

# Student Performance Prediction based on Multi-View Network Embedding

**Jianian Li, Yanwei Yu, Yunhong Lu, Peng Song**

**School of Computer and Control Engineering, Yantai University**

# Outline

**Motivation**

**Problem**

**Method**

**Experimental Evaluation**

**Conclusion**

# Motivation

- Education is the foundation of a nation.
- The phenomenon of failing examinations in universities has become more serious.
- Predicting students' academic performance in advance has become more important to both students and teachers.
  - ✓ Improving the enthusiasm for the students to learn
  - ✓ teachers can adjust the teaching plan in time and facilitate personalized education to enhance the learning efficiency and effect of all students.

## Related Work

**Using single data source**

**Independently consider the impact of each data source**

**Not consider the impact of students on similarity**

**Negative:**

**Assessment limitations, not comprehensive assessment of student performance**

# Problem

However, in addition to historical grades, varieties of potential factors affect students' academic performance, such as personal behavior and friend relationship.

## Our Problem Definition:

In a semester, given the set of **practice test records of all student**, the **historical grade records**, and **the campus social network**, our goal is to **predict the students' academic performance rank** at this semester.

# Method Overview

## Heterogeneous network construction :

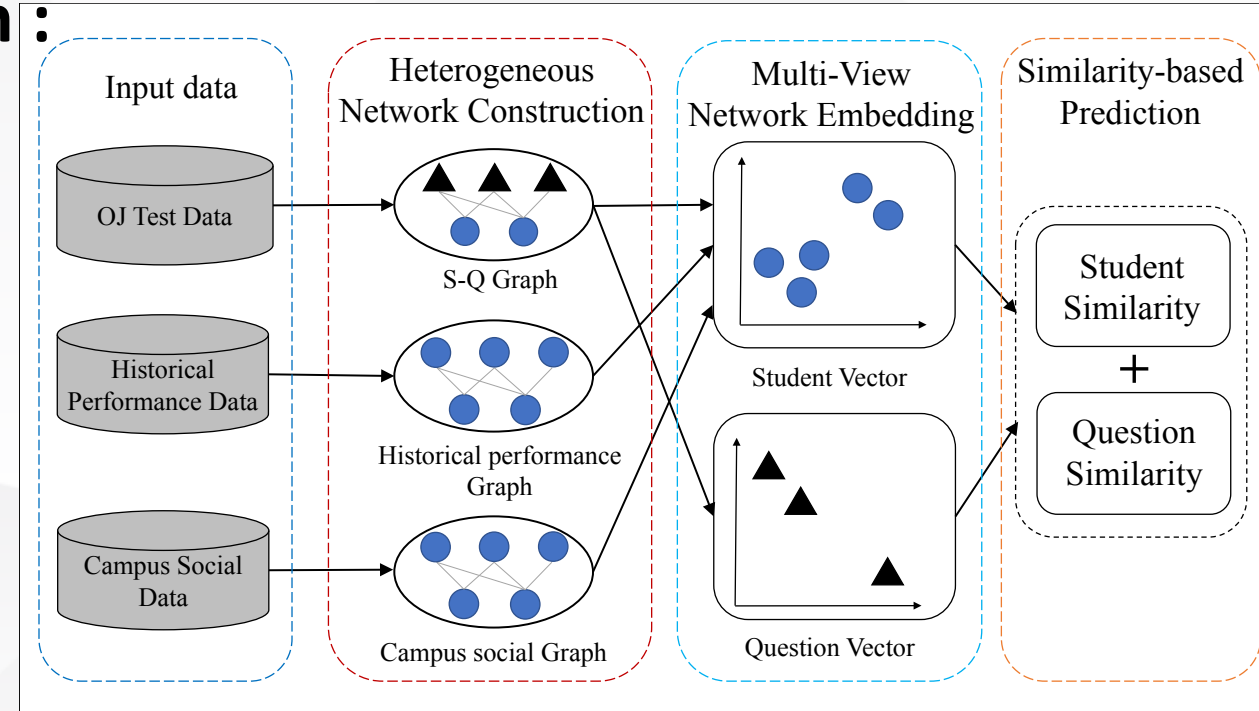
Capture all relationships  
among students, questions

