

HOW EFFECTIVE CAN SIMPLE ORDINAL PEER GRADING BE?

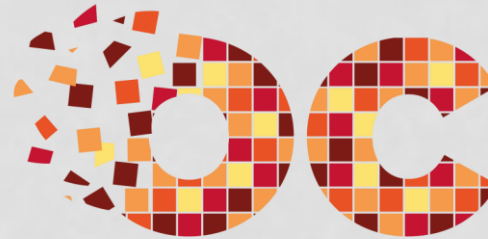
IOANNIS CARAGIANNIS, GEORGE A. KRIMPAS,
ALEXANDROS A. VOUDOURIS, University of Patras

Jakub Golinowski

MSc student in Computer Science at ETH Zürich

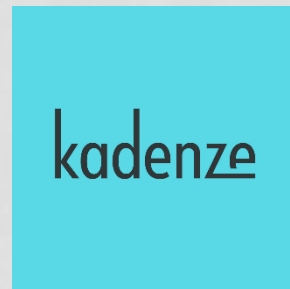
Work under supervision of Darya Melnyk

MASSIVE OPEN ONLINE COURSES



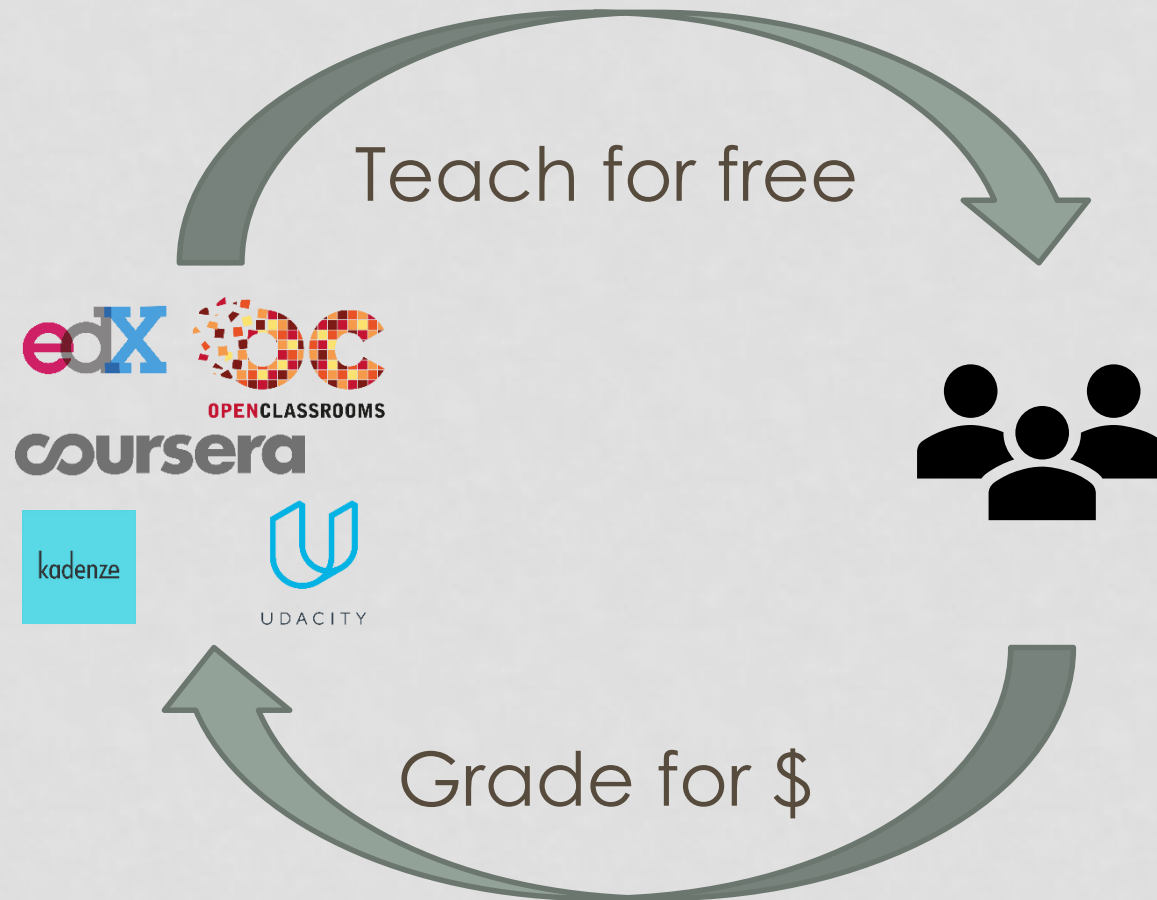
OPENCLASSROOMS

coursera



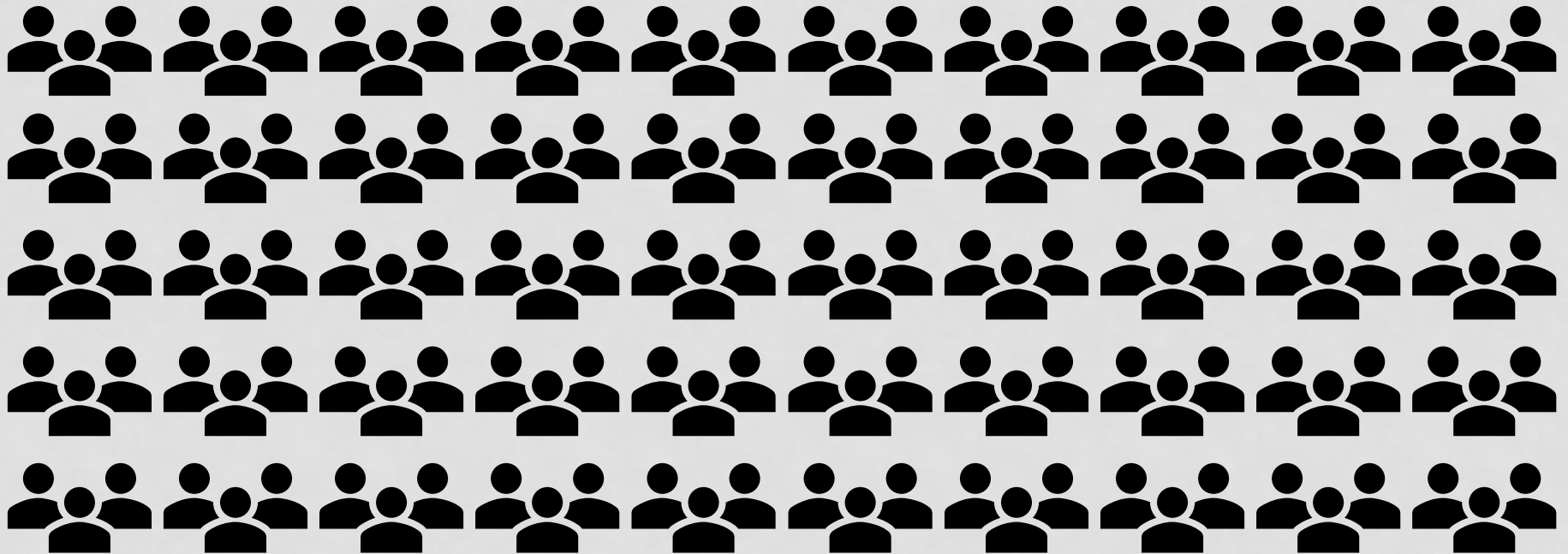
UDACITY

BUSINESS MODEL

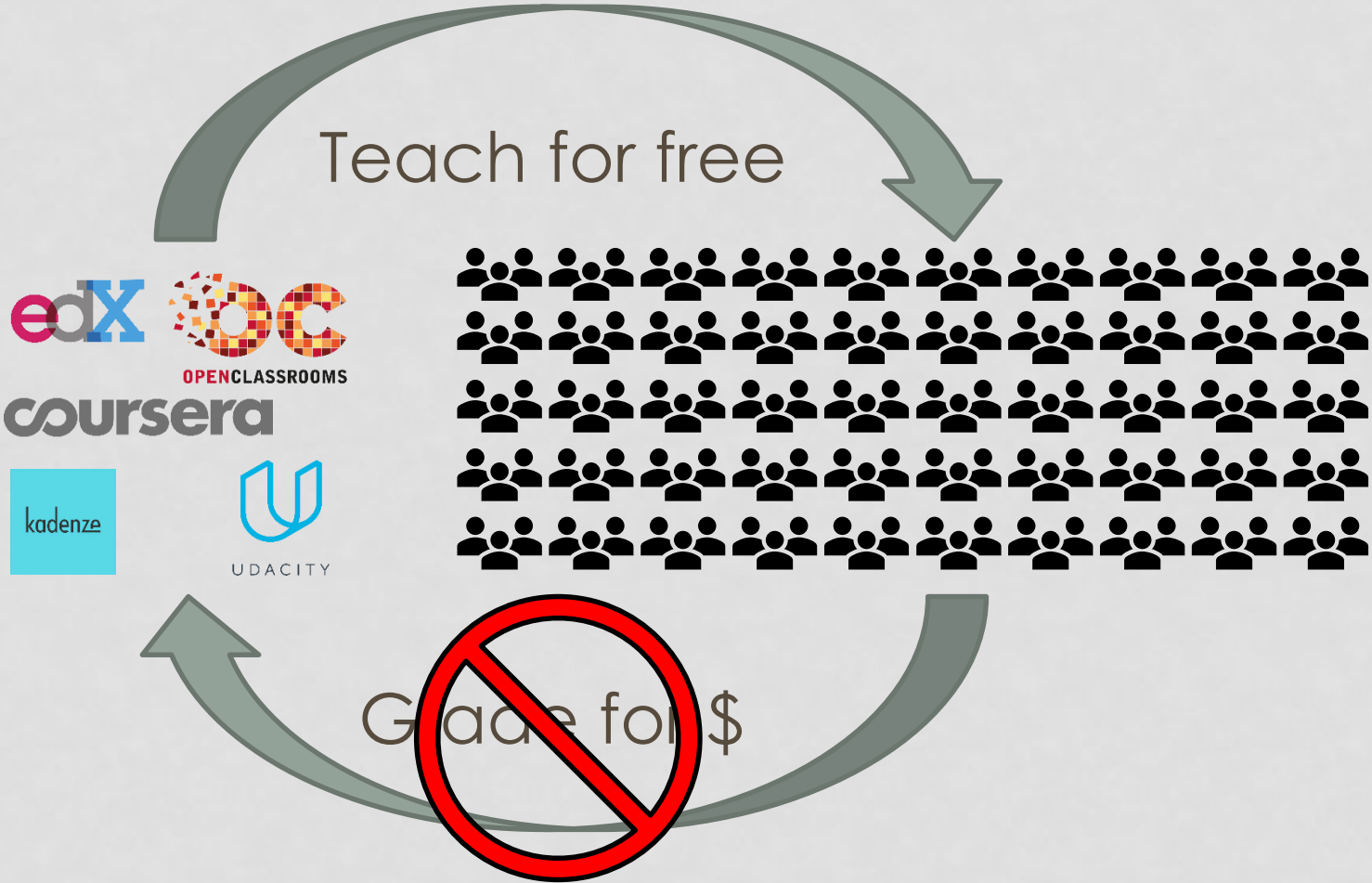


PROBLEM

Up to 50 000 students per course



BUSINESS MODEL VS PROBLEM



IDEA - PEER GRADING

Outsource grading to students



HOW TO GRADE

- Cardinal grading (absolute grading)

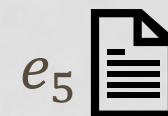
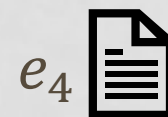
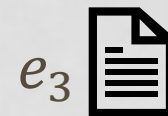
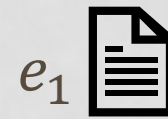
	Topic	Max. Points	Points	Signature
1	ML & Bayesian inference	20		
2	Kernels	20		
3	Neural Networks	20		
4	Gaussian processes	20		
5	Unsupervised learning	20		
Total		100		

Grade:

Source: Machine Learning Exam 2015 (ETHZ)

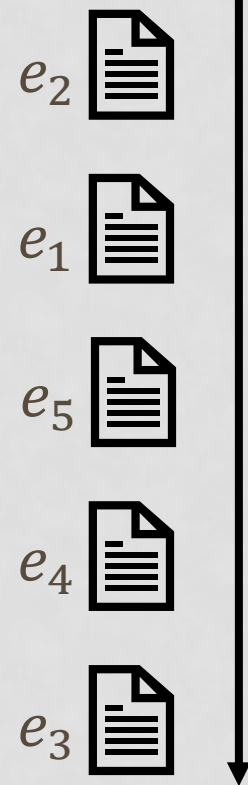
HOW TO GRADE

- Ordinal grading (sorting)



HOW TO GRADE


- Ordinal grading (sorting)




HOW TO GRADE

- Cardinal grading (absolute grading)
 - *Assign low grades → improve own performance,*
 - *Lack of experience.*
- Ordinal grading (sorting)
 - *Free from incentive to under-grade,*
 - *Requires less grading experience.*

HOW TO GRADE

- 
- Cardinal grading (absolute grading)
 - *Assign low grades → improve own performance,*
 - *Lack of experience.*

- 
- Ordinal grading (sorting)
 - *Free from incentive to under-grade,*
 - *Requires less grading experience.*

