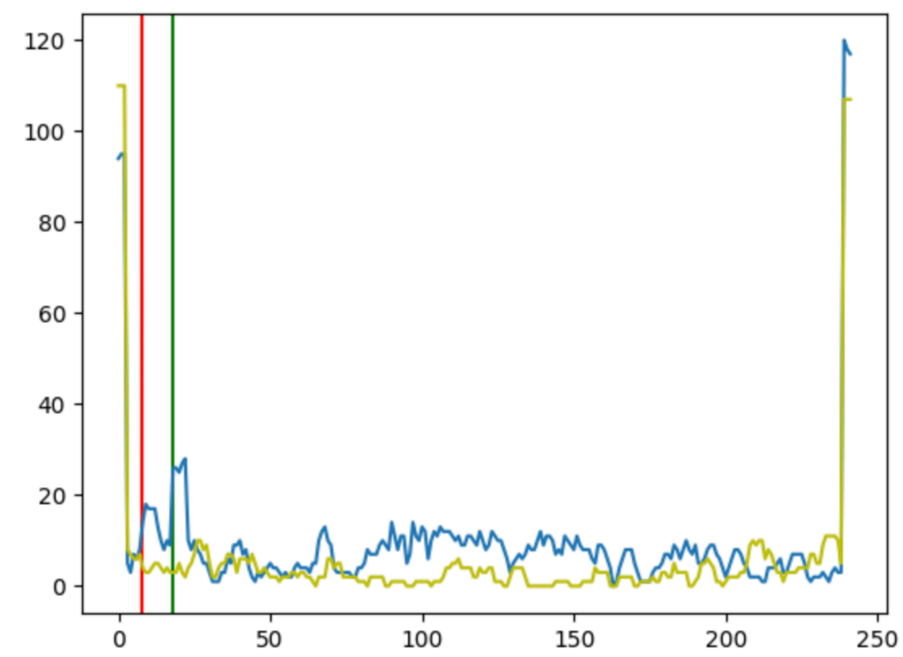
# Active Question

## New Peaks in in-video interaction:

Vertical line:
- Red: start of question
- Green: end of question

Curve:
- Yellow: without question displaying
- Blue: with question displaying

(Since the course is on-going, a full comparison is not available for now)



# Active Question

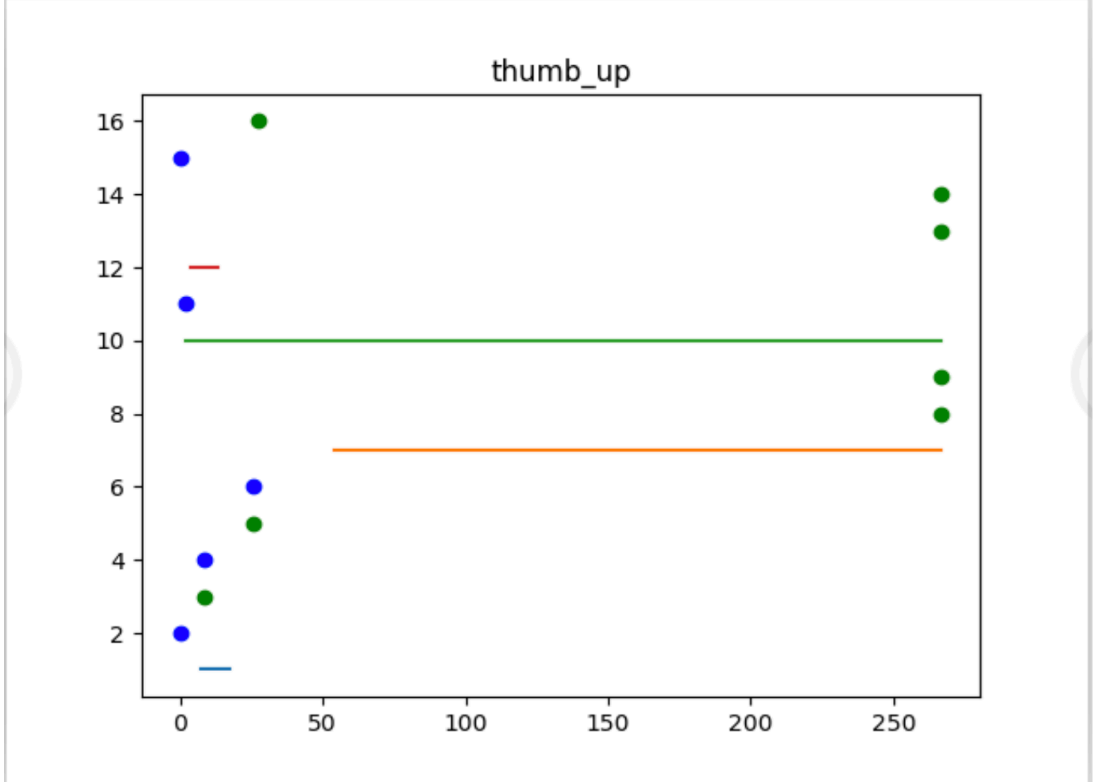
## A specific case of jumping back to the quetion time