## Network embedding module :

Learn the low-dimensional representations  
for students and questions

## Similarity-based performance predictor :

Predict students' academic performance



## ( I ) Input Data

### **Practice test record (OJ Test data)**

Reflecting the performance of students in class

### **Historical grade record**

Student historical performance data

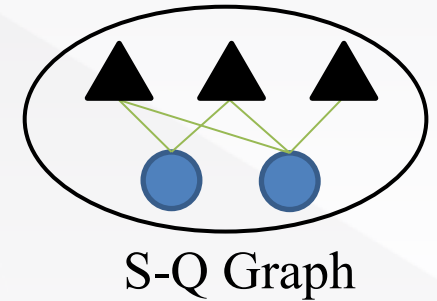
### **Campus Social Relationship Network**

Student activities in college life, such as co-attending competition

## ( II ) Heterogeneous Network Construction

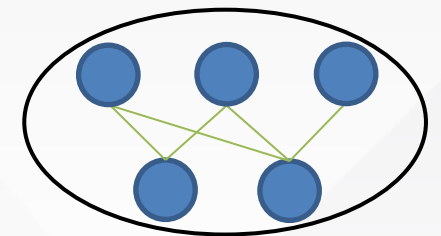
### S-Q Graph

Reflecting the performance of students in class



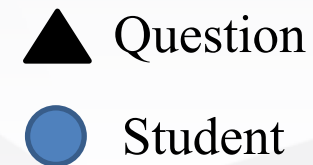
### Historical performance Graph

Student historical performance data

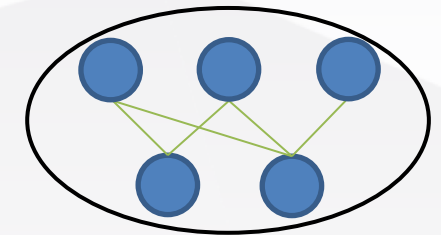


### Campus Social Relationship Network

Student awards & relationship between them



Historical performance Graph



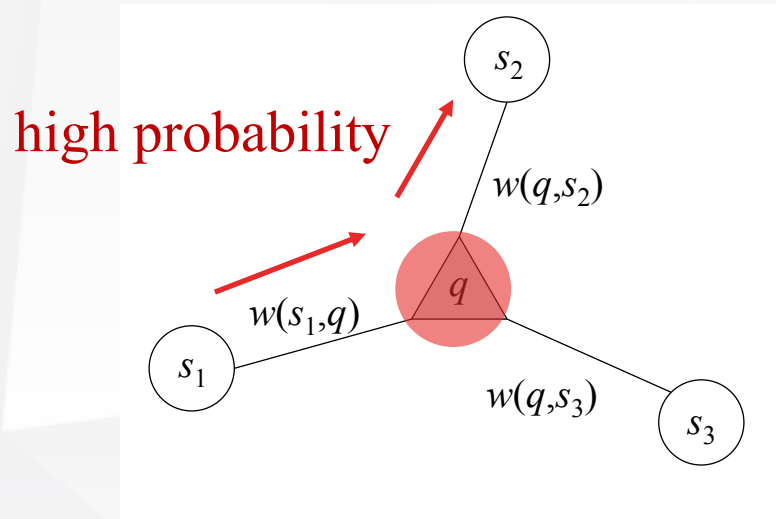
Campus social Graph



## (III) Multi-view Network Embedding

### Modeling the probability of random walk sampling

Our goal is that the higher the similarity between the two students, the higher the probability that the two students are in the same random walk.



For example: Now we stand on  $q$ , and last hop is  $s_1$

If  $|w(s_1, q) - w(q, s_2)| < |w(s_1, q) - w(q, s_3)|$

$s_2$  is more likely to become next hop

## (III) Multi-view Network Embedding

Modeling the probability of walk sampling in Network embedding

Design the transition probability  $Pr(q, s_i)$ :

$$Pr(q, s_i) = \begin{cases} 1 & s_i = s_1 \\ \exp(\lambda \frac{\min(w(s_1, q), w(q, s_i))}{\max(w(s_1, q), w(q, s_i))}) & |w(s_1, q) - w(q, s_i)| < r \\ \exp(-\frac{\max(w(s_1, q), w(q, s_i))}{\min(w(s_1, q), w(q, s_i))}) & otherwise \end{cases} \quad (1)$$