SETTING

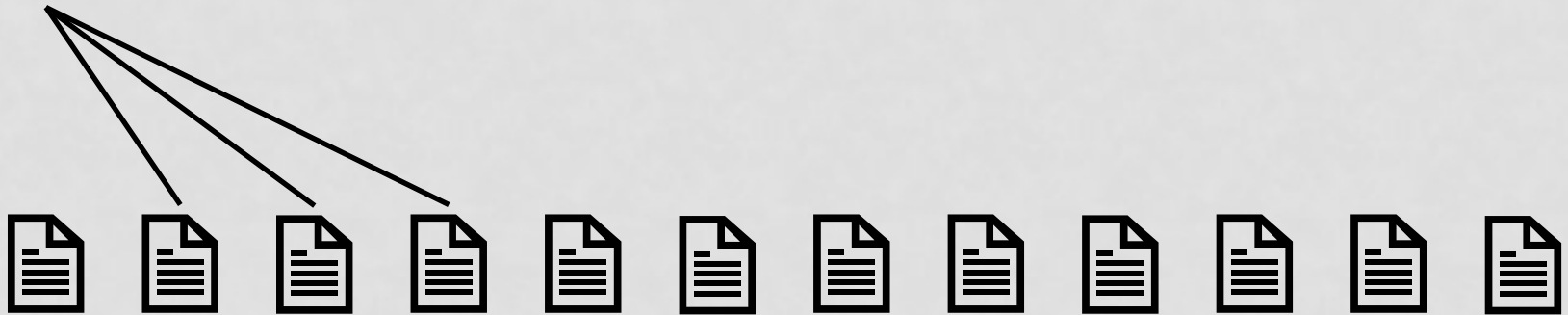
n students



n papers

BUNDLES OF k EXAMS

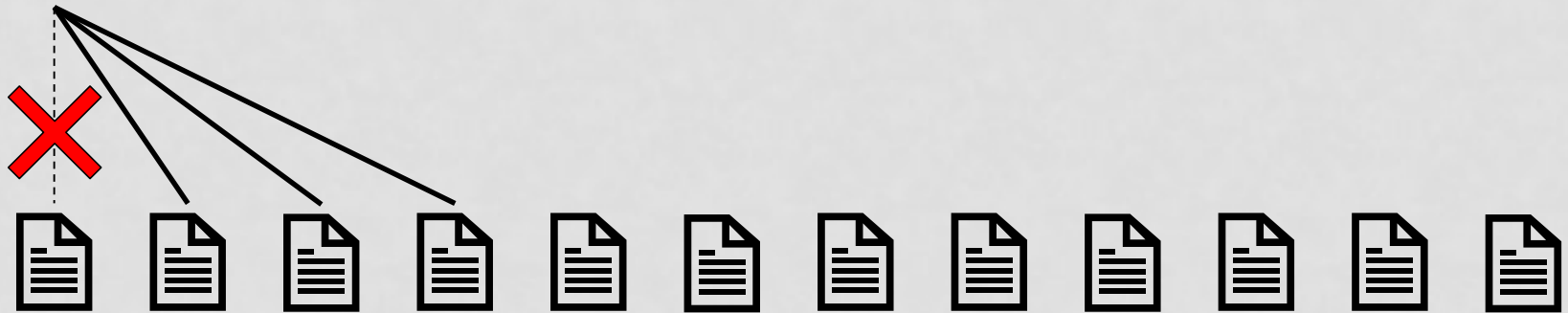
n students



n papers

BUNDLES OF k EXAMS

n students



n papers

Student cannot grade his own paper

SETTING

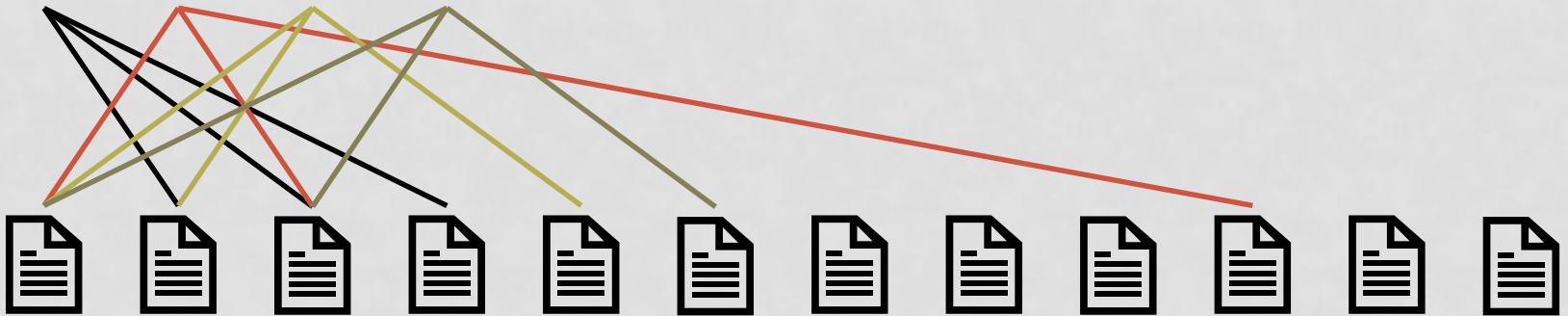
n students



n papers

SETTING

n students



n papers

SETTING

n students



n papers

SETTING

n students



n papers

SETTING

n students



n papers

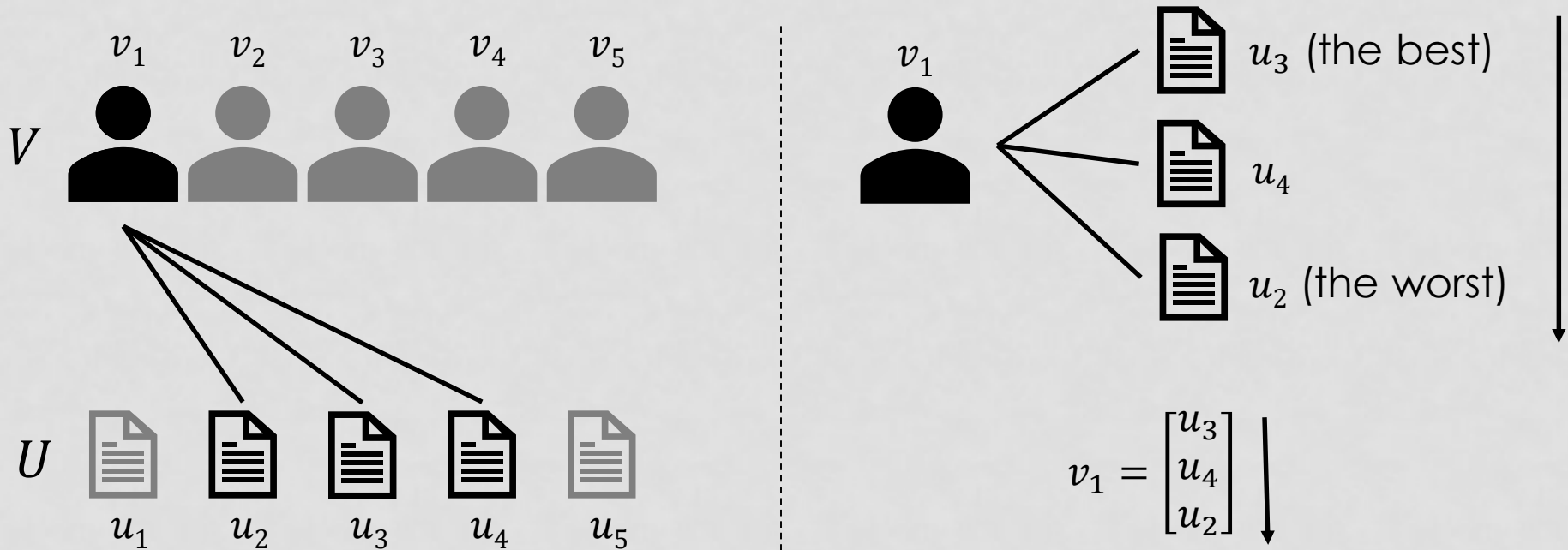
SETTING

n students



n papers






SINGLE GRADER



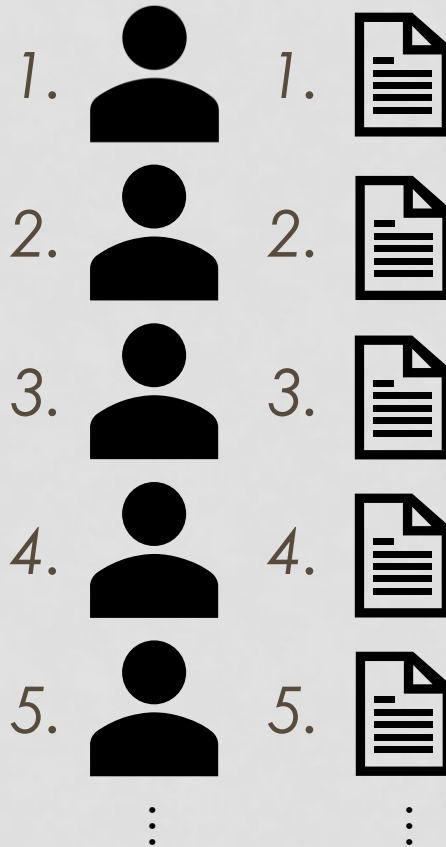
Is this ordering correct?

MODELLING STUDENTS' GRADING BEHAVIOUR

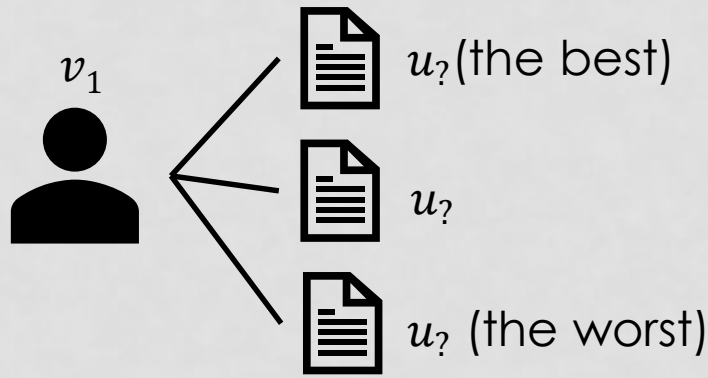
GROUND TRUTH

1. 
2. 
3. 
4. 
5. 
- ⋮

GROUND TRUTH



SINGLE STUDENT'S RANKING



$$v_1 = \begin{bmatrix} u_2 \\ u_3 \\ u_4 \end{bmatrix}$$

$$v_1 = \begin{bmatrix} u_3 \\ u_2 \\ u_4 \end{bmatrix}$$

$$v_1 = \begin{bmatrix} u_4 \\ u_3 \\ u_2 \end{bmatrix}$$

$$v_1 = \begin{bmatrix} u_2 \\ u_4 \\ u_3 \end{bmatrix}$$

$$v_1 = \begin{bmatrix} u_3 \\ u_4 \\ u_2 \end{bmatrix}$$

$$v_1 = \begin{bmatrix} u_4 \\ u_2 \\ u_3 \end{bmatrix}$$

Which ordering is correct?

AGGREGATE INFORMATION

$$P = \begin{bmatrix} p_{1,1} & \cdots & p_{1,k} \\ \vdots & \ddots & \vdots \\ p_{k,1} & \cdots & p_{k,k} \end{bmatrix}$$

EXAMPLE ($k = 3$)

Perfect Graders

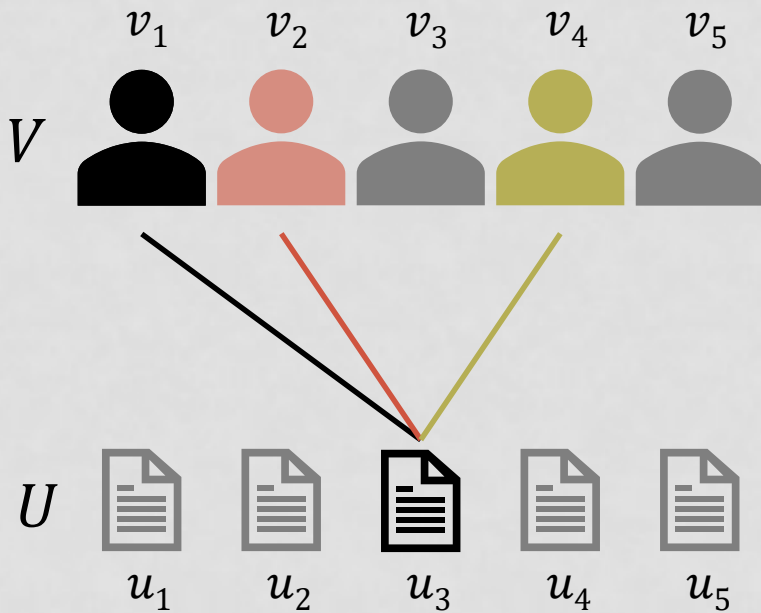
$$P = \begin{bmatrix} 1.0 & 0.0 & 0.0 \\ 0.0 & 1.0 & 0.0 \\ 0.0 & 0.0 & 1.0 \end{bmatrix}$$

EXAMPLE ($k = 3$)

Not Perfect Graders

$$P = \begin{bmatrix} 0.5 & 0.3 & 0.2 \\ 0.3 & 0.4 & 0.3 \\ 0.2 & 0.3 & 0.5 \end{bmatrix}$$

SINGLE EXAM



$$v_1 = \begin{bmatrix} u_3 \\ u_4 \\ u_2 \end{bmatrix} \quad v_2 = \begin{bmatrix} u_3 \\ u_5 \\ u_1 \end{bmatrix} \quad v_4 = \begin{bmatrix} u_7 \\ u_3 \\ u_1 \end{bmatrix}$$

Type – grading result
of exam paper

$$\sigma_{u_3} = (1, 1, 2)$$

AGGREGATION RULE - BORDA

Extract types



u_1



u_2



u_3



u_4



u_5

$$\sigma_{u_1} = (1,1,1)$$

$$\sigma_{u_2} = (1,2,3)$$

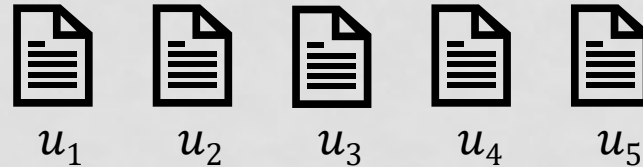
$$\sigma_{u_3} = (1,1,2)$$

$$\sigma_{u_4} = (2,2,3)$$

$$\sigma_{u_5} = (1,1,2)$$

AGGREGATION RULE - BORDA

Compute Borda Score



$$\sigma_{u_1} = (1, 1, 1) \rightarrow B(\sigma_{u_1}) = 3 + 3 + 3 = 9$$

$$\sigma_{u_2} = (1, 2, 3) \rightarrow B(\sigma_{u_1}) = 3 + 2 + 1 = 6$$

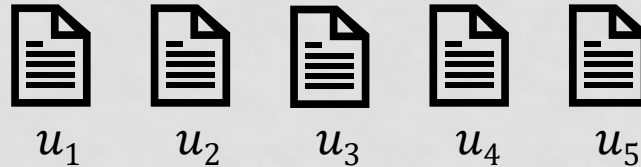
$$\sigma_{u_3} = (1, 1, 2) \rightarrow B(\sigma_{u_1}) = 3 + 3 + 2 = 8$$

$$\sigma_{u_4} = (2, 2, 3) \rightarrow B(\sigma_{u_1}) = 2 + 2 + 1 = 5$$

$$\sigma_{u_5} = (1, 1, 2) \rightarrow B(\sigma_{u_1}) = 3 + 3 + 2 = 8$$

AGGREGATION RULE - BORDA

Compute Borda Score



$$\sigma_{u_1} = (1,1,1) \rightarrow B(\sigma_{u_1}) = 9$$

$$\sigma_{u_2} = (1,2,3) \rightarrow B(\sigma_{u_1}) = 6$$

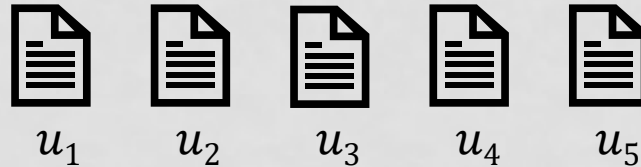
$$\sigma_{u_3} = (1,1,2) \rightarrow B(\sigma_{u_1}) = 8$$

$$\sigma_{u_4} = (2,2,3) \rightarrow B(\sigma_{u_1}) = 5$$

$$\sigma_{u_5} = (1,1,2) \rightarrow B(\sigma_{u_1}) = 8$$

AGGREGATION RULE - BORDA

Order by Borda Score



$$\sigma_{u_1} = (1,1,1) \rightarrow B(\sigma_{u_1}) = 9$$

$$\sigma_{u_3} = (1,1,2) \rightarrow B(\sigma_{u_1}) = 8$$

$$\sigma_{u_5} = (1,1,2) \rightarrow B(\sigma_{u_1}) = 8$$

$$\sigma_{u_2} = (1,2,3) \rightarrow B(\sigma_{u_1}) = 6$$

$$\sigma_{u_4} = (2,2,3) \rightarrow B(\sigma_{u_1}) = 5$$



TYPE-ORDERING AGGREGATION RULE

	Borda	Type-ordering aggregation rule
Ordering rule	Borda score	Optimal
Number of possible levels	$\mathcal{O}(k^2)$	$\mathcal{O}(a^k)$