X-axis: video time axis
Y-axis: event time axis

Bottom blue line:
- Red: start of question
- Green: end of question

Other lines:
- User's jump span

Dots:
- Other event, e.g., playing, pausing.



# Active Question

## Longer Video Watching Time in total:

| Class | Median Watch Time(second) | Average Watch Time(second) | User Count |
|---|---|---|---|
| On | 1329.5 | 3497.4 | 137 |
| Off | 1864.0 | 2946.3 | 129 |

(t-test, p=0.303)

# Active Question

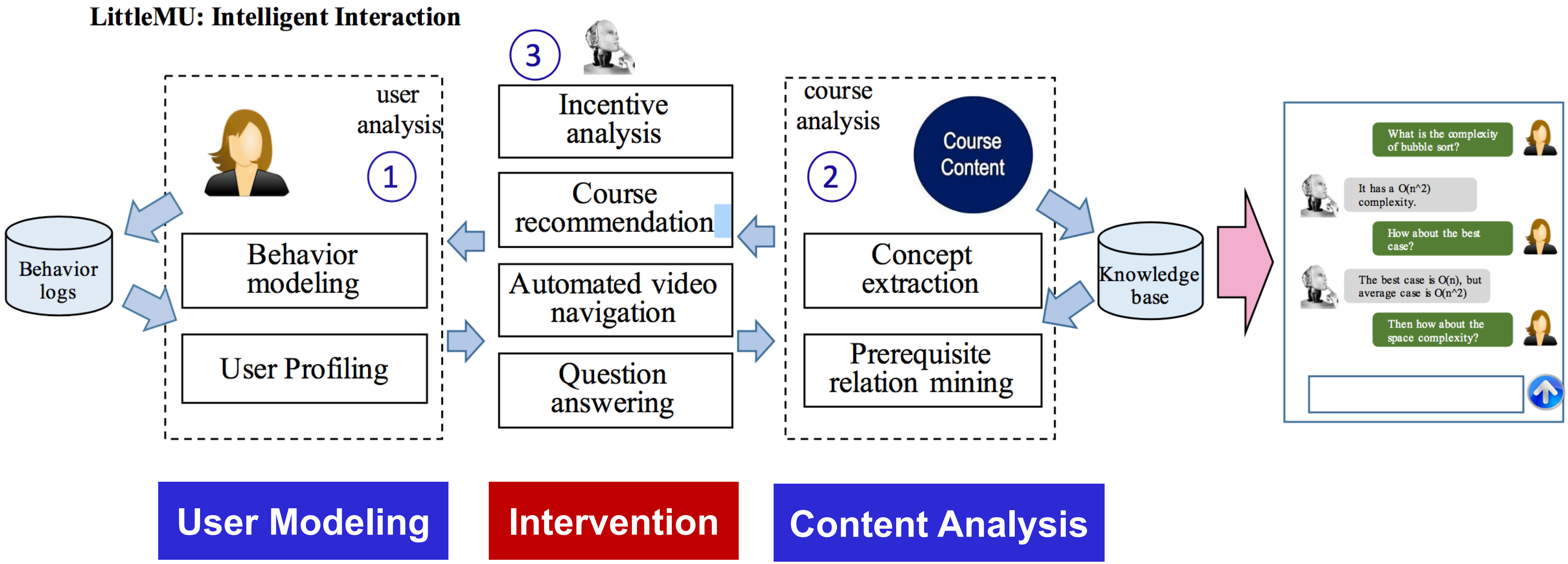
The fixed strategy has some major shortcomings:

1. It does not scale up well;
2. User difference is not considered;
3. The displaying time and duration is chosen intuitively and far from optimal.

Reinforcement learning may help.

1. Using users' history for personalization;
2. Iteratively update the strategy by users' feedback;
   - Careful design needed to integrate both explicit feedback (thumb_up or exit button) and implicit feedback (watching time, etc.);
3. Experiment is still on the way.

# LittleMU (小木)


LittleMU: Intelligent Interaction
user analysis
1
Behavior modeling
User Profiling
Behavior logs
3
Incentive analysis
Course recommendation
Automated video navigation
Question answering
course analysis
2
Course Content
Concept extraction
Prerequisite relation mining
Knowledge base
What is the complexity of bubble sort?
It has a O(n^2) complexity.
How about the best case?
The best case is O(n), but average case is O(n^2)
Then how about the space complexity?
User Modeling
Intervention
Content Analysis

# Recent Publications


- Liangming Pan, Chengjiang Li, Juanzi Li, and Jie Tang. Prerequisite Relation Learning for Concepts in MOOCs. In ACL'17.
- Xia Jing, Jie Tang, Wenguang Chen, Maosong Sun, and Zhengyang Song. Guess You Like: Course Recommendation in MOOCs. WI'17.
- Han Zhang, Maosong Sun, Xiaochen Wang, Zhengyang Song, Jie Tang, and Jimeng Sun. 2017. Smart Jump: Automated Navigation Suggestion for Videos in MOOCs. In WWW'17 Companion.
- Jiezhong Qiu, Jie Tang, Tracy Xiao Liu, Jie Gong, Chenhui Zhang, Qian Zhang, and Yufei Xue. 2016. Modeling and Predicting Learning Behavior in MOOCs. In WSDM'16. 93–102.
- Jie Gong, Tracy Xiao Liu, Jie Tang, and Fang Zhang. Incentive Design on MOOC: a Field Experiment on XuetangX, Management Science (top in management). Submitted.
- Jie Tang, Tracy Xiao Liu, Zhenyang Song, Xiaochen Wang, Xia Jing, Jiezhong Qiu, Zhenhuan Chen, Chaoyang Li, Han Zhang, Liangmin Pan, Yi Qi, Xiuli Li, Jian Guan, Juanzi Li, and Maosong Sun. LittleMU: Enhancing Learning Engagement Using Intelligent Interaction on MOOCs. submitted to KDD.
- 李曼丽, 徐舜平, 孙梦嫽. MOOC 学习者课程学习行为分析——以“电路原理”课程为例[J]. 开放教育研究, 2015, 21(2): 63-69.
- 薛宇飞, 黄振中, 石菲. MOOC 学习行为的国际比较研究--以“财务分析与决策”课程为例[J]. 开放教育研究, 2015 (2015 年 06): 80-85.
- 薛宇飞，敬峡，裘捷中，唐杰，孙茂松. 一种在线课程中的作业互评方法：中国，201510531490.2.（中国专利申请号）
- 唐杰,张茜,刘德兵. 用户退课行为预测方法及装置. 201610292389.0 （中国专利申请号）

# Thank you！

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Jie Tang, KEG, Tsinghua U, http://keg.cs.tsinghua.edu.cn/jietang

**Download all data & Codes,** http://arnetminer.org/data

http://arnetminer.org/data-sna