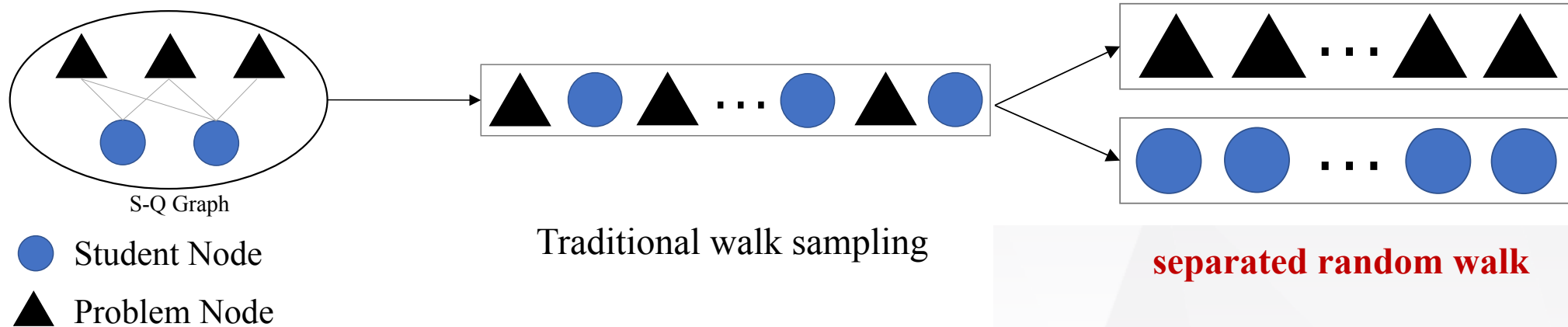
$r$  controls the walk to tend to visit the student nodes who take similar time with  $s_1$  with respect to question  $q$ .

$\lambda$  allows the search to differentiate between similar nodes and dissimilar nodes by scaling the transition probability.

## (III) Multi-view Network Embedding

### From traditional walk sampling to the separated random walk sampling

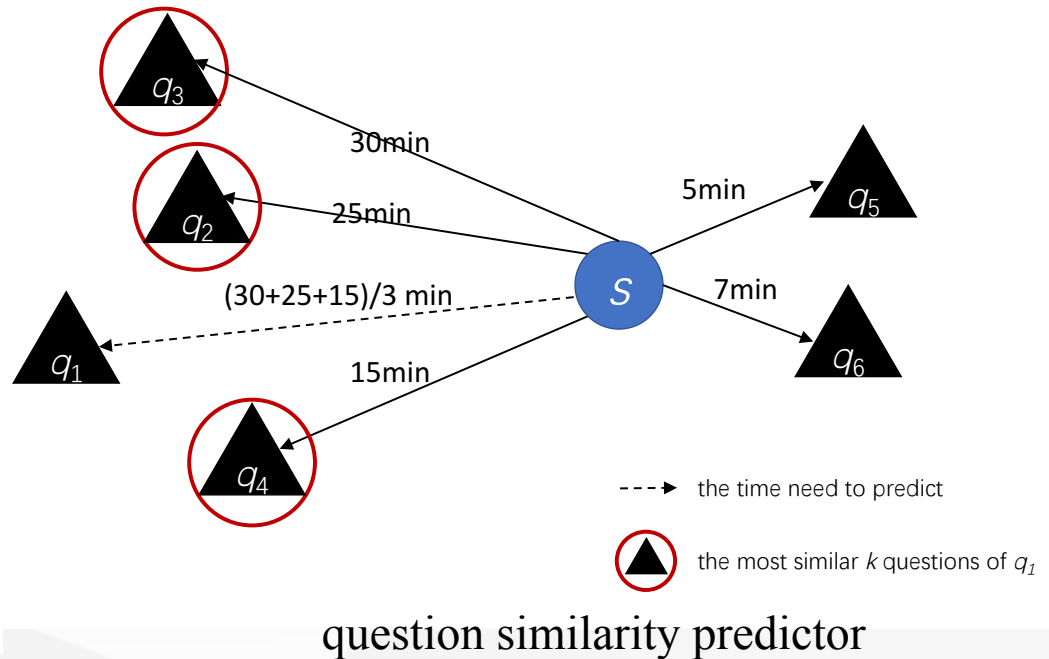
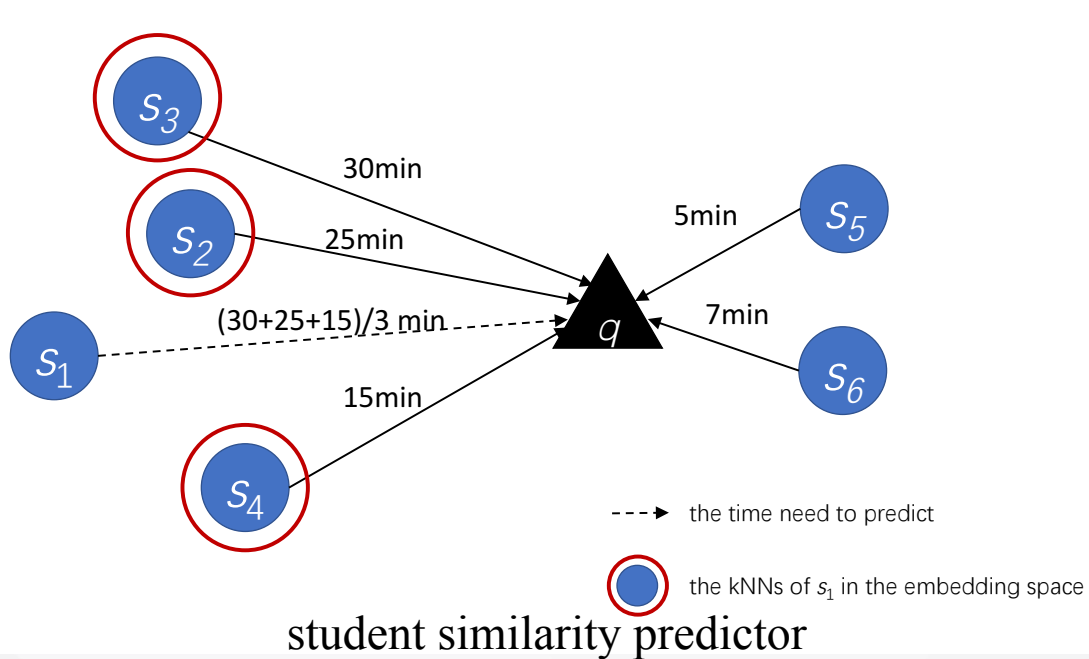
- It is not necessary to map students and questions into the same vector space
- Traditional walk sampling hurts the prediction accuracy
- So, we proposed the **separated random walk**