THEORETICAL ANALYSIS

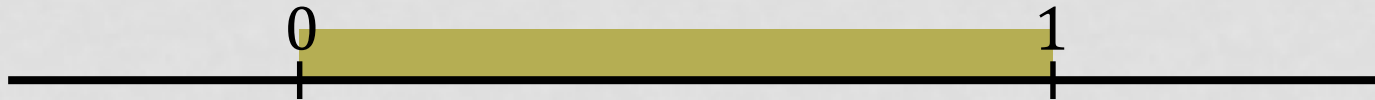
ASSUMPTIONS

∞ many students



ASSUMPTIONS

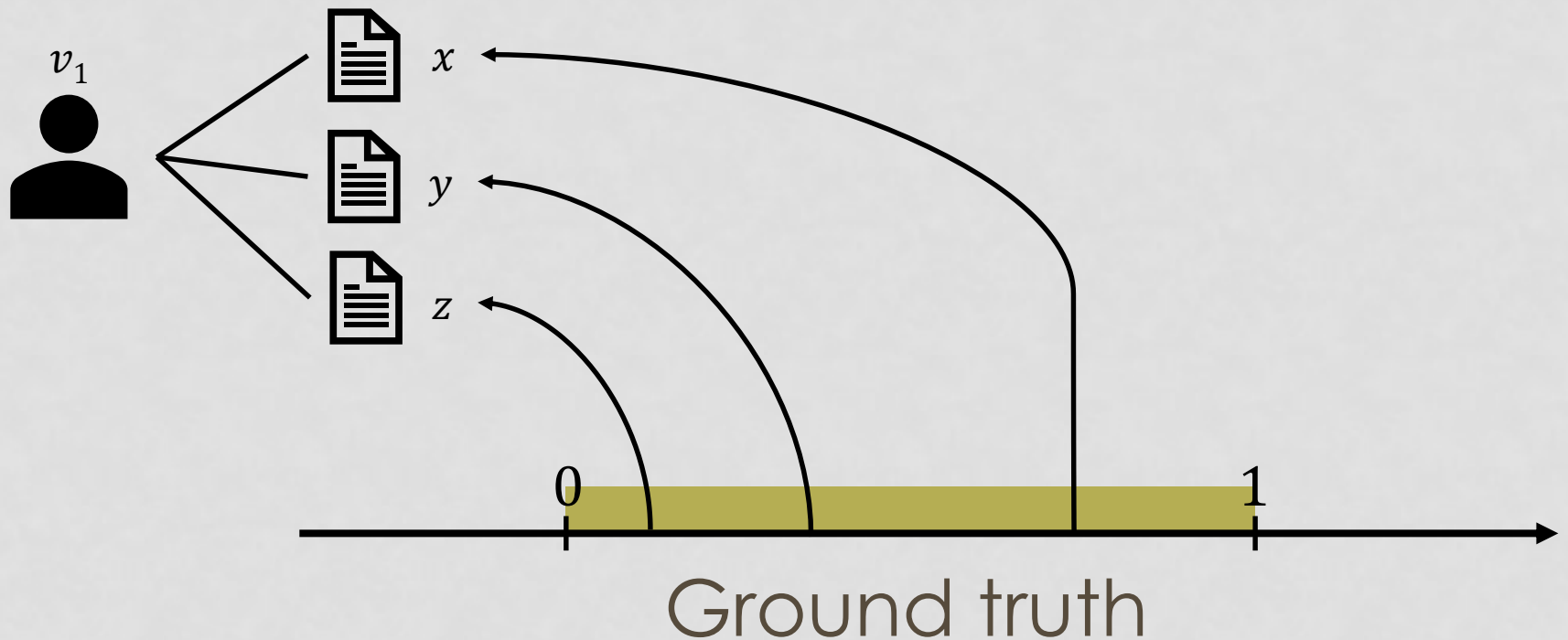
Ground truth



Lower number means better student

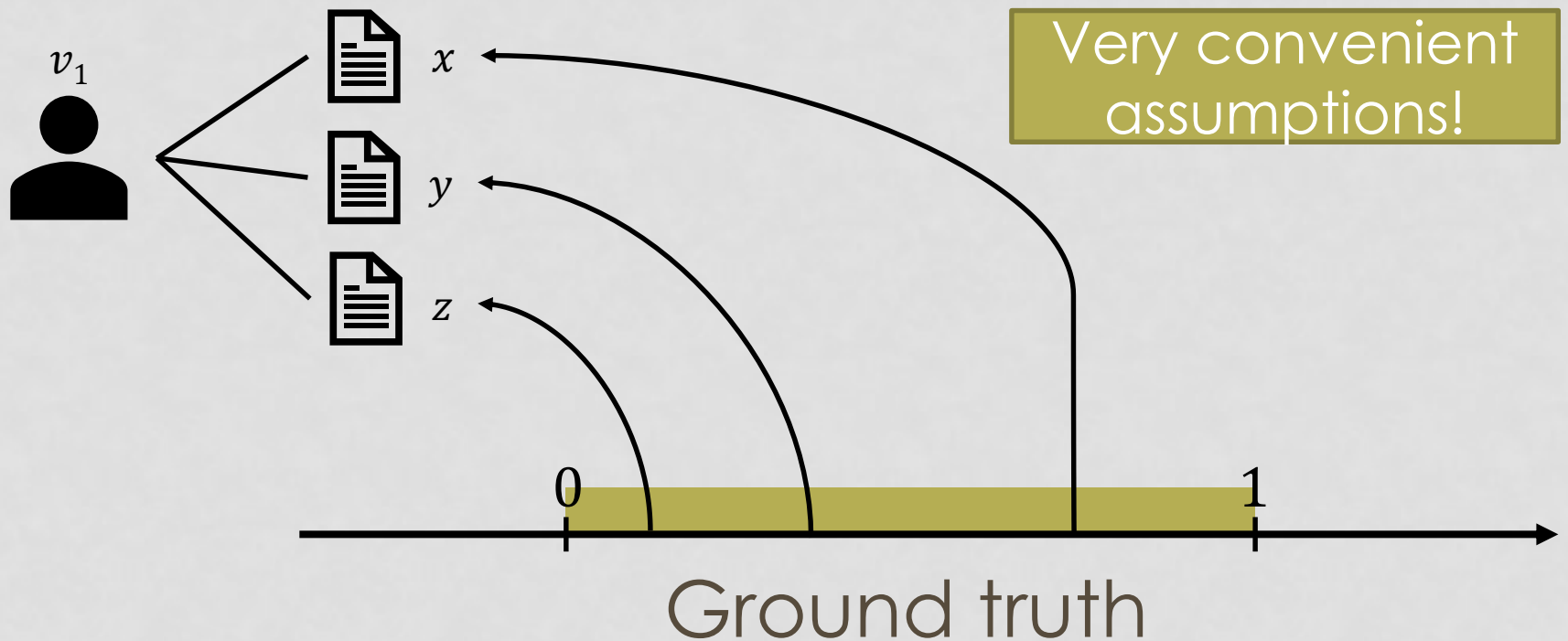
ASSUMPTIONS

Exams in a bundle \sim i. i. d.

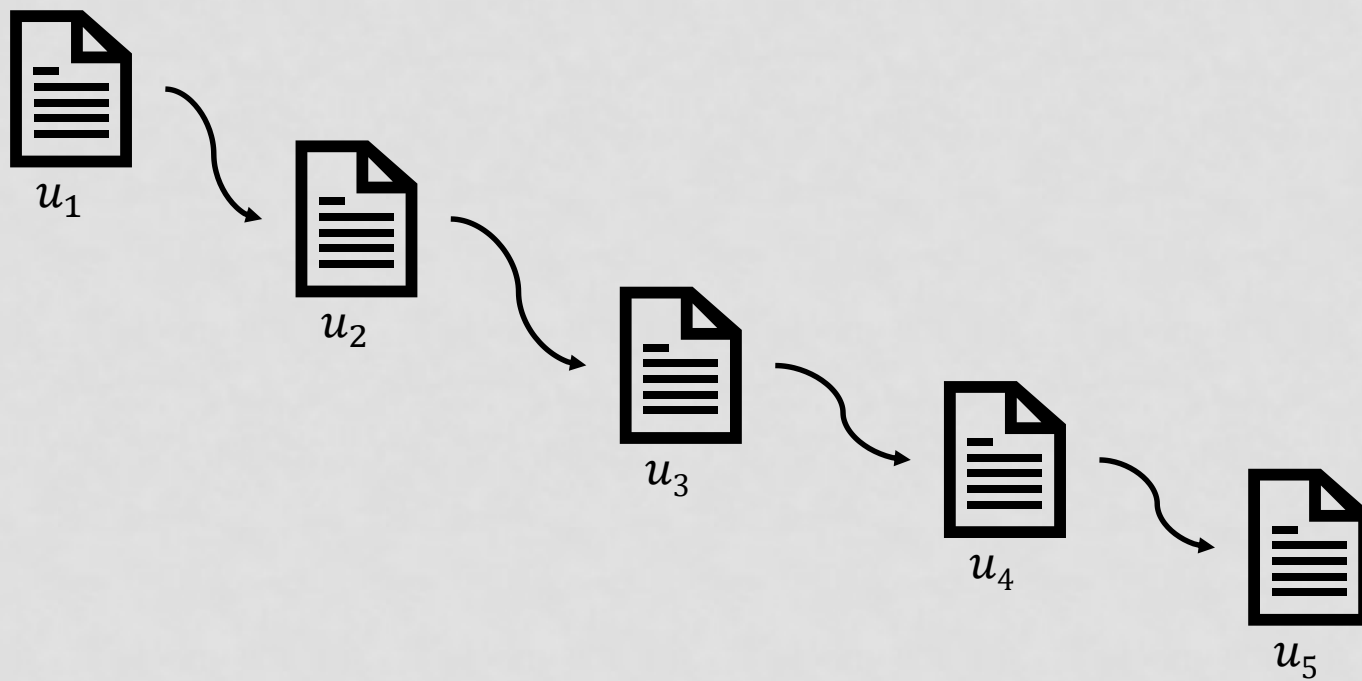


ASSUMPTIONS

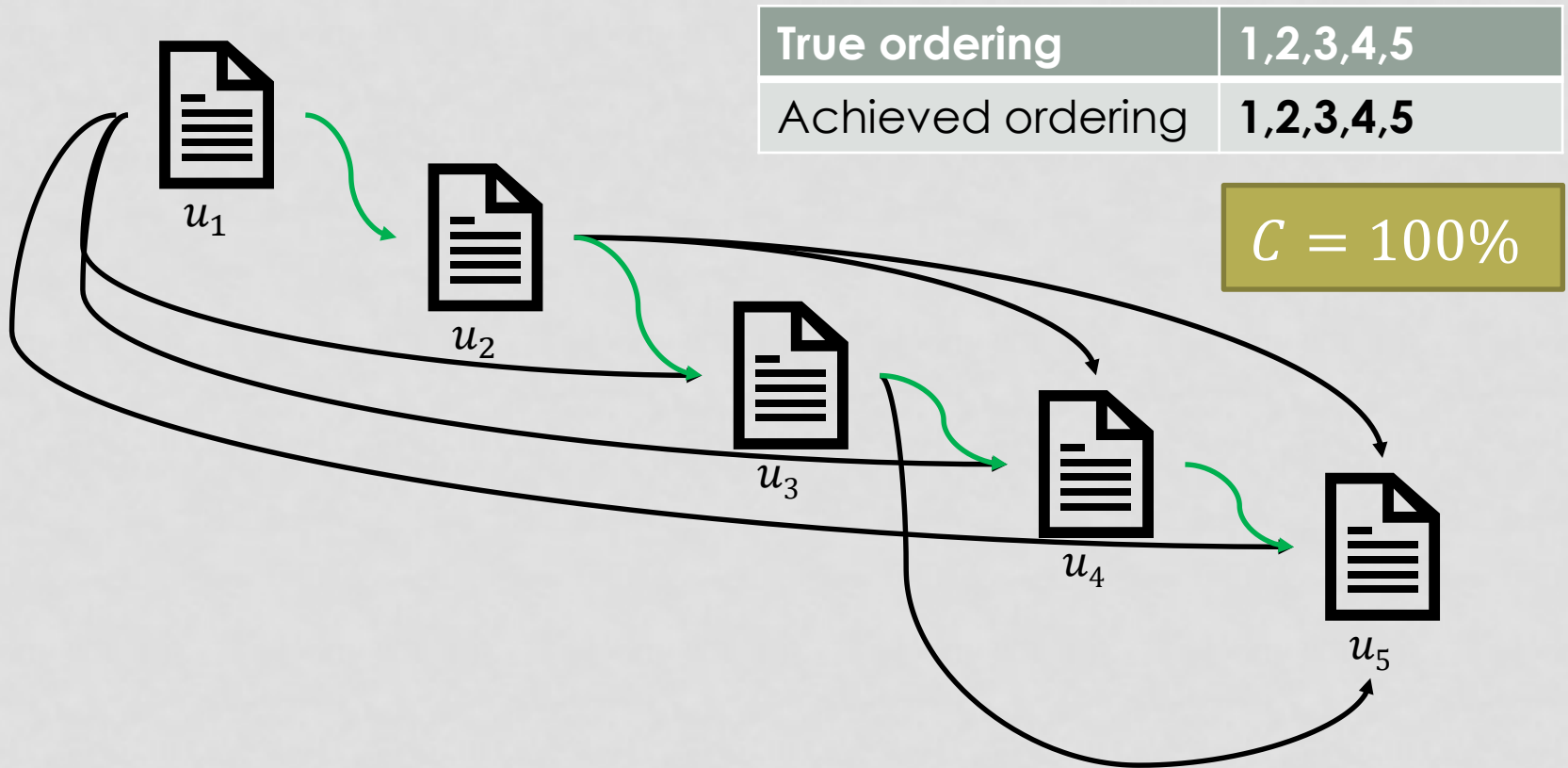
Exams in a bundle \sim i. i. d.



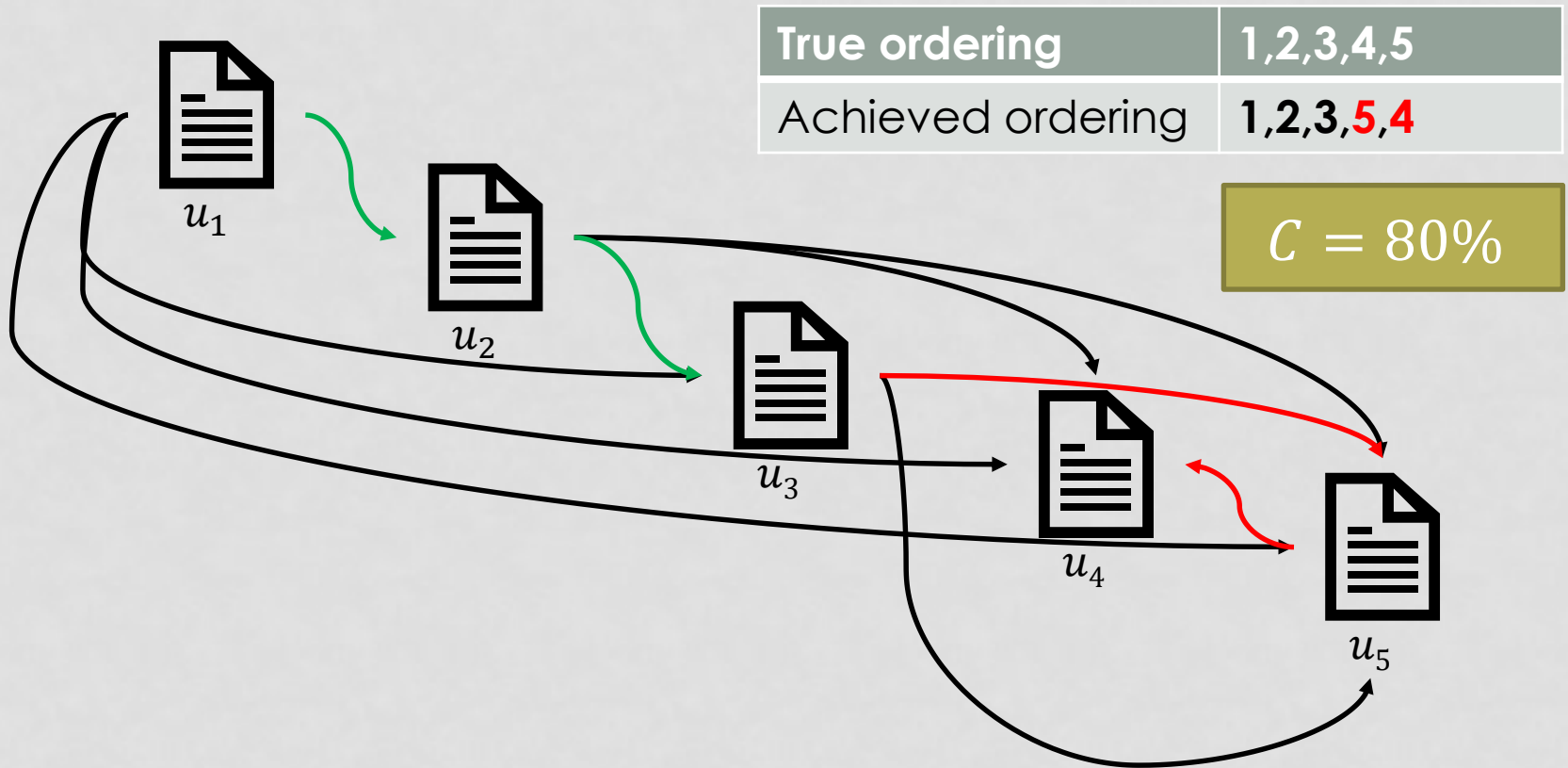
EFFICIENCY



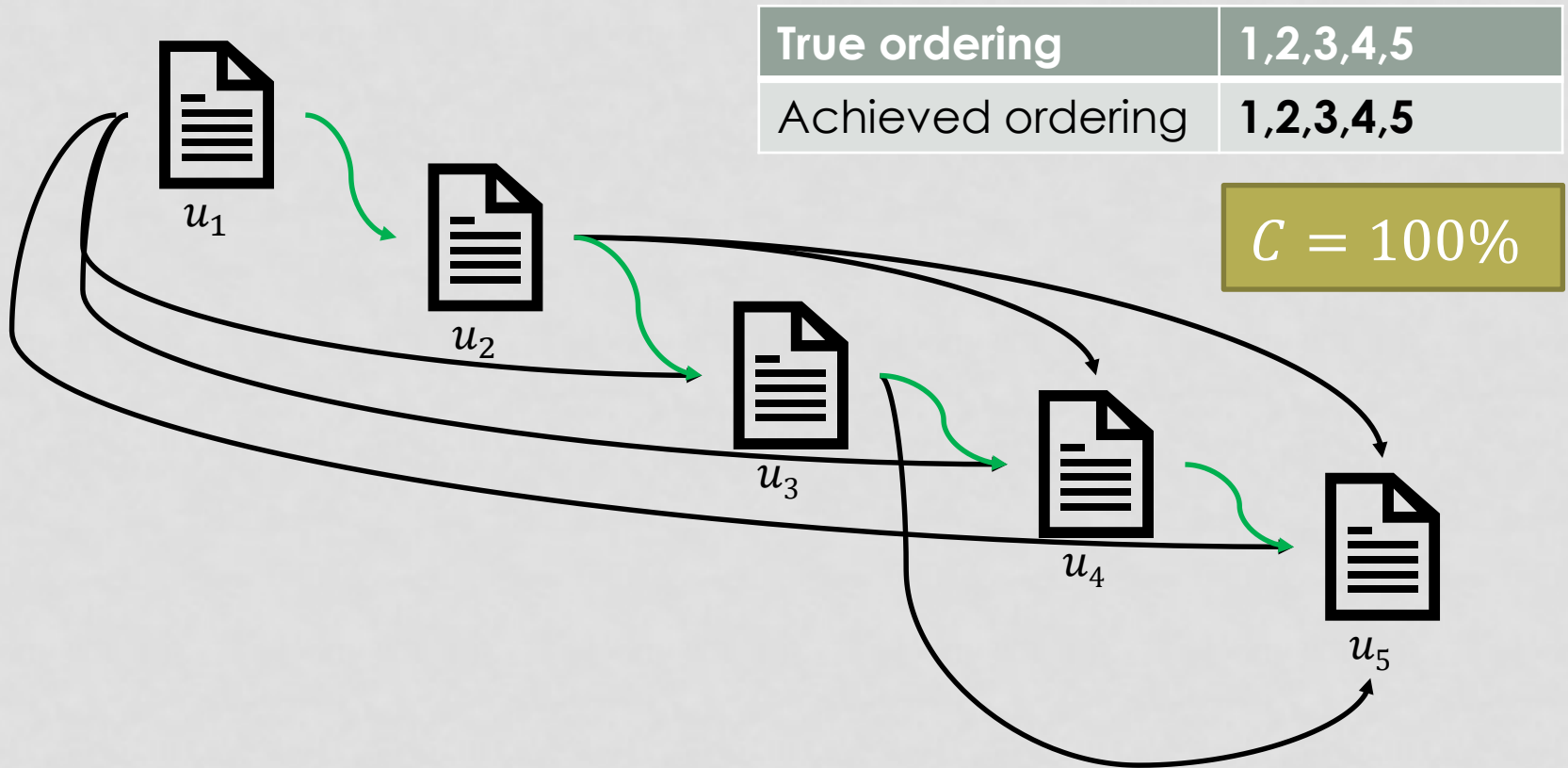
EFFICIENCY



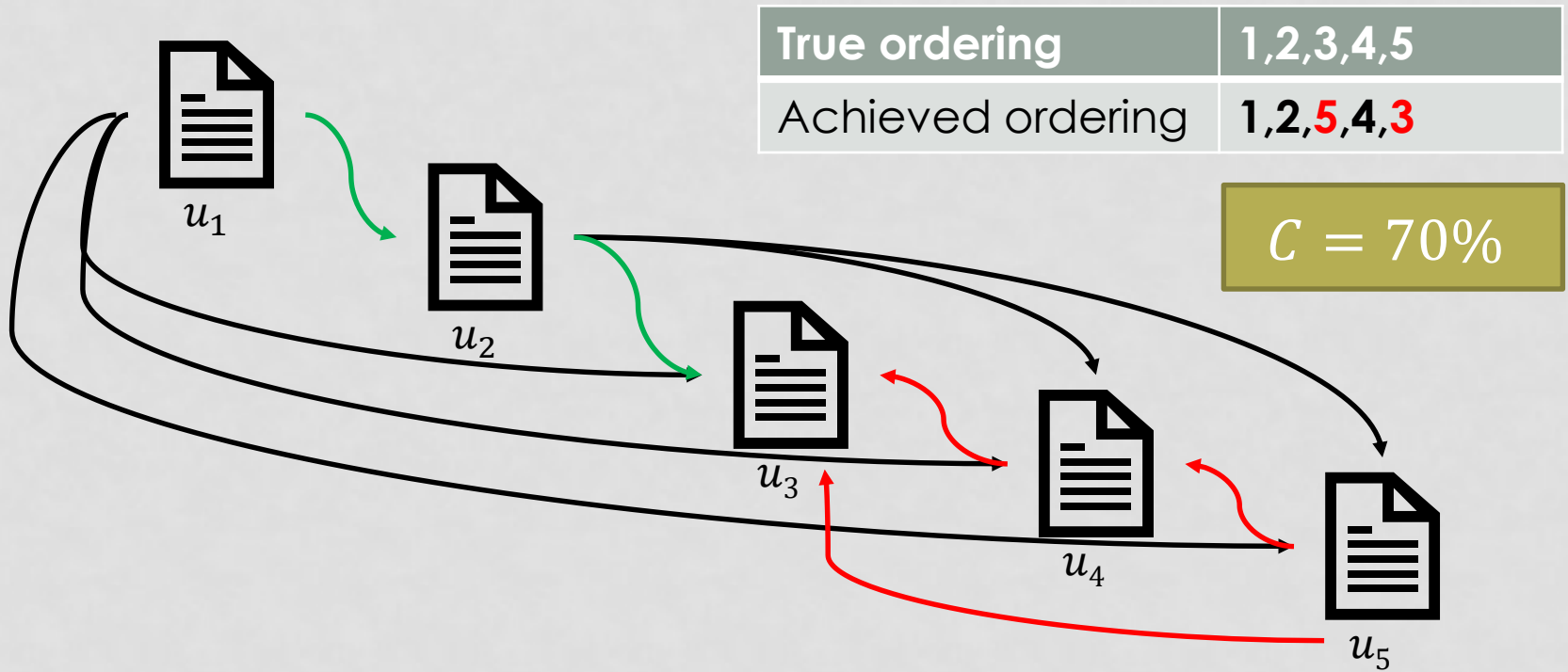
EFFICIENCY



EFFICIENCY



EFFICIENCY



EXPECTED EFFICIENCY

$$\hat{C} = \int_0^1 \int_x^1 \left(\sum_{\sigma, \sigma': \sigma > \sigma'} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] + \frac{1}{2} \sum_{\sigma} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma] \right) dy dx$$

EXPECTED FRACTION OF CORRECTLY RECOVERED PAIRWISE RELATIONS

$$\hat{C} = \int_0^1 \int_x^1 \left(\sum_{\sigma, \sigma': \sigma > \sigma'} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] + \frac{1}{2} \sum_{\sigma} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma] \right) dy dx$$

Wanted: x has better type as y

EXPECTED FRACTION OF CORRECTLY RECOVERED PAIRWISE RELATIONS

$$\hat{C} = \int_0^1 \int_x^1 \left(\sum_{\sigma, \sigma': \sigma > \sigma'} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] + \frac{1}{2} \sum_{\sigma} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma] \right) dy dx$$

Less wanted: x has the same type as y

EXPECTED FRACTION OF CORRECTLY RECOVERED PAIRWISE RELATIONS

$$\hat{C} = \int_0^1 \int_x^1 \left(\sum_{\sigma, \sigma': \sigma > \sigma'} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] + \frac{1}{2} \sum_{\sigma} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma] \right) dy dx$$

$\sigma > \sigma' \Rightarrow \sigma$ is a better type

EXPECTED FRACTION OF CORRECTLY RECOVERED PAIRWISE RELATIONS

$$\hat{C} = \int_0^1 \int_x^1 \left(\sum_{\sigma, \sigma': \sigma > \sigma'} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] + \frac{1}{2} \sum_{\sigma} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma] \right) dy dx$$

For all exam papers $1 > y > x$

EXPECTED FRACTION OF CORRECTLY RECOVERED PAIRWISE RELATIONS

$$\hat{C} = \int_0^1 \int_x^1 \left(\sum_{\sigma, \sigma': \sigma > \sigma'} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] + \frac{1}{2} \sum_{\sigma} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma] \right) dy dx$$

For all exam papers $1 > x > 0$

WEIGHTS

$$\hat{C} = \int_0^1 \int_x^1 \left(\sum_{\sigma, \sigma': \sigma > \sigma'} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] + \frac{1}{2} \sum_{\sigma} \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma] \right) dy dx$$

$$\hat{C} = \sum_{\sigma, \sigma': \sigma > \sigma'} \int_0^1 \int_x^1 \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] dy dx + \frac{1}{2} \sum_{\sigma} \int_0^1 \int_x^1 \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma] dy dx$$

WEIGHTS

$$\hat{C} = \sum_{\sigma, \sigma': \sigma > \sigma'} \int_0^1 \int_x^1 \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] dy dx + \frac{1}{2} \sum_{\sigma} \int_0^1 \int_x^1 \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma] dy dx$$

$$C = \sum_{\sigma, \sigma': \sigma > \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

weight: $W(\sigma, \sigma') = \int_0^1 \int_x^1 \mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] dy dx$

Calculus

Probability
Theory

Linear
Algebra

RESULTS

$$\hat{C} = \sum_{\sigma, \sigma': \sigma > \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

$$W(\sigma, \sigma') = \int_0^1 \int_x^1 \mathbb{P}[x \triangleright \sigma] \cdot \mathbb{P}[y \triangleright \sigma'] dy dx$$

Probabilities are **polynomials** → integrals can be **analytically** solved!

RESULTS

$$\hat{C} = \sum_{\sigma, \sigma': \sigma > \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

$$W(\sigma, \sigma') = \int_0^1 \int_x^1 \mathbb{P}[x \triangleright \sigma] \cdot \mathbb{P}[y \triangleright \sigma'] dy dx$$

Weights are easy to compute (closed form solution)

CONCLUSION

$$\hat{C}(k, \succ, P) = \sum_{\sigma, \sigma' : \sigma > \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

OPTIMIZATION

$$\hat{C}(k, \succ, P) = \sum_{\sigma, \sigma': \sigma \succ \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

$$\max_{\succ} \sum_{\sigma, \sigma': \sigma \succ \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

Weights are independent of $\succ \rightarrow$ computed only once

ADDING ELASTICITY

$$W(\sigma, \sigma') = \int_0^1 \int_x^1 f(x, y) \mathbb{P}[x \triangleright \sigma] \cdot \mathbb{P}[y \triangleright \sigma'] dy dx$$

$$f(x, y) = \begin{cases} 1 & \text{if } y - x \geq 5\% \\ 0 & \text{otherwise} \end{cases}$$

ADDING ELASTICITY

$$W(\sigma, \sigma') = \int_0^1 \int_x^1 f(x, y) \mathbb{P}[x \triangleright \sigma] \cdot \mathbb{P}[y \triangleright \sigma'] dy dx$$

$$f(x, y) = \begin{cases} 1 & \text{if } x \leq 20\% \\ 0 & \text{otherwise} \end{cases}$$

OPTIMIZATION

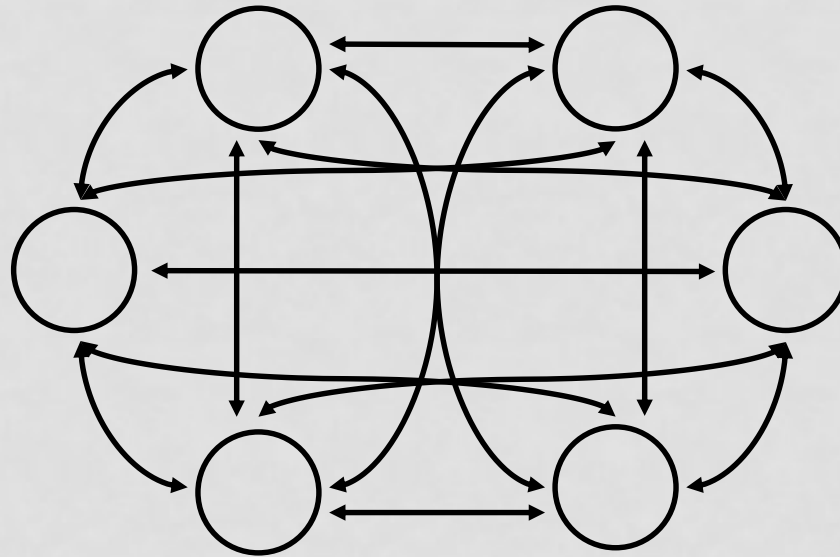
$$\hat{C}(k, \succ, P, \mathbf{f}) = \sum_{\sigma, \sigma': \sigma \succ \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

$$\max_{\succ} \sum_{\sigma, \sigma': \sigma \succ \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

Weights are **still** independent of $\succ \rightarrow$ computed only once

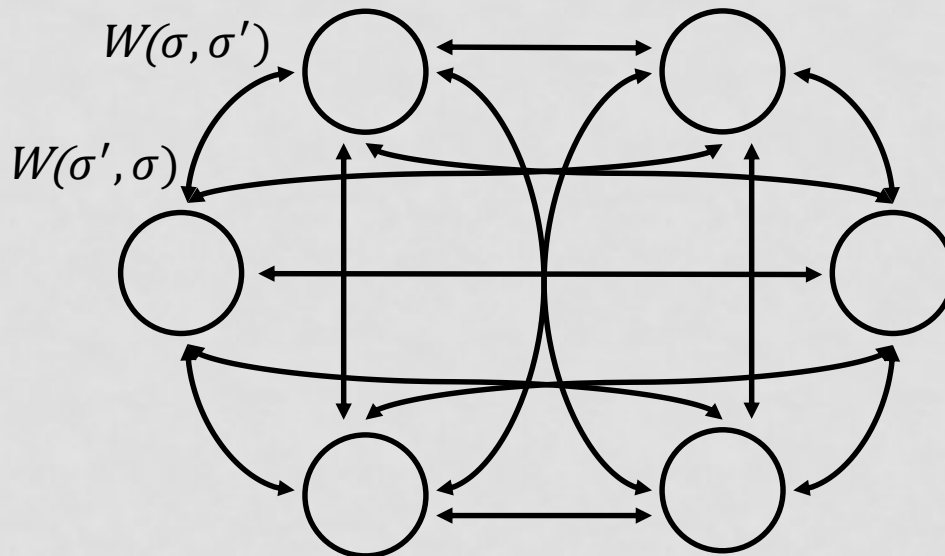
REFORMULATE PROBLEM

$$\max_{\gamma} \sum_{\sigma, \sigma' : \sigma > \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$