# (IV) Similarity-based Performance Prediction

Exploring a predictor that predicts student achievement

Design **student similarity predictor** and **question similarity predictor**



## (IV) Similarity-based Performance Prediction

Exploring a predictor that predicts student achievement

- Use cosine distance to measure student similarity and question similarity in the embedding space.
- Predict the total time took by students to finish random selected questions and rank them.

$$t_i(q) = \alpha \frac{\sum_{s_j \in N_k(s_i)} t_j(q)}{k} + \beta \frac{\sum_{q_j \in N_k(q)} t_i(q_j)}{k},$$

$q$ : a selected questions

$t_i(q)$ : Time spent by student  $s_i$

$N_k(s_i)$ : the kNNs of  $s_i$  in the embedding space

$N_k(q)$ : the most similar  $k$  questions of  $q$

# Experiment

## Datasets

- **OJ practice test data:** contains almost 2.1 millions test records from 5,000 students.
- **Historical performance data:** contains all historical course grades for the selected students in their first two years of college.
- **Campus social data:** collect 25 campus activities of the selected students reflecting the campus social relationships among students.

# Experiment

## Baselines:

Average-based methods(Global-Avg and Neighbor-Avg )

Matrix Factorization(MF)

Collaborative Filtering (CF)

## Three variations:

Single-view variations(OJ-view, History-view, and Social-view )

Dual-view variations : each variation considers both two different data sources.

MVNE/s : use the original random walk sampling in MVNE

# Experiment

## Prediction Performance

- MVNE method significantly outperforms all baselines on two datasets.
- Accuracy is also rising as the dimension of view increases.
- MVNE performs significantly better than MVNE/s on two majors.

**Table 1: Experimental results of all methods**

Method	Major I	Major II
Global-Avg	0.3929	0.3884
Neighbor-Avg	0.3810	0.3674
User-CF	0.3623	0.3587
Item-CF	0.3645	0.3658
MF	0.3524	0.3395
Social-view	0.3262	0.3140
History-view	0.3215	0.3163
OJ-view	0.3095	0.3070
Social-History-view	0.3119	0.3023
Social-OJ-view	0.3048	0.2884
OJ-History-view	0.2905	0.2930
MVNE/s	0.3584	0.3628
MVNE	0.2881	0.2860



# Conclusion

- Construct a heterogeneous network and two homogeneous networks to model the relationships between students, questions, and students and questions from the three types of data sources.
- Design a separated random walk sampling for the heterogeneous network.
- Implement a similarity-based performance prediction to estimate students' academic performance using student similarity and question.
- Experiments on the real-world datasets demonstrated the effectiveness of our proposed method.

**Q & A**

**Thanks!**