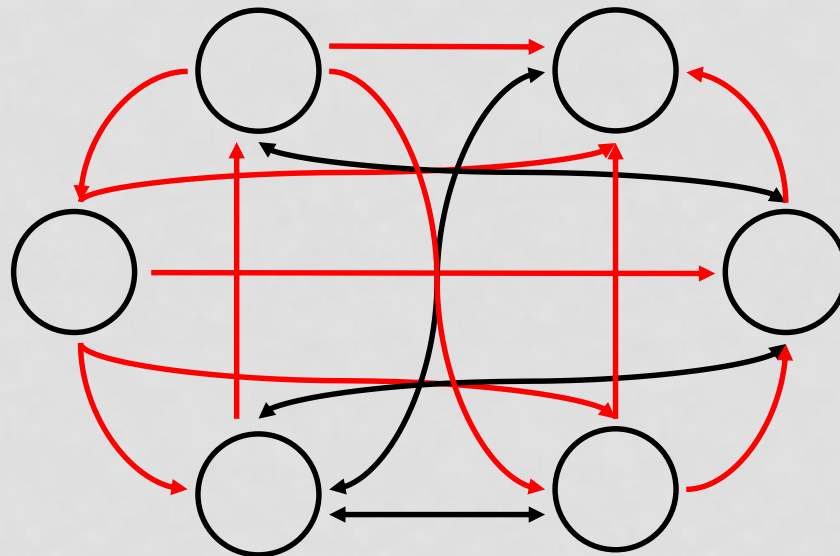
REFORMULATE PROBLEM

$$\max_{\gamma} \sum_{\sigma, \sigma' : \sigma > \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$



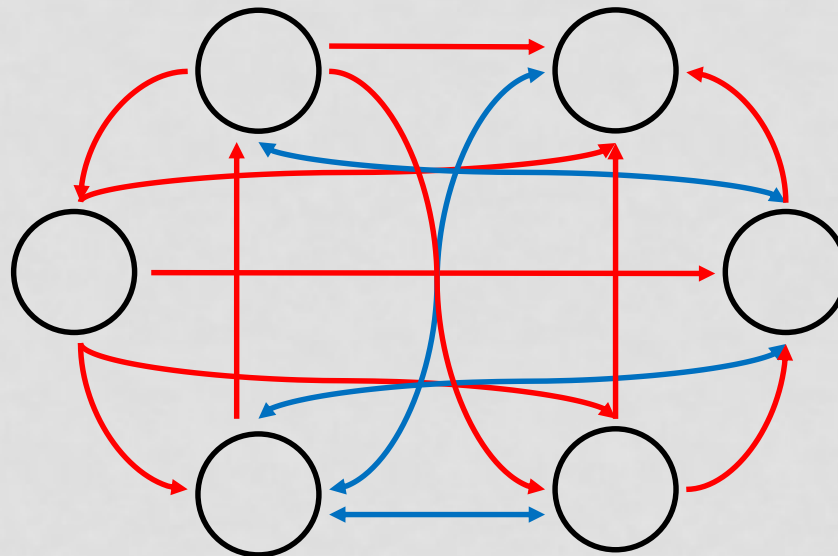
AUXILIARY GRAPH

Different weights \Rightarrow Keep edge with bigger weight



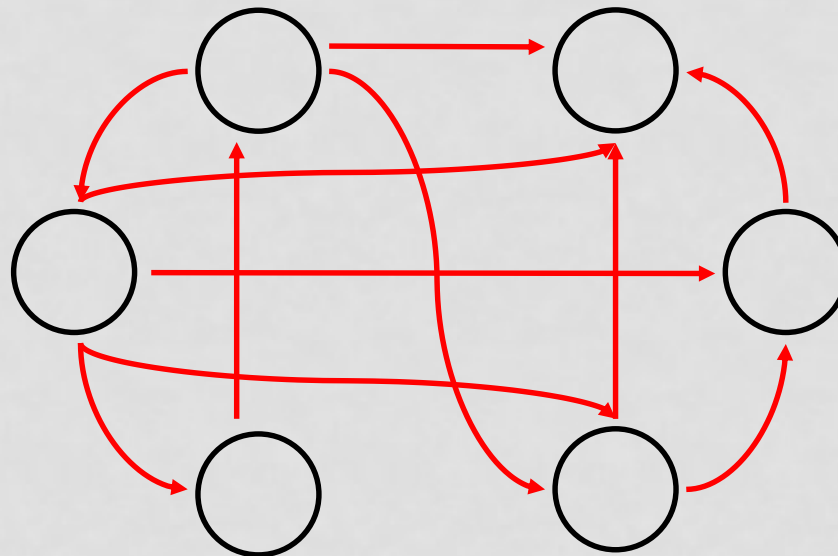
AUXILIARY GRAPH

Equal weights \Rightarrow discard



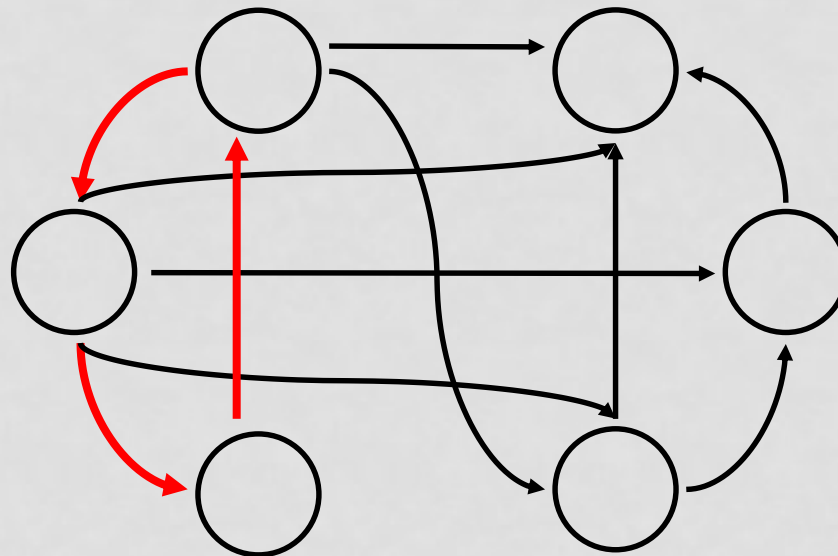
AUXILIARY GRAPH

Equal weights \Rightarrow discard



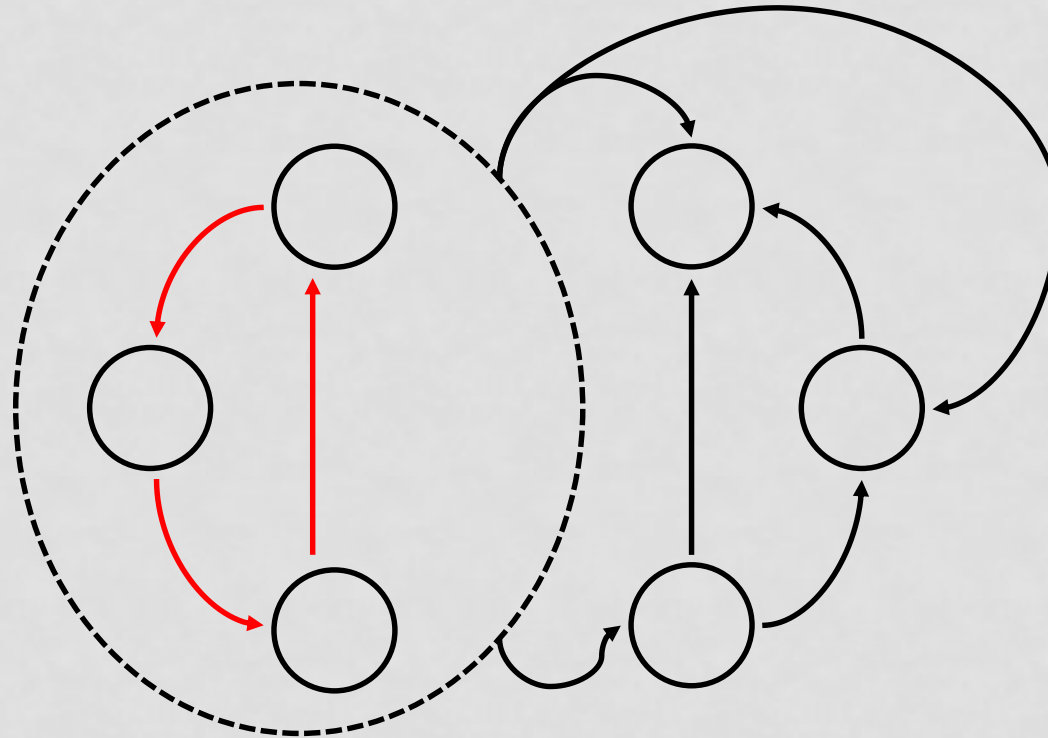
AUXILIARY GRAPH

Strongly connected regions (cycles)



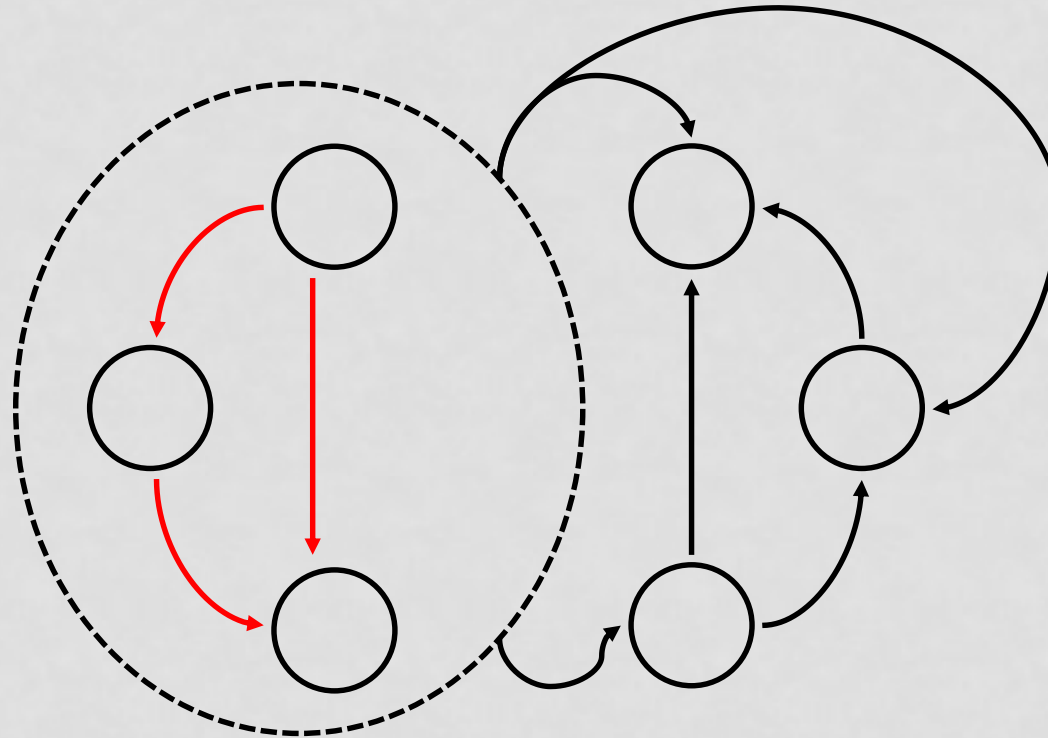
AUXILIARY GRAPH

Strongly connected regions (cycles)



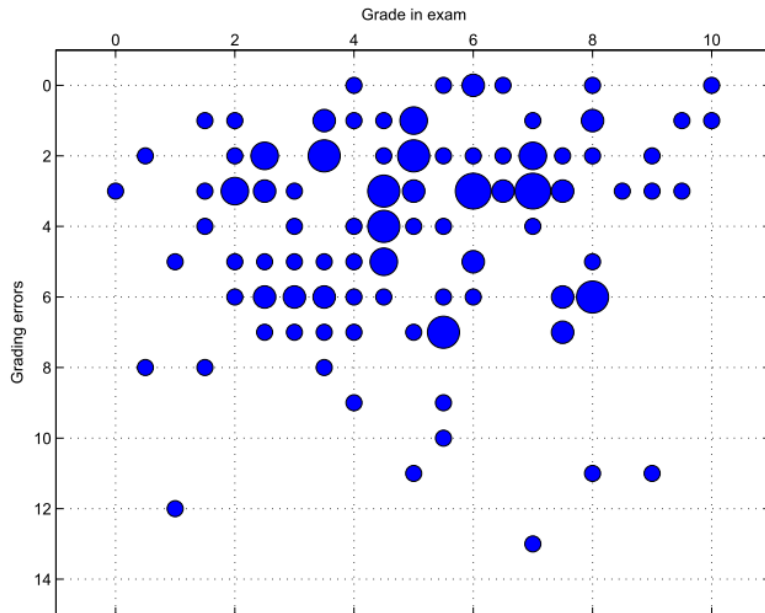
AUXILIARY GRAPH

Brute force (or Borda in case of large cycle)

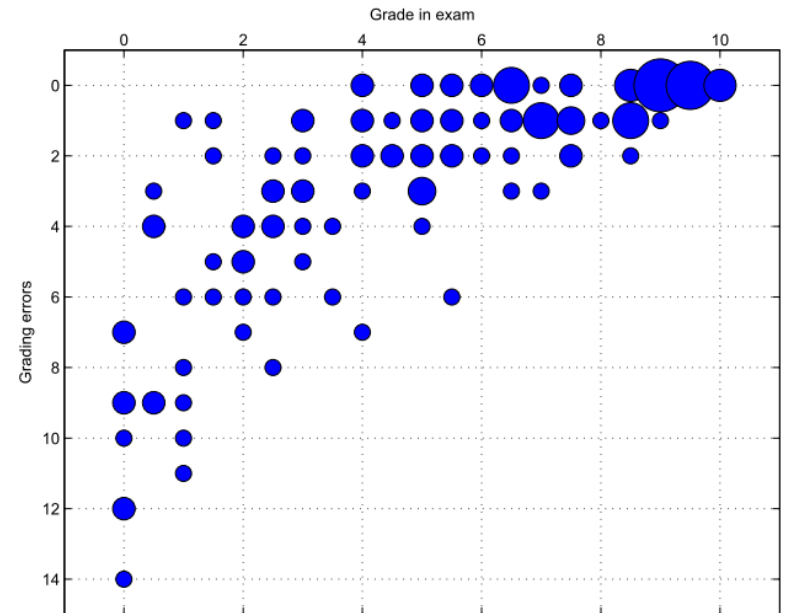


FIELD EXPERIMENT

$$k = 6, n = 136$$



(a) Realistic noise



(b) Mallows noise

FIELD EXPERIMENT

$$P_{\text{real}} = \begin{bmatrix} 0.463 & 0.257 & 0.102 & 0.058 & 0.058 & 0.058 \\ 0.205 & 0.316 & 0.227 & 0.110 & 0.066 & 0.073 \\ 0.161 & 0.191 & 0.257 & 0.205 & 0.132 & 0.051 \\ 0.102 & 0.117 & 0.191 & 0.242 & 0.279 & 0.066 \\ 0.044 & 0.066 & 0.139 & 0.220 & 0.301 & 0.227 \\ 0.022 & 0.051 & 0.080 & 0.161 & 0.161 & 0.522 \end{bmatrix}$$

$$P_{\text{mallows}} = \begin{bmatrix} 0.6337 & 0.1753 & 0.0824 & 0.0494 & 0.0339 & 0.0253 \\ 0.1753 & 0.5112 & 0.1549 & 0.0768 & 0.0479 & 0.0339 \\ 0.0824 & 0.1549 & 0.4865 & 0.1500 & 0.0768 & 0.0494 \\ 0.0494 & 0.0768 & 0.1500 & 0.4865 & 0.1549 & 0.0824 \\ 0.0339 & 0.0479 & 0.0768 & 0.1549 & 0.5112 & 0.1753 \\ 0.0253 & 0.0339 & 0.0494 & 0.0824 & 0.1753 & 0.6337 \end{bmatrix}$$

SIMULATIONS

All2all:
 $f(x, y) = 1$

SIMULATIONS

Th-10% and Th-50%:

$$f(x, y) = \begin{cases} 1 & \text{if } x \leq th\% \\ 0 & \text{otherwise} \end{cases}$$

SIMULATIONS

Acc-2% and Acc-5%:

$$f(x, y) = \begin{cases} 1 & \text{if } y - x \geq acc\% \\ 0 & \text{otherwise} \end{cases}$$

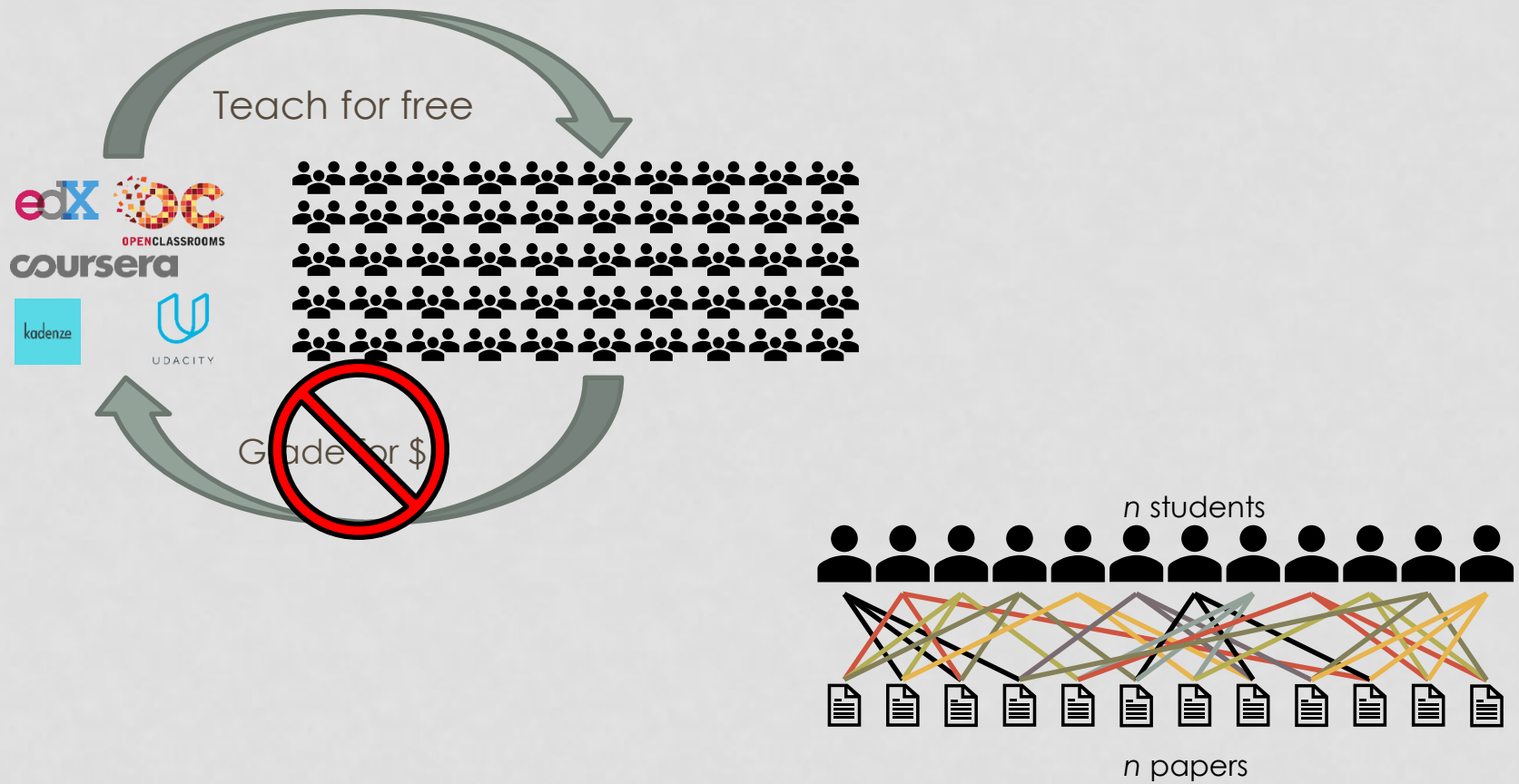
SMALL STRONGLY CONNECTED COMPONENTS

size	realistic model				mallows model			
	all2all	th-50%	acc-2%	acc-5%	all2all	th-50%	acc-2%	acc-5%
1	448	460	449	451	453	459	449	449
3-7	13	2	12	10	6	3	10	12
8-11	1	0	1	1	2	0	2	0
≥ 12	0	0	0	0	1	0	1	1
max	10	3	10	10	20	4	20	20

PERFORMANCE

noise	perfect grading		realistic grading				mallows grading			
setting	theory	$n = 10^4$	theory		$n = 10^4$		theory		$n = 10^4$	
method	borda	borda	opt	borda	opt	borda	opt	borda	opt	borda
all2all	92.01	92.02	80.01	79.57	80.09	79.57	85.15	84.38	85.16	84.39
th-10%	96.94	96.95	87.61	87.18	87.60	87.17	92.05	90.52	92.07	90.54
th-50%	94.13	94.14	83.62	83.43	83.62	83.43	88.39	87.80	88.40	87.81
acc-2%	93.57	93.57	81.27	80.73	81.27	80.74	86.52	85.72	86.52	85.73
acc-5%	95.47	95.47	82.97	82.42	82.97	82.42	88.42	87.61	88.42	87.62

CONCLUSION

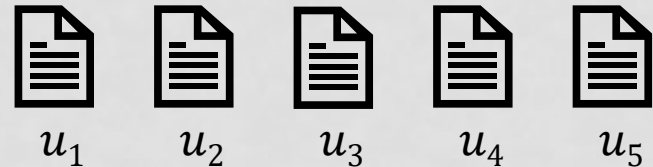


CONCLUSION

$$v_1 = \begin{bmatrix} u_3 \\ u_4 \\ u_2 \end{bmatrix} \quad v_2 = \begin{bmatrix} u_3 \\ u_5 \\ u_1 \end{bmatrix} \quad v_4 = \begin{bmatrix} u_7 \\ u_3 \\ u_1 \end{bmatrix}$$

Type – grading result of exam paper

$$\sigma_{u_3} = (1, 1, 2)$$



$$\sigma_{u_1} = (1, 1, 1) \rightarrow B(\sigma_{u_1}) = 9$$

$$\sigma_{u_3} = (1, 1, 2) \rightarrow B(\sigma_{u_1}) = 8$$

$$\sigma_{u_5} = (1, 1, 2) \rightarrow B(\sigma_{u_1}) = 8$$

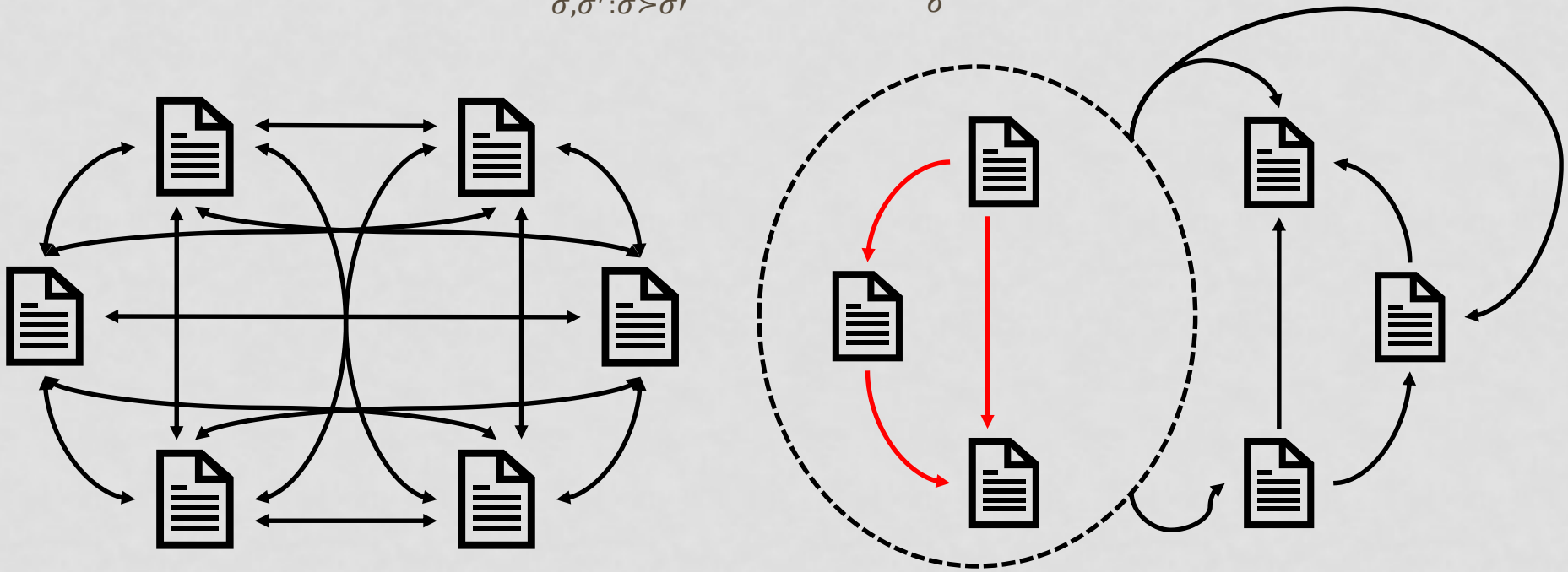
$$\sigma_{u_2} = (1, 2, 3) \rightarrow B(\sigma_{u_1}) = 6$$

$$\sigma_{u_4} = (2, 2, 3) \rightarrow B(\sigma_{u_1}) = 5$$



CONCLUSION

$$\max_{\sigma} \sum_{\sigma, \sigma': \sigma > \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$



CONCLUSION

noise	perfect grading		realistic grading				mallows grading			
setting	theory	$n = 10^4$	theory		$n = 10^4$		theory		$n = 10^4$	
method	borda	borda	opt	borda	opt	borda	opt	borda	opt	borda
all2all	92.01	92.02	80.01	79.57	80.09	79.57	85.15	84.38	85.16	84.39
th-10%	96.94	96.95	87.61	87.18	87.60	87.17	92.05	90.52	92.07	90.54
th-50%	94.13	94.14	83.62	83.43	83.62	83.43	88.39	87.80	88.40	87.81
acc-2%	93.57	93.57	81.27	80.73	81.27	80.74	86.52	85.72	86.52	85.73
acc-5%	95.47	95.47	82.97	82.42	82.97	82.42	88.42	87.61	88.42	87.62

What about combining filters?

How to interpret a grade?

THANK YOU!

PLEASE ASK QUESTIONS

ADDITIONAL SLIDES

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MODELLING WHOLE
POPULATION FROM SAMPLE

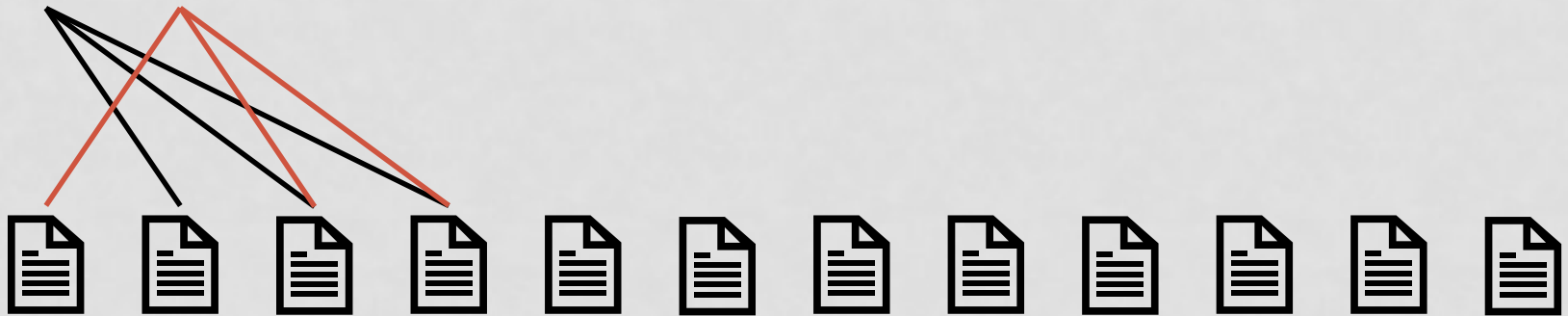
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WRONG BUNDLING EXAMPLE

SETTING

n students



n papers

SETTING

n students



n papers

SETTING

n students



n papers

SETTING

n students

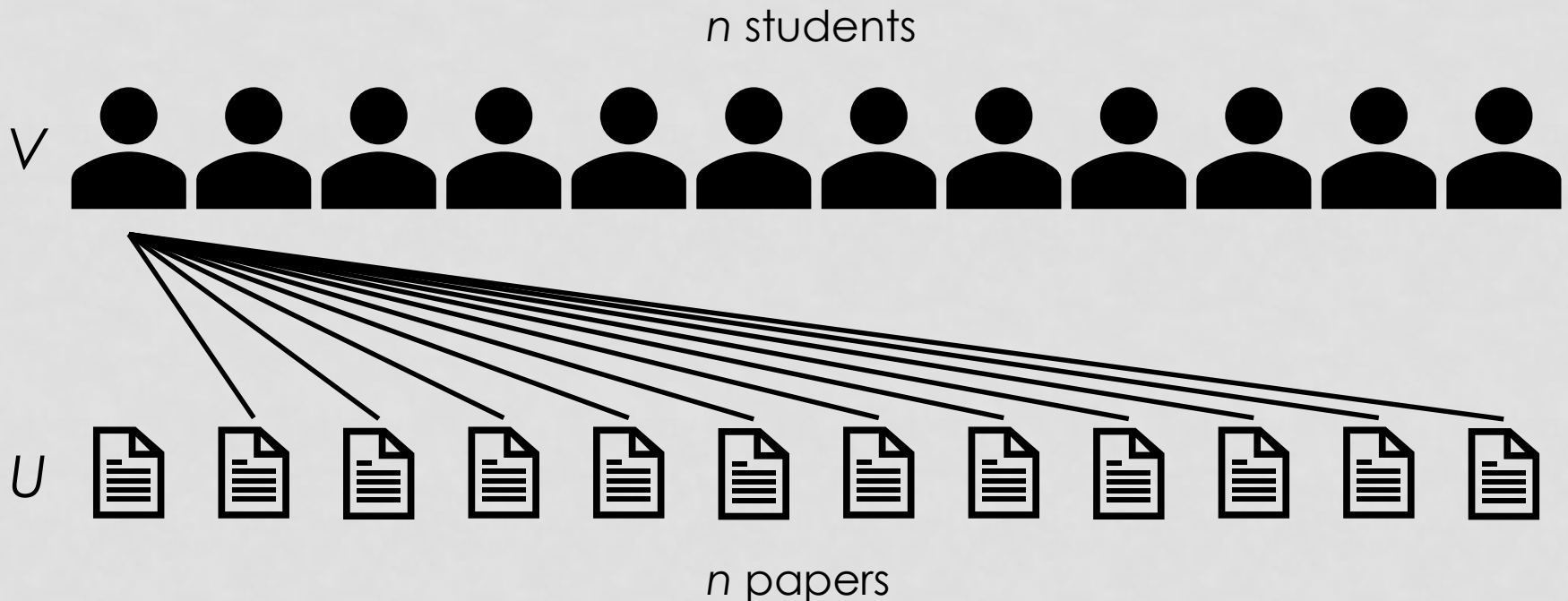


n papers

BUILDING BUNDLE GRAPH

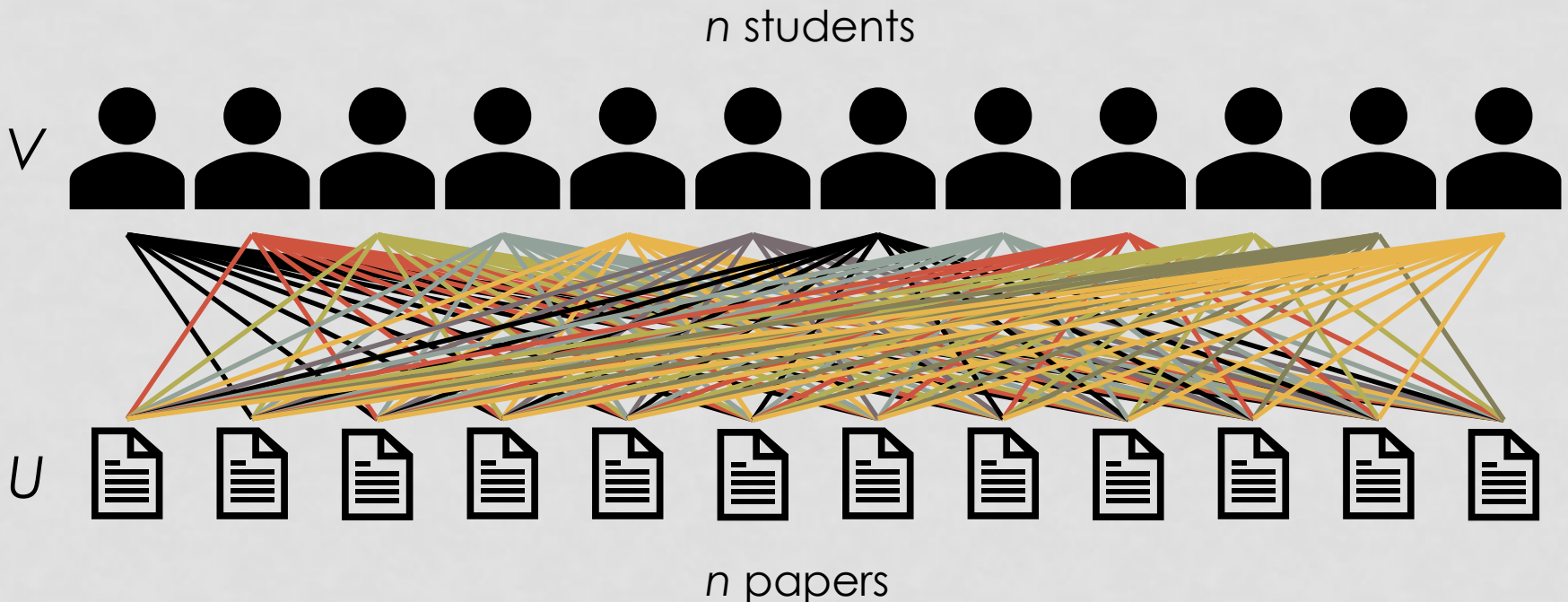
HOW TO BUILD BUNDLE GRAPH

- Start from complete bipartite graph $K_{n,n}$ (all graders connected to all papers),
- Remove the edges between graders and their own papers,
- Draw a perfect matching uniformly at random among all perfect matchings (that do not include previously removed edges),
- Repeat previous step until each grader has k papers (and each paper has 3 graders)



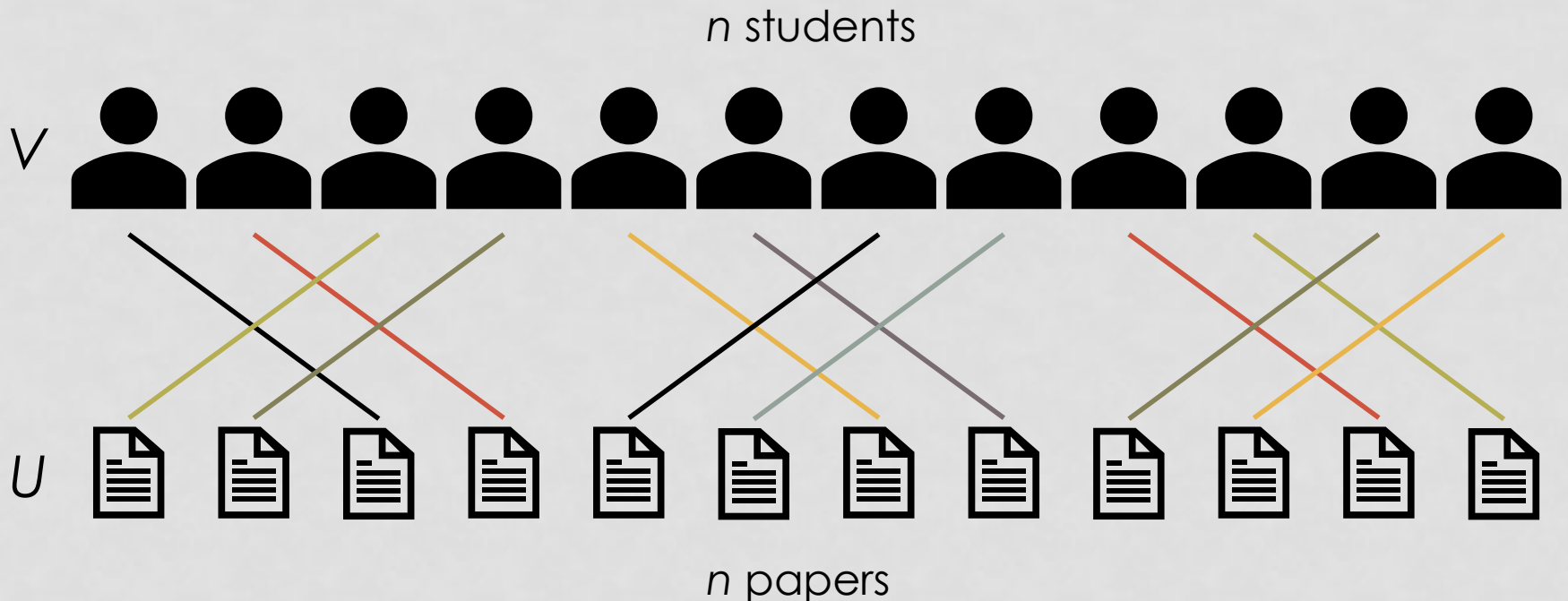
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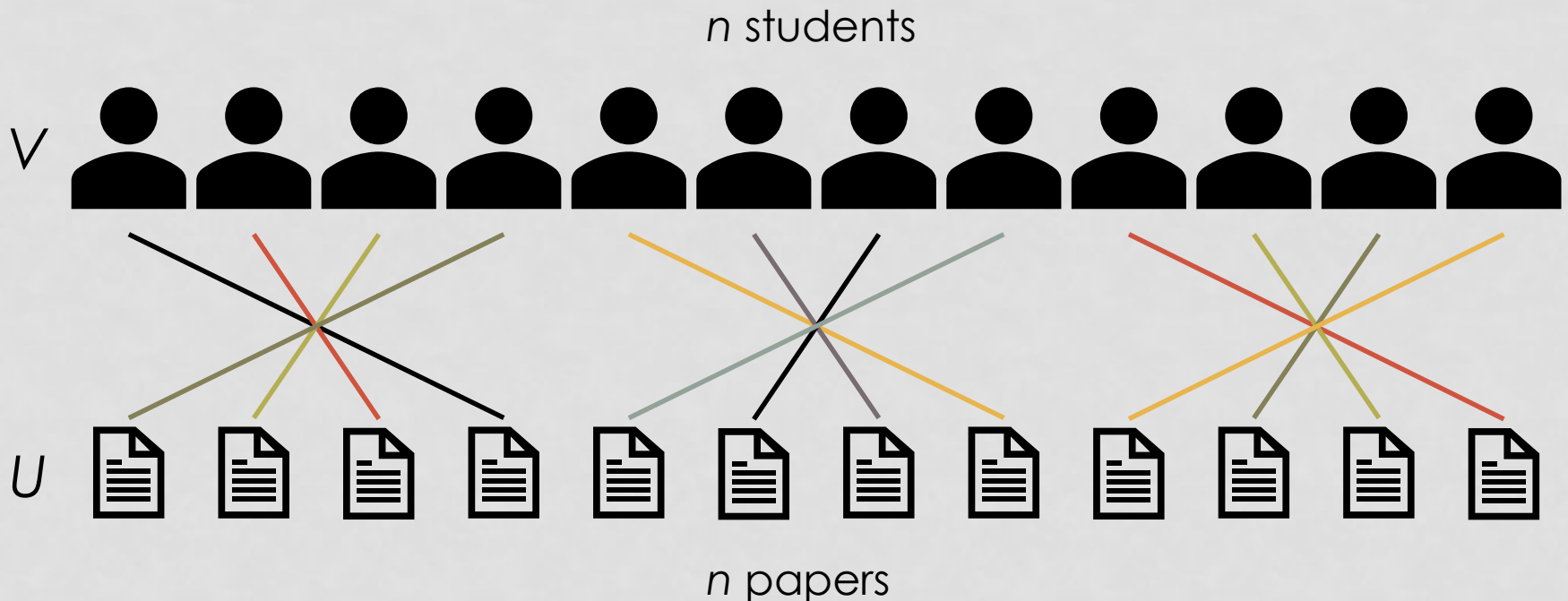
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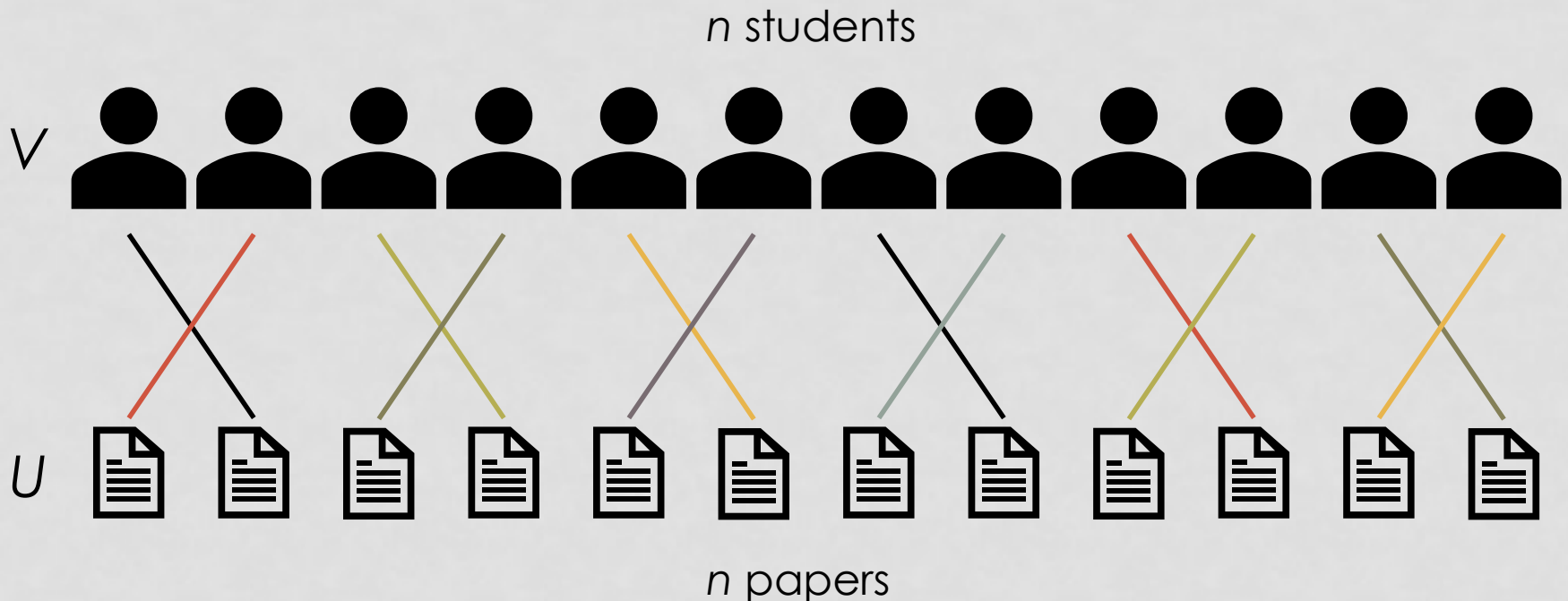
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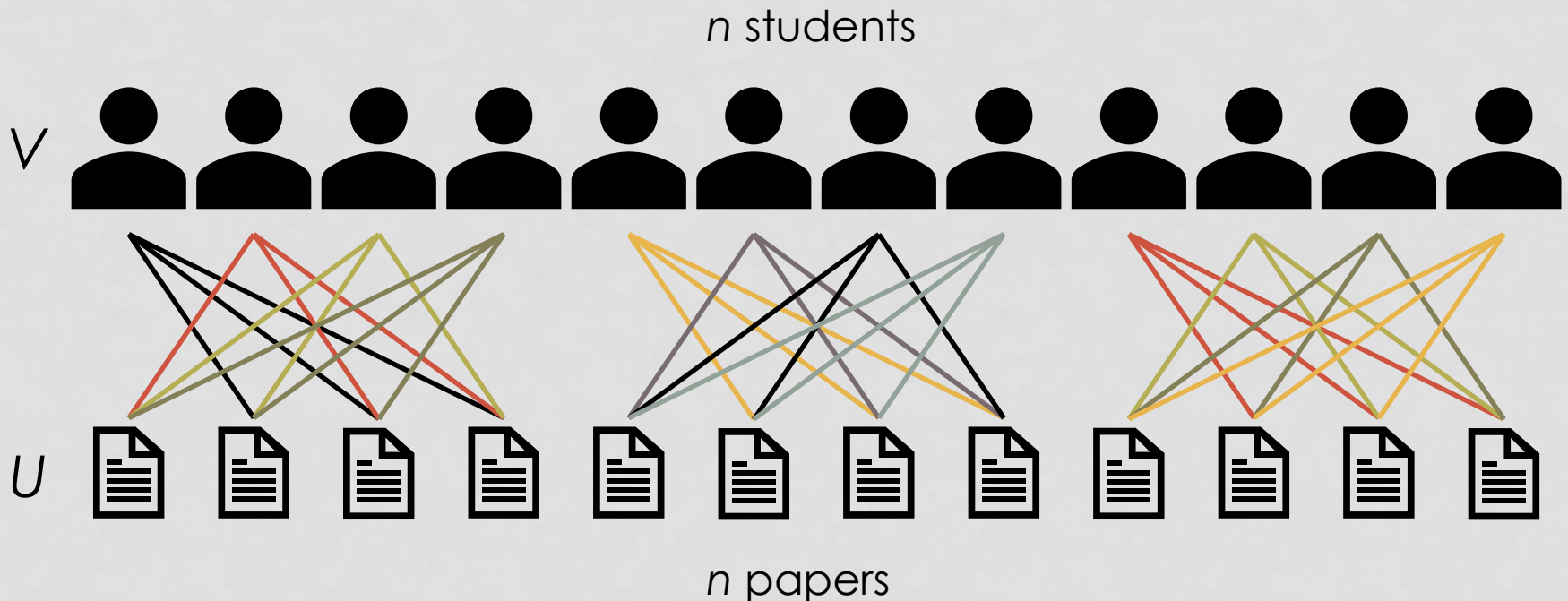
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- Remove the edges between graders and their own papers,
- Draw a perfect matching uniformly at random among all perfect matchings (that do not include previously removed edges),
- Repeat previous step until each grader has k papers (and each paper has 3 graders)



SETTING

- k -regular bipartite graph $G = (U, V, E)$ with n nodes on each side. U contains exam papers and V contains graders,
- k edges from each grader v_i to k exam papers from U .
- Student cannot grade her own paper edge from v_i to u_i is forbidden for all values of i .

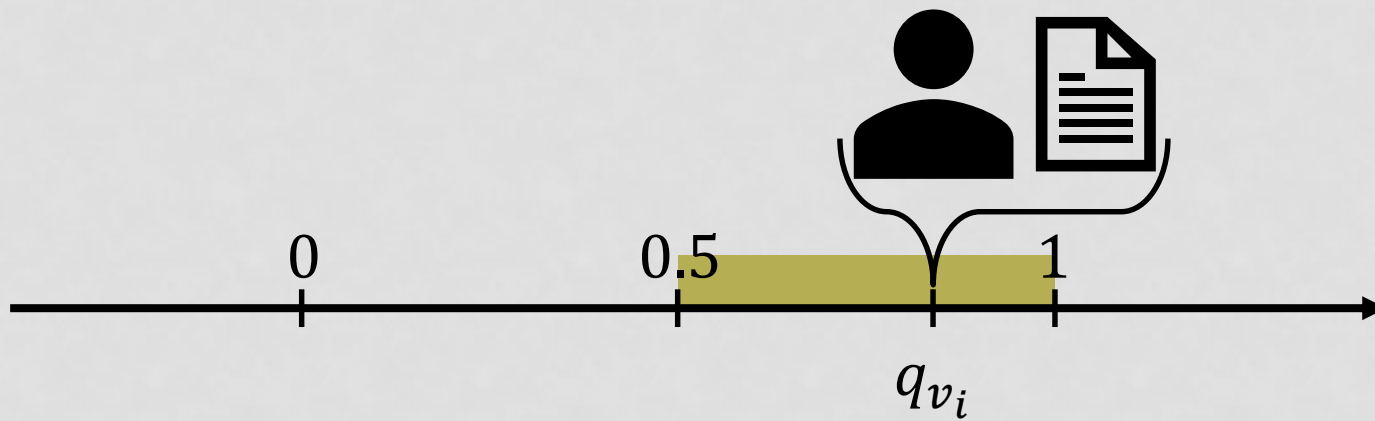
n students



n papers

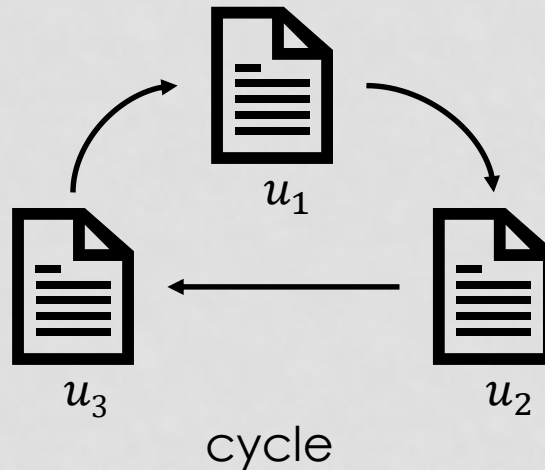
MODELLING STUDENT'S GRADING BEHAVIOUR

QUALITY $q \in \left[\frac{1}{2}, 1 \right]$



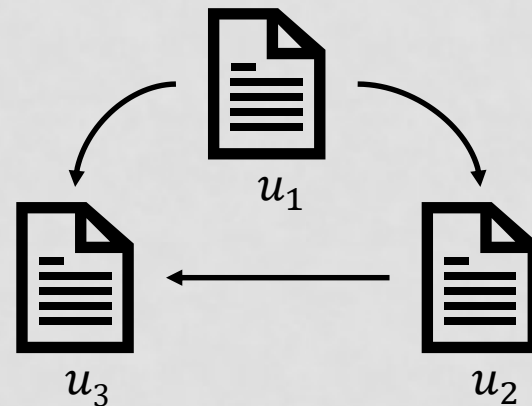
GRADING BEHAVIOUR

- Let $k = 3$, $q = 0.7$, true rank $v_i^{true} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$.
- First attempt:



GRADING BEHAVIOUR

- Let $k = 3$, $q = 0.7$, true rank $v_i^{true} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$.
- Second attempt:



no cycle – grading outcome

DERIVATIONS

EXPECTED FRACTION OF CORRECTLY RECOVERED PAIRWISE RELATIONS

$$C = \sum_{\sigma, \sigma': \sigma > \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

From assumptions:

infinite number of students \Rightarrow no dependency between the rank vectors that the exam papers x and y get after grading:

$$\mathbb{P}[x \triangleright \sigma \text{ and } y \triangleright \sigma'] = \mathbb{P}[x \triangleright \sigma] \cdot \mathbb{P}[y \triangleright \sigma']$$

Now problem boils down to finding explicit formula for $\mathbb{P}[x \triangleright \sigma]$, which is a probability that an exam paper x has type $\sigma = (\sigma_1, \dots, \sigma_k)$.

FINDING $\mathbb{P}[x \triangleright \sigma]$

Now problem boils down to finding explicit formula for $\mathbb{P}[x \triangleright \sigma]$, that is a probability that an exam paper x has type $\sigma = (\sigma_1, \dots, \sigma_k)$.

Procedure:

- Denote by $\mathcal{E}(x, \sigma_i)$ an event that i -th element of exam paper's x type is σ_i , which is equivalent to the event that the exam paper x was ranked σ_i -th in a bundle,
- Based on above determine the probability that $\sigma = (\sigma_1, \dots, \sigma_k)$ is of a particular type,
- Multiply above calculated probability by the number of ways in which such a type could have been achieved.

FINDING $\mathbb{P}[x \triangleright \sigma]$

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- Multiply above calculated probability by the number of ways in which such a type could have been achieved.

$$\sigma = (\sigma_1, \dots, \sigma_k)$$

$$\mathbb{P}[\mathcal{E}(x, \sigma_1) \text{ and } \dots \text{ and } \mathcal{E}(x, \sigma_k)] = \prod_{i=1}^k \mathbb{P}[\mathcal{E}(x, \sigma_i)]$$

Infinitely many students => the quality of each exam paper in the bundle does not affect quality of other exam papers

FINDING $\mathbb{P}[x \triangleright \sigma]$

Now problem boils down to finding explicit formula for $\mathbb{P}[x \triangleright \sigma]$, that is a probability that an exam paper x has type $\sigma = (\sigma_1, \dots, \sigma_k)$.

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$$\sigma = (\sigma_1, \dots, \sigma_k)$$

$$\mathbb{P}[\mathcal{E}(x, \sigma_1) \text{ and } \dots \text{ and } \mathcal{E}(x, \sigma_k)] = \prod_{i=1}^k \mathbb{P}[\mathcal{E}(x, \sigma_i)]$$

In how many ways can a given type be distributed among bundles it originates from.

$$N(\sigma) = \frac{k!}{d_1! \cdots d_k!}$$

FINDING $\mathbb{P}[x \triangleright \sigma]$

Now problem boils down to finding explicit formula for $\mathbb{P}[x \triangleright \sigma]$, that is a probability that an exam paper x has type $\sigma = (\sigma_1, \dots, \sigma_k)$.

$$\mathbb{P}[x \triangleright \sigma] = N(\sigma) \prod_{i=1}^k \mathbb{P}[\mathcal{E}(x, \sigma_i)]$$

Probability that the exam paper x was ranked σ_i -th in a bundle can be further decomposed. How?

Idea: use the definition of noise matrix P

NOISE MATRIX REMINDER

Model students' **grading behaviour** by introducing a $k \times k$ **noise matrix** $P = (p_{i,j})_{i,j \in [k]}$, where $p_{i,j}$ denotes the probability that the student will rank the paper on the position i when its true rank is j .

Example: $p_{2,3} = 0.4$ means that the students will put the paper on the position 2 with probability 0.4 if its true ranking is 3.

FINDING $\mathbb{P}[\mathcal{E}(x, \sigma_i)]$

Intermediate problem of finding the probability that the exam x was ranked σ_i -th in a bundle.

Procedure:

- Consider all possible **true rankings** that an exam paper x may have in a bundle,
- Account for x having such a **true ranking** and in the same time being ranked σ_i -th by the grader (**noise matrix!**),

$$\mathbb{P}[\mathcal{E}(x, \sigma_i)] = \sum_{j=1}^k p_{\sigma_i, j} \binom{k-1}{j-1} x^{j-1} (1-x)^{k-j}$$

Sum over all possible **true rankings** of an exam paper in a bundle

FINDING $\mathbb{P}[\mathcal{E}(x, \sigma_i)]$

Intermediate problem of finding the probability that the exam x was ranked σ_i -th in a bundle.

Procedure:

- Consider all possible **true rankings** that an exam paper x may have in a bundle,
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$$\mathbb{P}[\mathcal{E}(x, \sigma_i)] = \sum_{j=1}^k p_{\sigma_i, j} \binom{k-1}{j-1} x^{j-1} (1-x)^{k-j}$$

Probability of giving exam x rank σ_i if the **true rank** is j (**noise matrix**)

FINDING $\mathbb{P}[\mathcal{E}(x, \sigma_i)]$

Intermediate problem of finding the probability that the exam x was ranked σ_i -th in a bundle.

Procedure:

- Consider all possible **true rankings** that an exam paper x may have in a bundle,
- Account for x having such a **true ranking** and in the same time being ranked σ_i -th by the grader (**noise matrix!**),

$$\mathbb{P}[\mathcal{E}(x, \sigma_i)] = \sum_{j=1}^k p_{\sigma_i, j} \underbrace{\binom{k-1}{j-1} x^{j-1} (1-x)^{k-j}}_{\text{Probability that the true rank of } x \text{ in the bundle is } j}$$

Probability that the **true rank** of x in the bundle is j

FINDING $\mathbb{P}[\mathcal{E}(x, \sigma_i)]$

Intermediate problem of finding the probability that the exam x was ranked σ_i -th in a bundle.

Procedure:

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$$\mathbb{P}[\mathcal{E}(x, \sigma_i)] = \sum_{j=1}^k p_{\sigma_i, j} \binom{k-1}{j-1} x^{j-1} (1-x)^{k-j}$$

Number of ways in which papers ahead of x can be distributed in a bundle.

FINDING $\mathbb{P}[\mathcal{E}(x, \sigma_i)]$

Intermediate problem of finding the probability that the exam x was ranked σ_i -th in a bundle.

Procedure:

- Consider all possible **true rankings** that an exam paper x may have in a bundle,
- Account for x having such a **true ranking** and in the same time being ranked σ_i -th by the grader (**noise matrix!**),

$$\mathbb{P}[\mathcal{E}(x, \sigma_i)] = \sum_{j=1}^k p_{\sigma_i, j} \binom{k-1}{j-1} x^{j-1} (1-x)^{k-j}$$

Reminder: x is in range $[0,1]$ and the lower x , the better is its true ranking

Conclusion: $x^{j-1}(1-x)^{k-j}$ is the probability that there are $j-1$ papers in the bundle ahead of x .

FINDING $\mathbb{P}[x \triangleright \sigma]$

Now problem boils down to finding explicit formula for $\mathbb{P}[x \triangleright \sigma]$, that is a probability that an exam paper x has type $\sigma = (\sigma_1, \dots, \sigma_k)$.

$$\mathbb{P}[x \triangleright \sigma] = N(\sigma) \prod_{i=1}^k \mathbb{P}[\mathcal{E}(x, \sigma_i)] = N(\sigma) \prod_{i=1}^k \sum_{j=1}^k p_{\sigma_i, j} \binom{k-1}{j-1} x^{j-1} (1-x)^{k-j}$$

Exchange sum and products operator and denoting by L_k set of **all** k -entry vectors $l = (l_1, \dots, l_k)$ with $l_i \in \{1, \dots, k\}$:

$$\mathbb{P}[x \triangleright \sigma] = N(\sigma) \sum_{l \in L_k} \prod_{i=1}^k p_{\sigma_i, l_i} \binom{k-1}{l_i-1} x^{l_i-1} (1-x)^{k-l_i}$$

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Push multiplication to the exponent and denote $\|l\|_1 = \sum_{i=1}^k l_i$:

$$\mathbb{P}[x \triangleright \sigma] = N(\sigma) \sum_{l \in L_k} \left(\prod_{i=1}^k p_{\sigma_i, l_i} \binom{k-1}{l_i-1} \right) x^{\|l\|_1 - k} (1-x)^{k^2 - \|l\|_1}$$

FINDING $\mathbb{P}[x \triangleright \sigma]$

Now problem boils down to finding explicit formula for $\mathbb{P}[x \triangleright \sigma]$, that is a probability that an exam paper x has type $\sigma = (\sigma_1, \dots, \sigma_k)$.

$$\mathbb{P}[x \triangleright \sigma] = N(\sigma) \sum_{l \in L_k} \left(\prod_{i=1}^k p_{\sigma_i, l_i} \binom{k-1}{l_i-1} \right) x^{|\mathbb{l}|_1 - k} (1-x)^{k^2 - |\mathbb{l}|_1}$$

$$\text{Use } (1-x)^m = \sum_{j=0}^m \binom{m}{j} (-1)^j x^j$$

$$\mathbb{P}[x \triangleright \sigma] = N(\sigma) \sum_{l \in L_k} \left(\prod_{i=1}^k p_{\sigma_i, l_i} \binom{k-1}{l_i-1} \right) x^{|\mathbb{l}|_1 - k} \sum_{j=0}^{k^2 - |\mathbb{l}|_1} \binom{k^2 - |\mathbb{l}|_1}{j} (-1)^j x^j$$

FINDING $\mathbb{P}[x \triangleright \sigma]$

Now problem boils down to finding explicit formula for $\mathbb{P}[x \triangleright \sigma]$, that is a probability that an exam paper x has type $\sigma = (\sigma_1, \dots, \sigma_k)$.

$$\mathbb{P}[x \triangleright \sigma] = N(\sigma) \sum_{l \in L_k} \left(\prod_{i=1}^k p_{\sigma_i, l_i} \binom{k-1}{l_i-1} \right) x^{|\mathbb{l}|_1 - k} \sum_{j=0}^{k^2 - |\mathbb{l}|_1} \binom{k^2 - |\mathbb{l}|_1}{j} (-1)^j x^j$$

Order the terms:

$$\mathbb{P}[x \triangleright \sigma] = N(\sigma) \sum_{l \in L_k} \sum_{j=0}^{k^2 - |\mathbb{l}|_1} \left(\prod_{i=1}^k p_{\sigma_i, l_i} \binom{k-1}{l_i-1} \right) \binom{k^2 - |\mathbb{l}|_1}{j} (-1)^j x^{|\mathbb{l}|_1 - k + j}$$

KEY Conclusion: $\mathbb{P}[x \triangleright \sigma]$ is a univariate **polynomial** of degree $k^2 - k$

MODELLING WHOLE POPULATION FROM SAMPLE

MODELLING A POPULATION

Table III. Performance of the optimal type-ordering aggregation rules for approximations of the Mallows model. The data for Mallows are presented again here for direct comparison.

# samples	100		1000		Mallows	
setting	theory	$n = 10^4$	theory	$n = 10^4$	theory	$n = 10^4$
all2all	84.95	84.95	85.14	85.15	85.15	85.16
th-10%	91.82	91.85	92.05	92.04	92.05	92.07
th-50%	88.21	88.21	88.39	88.38	88.39	88.40
acc-2%	86.31	86.31	86.51	86.51	86.52	86.52
acc-5%	88.19	88.20	88.41	88.41	88.42	88.42

EXAMPLE ($k = 3$)

Very bad Graders

$$P = \begin{bmatrix} 0.1 & 0.3 & 0.6 \\ 0.3 & 0.4 & 0.3 \\ 0.6 & 0.3 & 0.1 \end{bmatrix}$$

REFORMULATE PROBLEM

$$\max_{\succ} \sum_{\sigma, \sigma' : \sigma > \sigma'} W(\sigma, \sigma') + \frac{1}{2} \sum_{\sigma} W(\sigma, \sigma)$$

