

# VK Analysis

## Network Analysis

Anastasia Ignatyeva, AISA

NATIONAL RESEARCH UNIVERSITY

«HIGHER SCHOOL OF ECONOMICS»

FACULTY OF COMPUTER SCIENCE

April, 2016

### Part I

Common  
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### Part II

Centralities  
Page - Rank  
Assortative  
Mixing  
The closest RG  
model

### Part III

Cliques search  
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Detection  
Communities'  
Detection  
Communities'  
Detection  
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The End

## 1. Part I

- ▶ Common Summary
- ▶ Friends' Description
- ▶ Graph's Parameters

## 2. Part II

- ▶ Centralities
- ▶ Page - Rank
- ▶ Assortative Mixing
- ▶ The closest random graph model

## 3. Part III

- ▶ Cliques search
- ▶ Communities' Detection

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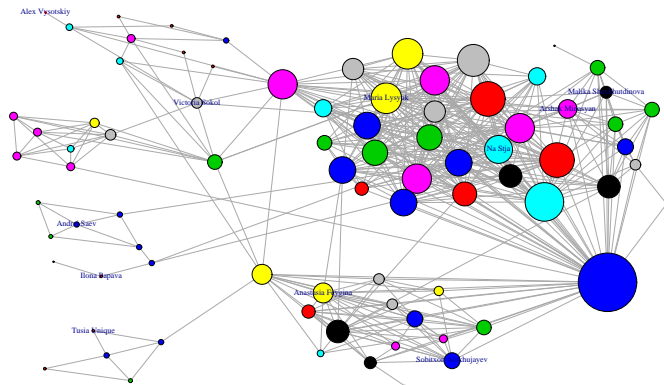
### The End

# Graph of friends

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Graph : 85 nodes, 454 edges



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# Who is my freind?

**Graph** : 85 nodes, 454 edges

which includes:



two Vasiliy Rubtzov



Василий Рубцов  
НИУ ВШЭ (ГУ-ВШЭ)

=



Василий Рубцов  
НИУ ВШЭ (ГУ-ВШЭ)

- ▶ three friends with last name — «Scolov(a)» (not relatives)



one friends with deleted account



Василиса Кондратюк

- ▶ three cage friends have no accounts' photo



Богдан Краснов  
НИУ ВШЭ (ГУ-ВШЭ)



Артём Данилов



Татьяна Рамазанова



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# Who is my friend?

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## Birth day:

- ▶ only day & month — 29
- ▶ no information — 18
- ▶ most popular date — the 3 of August (3 persons)

## Relationship Status:

- ▶ not married — 13
- ▶ has boyfriend/girlfriend — 2
- ▶ fell in love — 7
- ▶ engaged — 1
- ▶ married — 1
- ▶ no information — 61

## Faculty name:

- ▶ economic science — 29
- ▶ computer science — 10
- ▶ physical — 2
- ▶ ...
- ▶ no information — 8

## Sex:

- ▶ male — 54/85
- ▶ female — 31/85

## Number of posts:

- ▶ max — 8303
- ▶ 6 individuals have no posts
- ▶ average value  $\approx 1148$

## Days of inactivity:

(25.09.2016 - date of last post)

- ▶ max — 1302 (Nikolay Pilnik)
- ▶ average number  $\approx 132$
- ▶ (Alexander Salnikov, Danil Fedorovych, Victoria Socol) — 0

## University:

- ▶ NRU HSE — 46
- ▶ MSU — 7
- ▶ MIPT — 2
- ▶ ...
- ▶ no information — 8

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# Who is my friend?

## Node Degree:

- ▶ max degree — 44 (Sasha

Kuznetzova)



- ▶ min degree — 0
- ▶ 4 persons have only 1 friend
- ▶ average degree  $\approx 11$

## Number of Groups:

- ▶ max value — 355 (Danil

Fyodorovych)



- ▶ 19 persons limit the access
- ▶ average number  $\approx 43$

## The most popular vk groups:

1. Высшая школа экономики (24)
2. Лентач (18)
3. The Vyshka (16)

ВЫСШАЯ  
ШКОЛА  
ЭКОНОМИКИ



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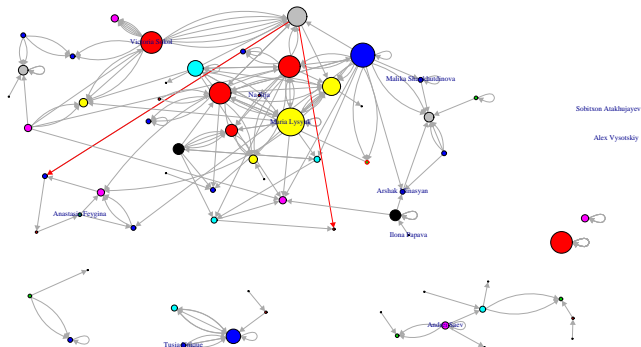
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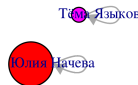
	Graph of Likes	Graph of Friends
average node degree	<b>2</b>	<b>11</b>

merely 9 last actions(photos,notes,posts) were taken into account

# Do the likes matter? Some more Statistics

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	Department of <b>Computer Science</b>	Department of <b>Economic Science</b>	total
average node degree (likes)	$\approx 1$	$\approx 3$	$\approx 2.23$
<b>female</b>	$\approx 1.6$	$\approx 3.7$	$\approx 2$
<b>male</b>	1	$\approx 2.5$	$\approx 1.8$

	in_likes	out_likes	efficient likes givers
1	Danil Fedorovysh (12)	Sasha Kuznetzova (18)	Danil Fedorovysh (8)
2	Yana Myachenkova (11)	Victoria Socol (17)	Kirill Ponomarev (8)
3	Maria Lysyuk (9)	Maria Lysyuk (14)	Yana Myachenkova (7)

17 out of 20 persons with 0 node degree are males

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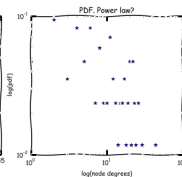
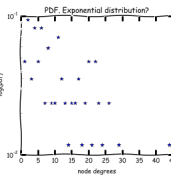
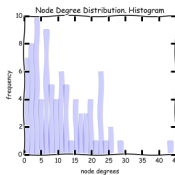
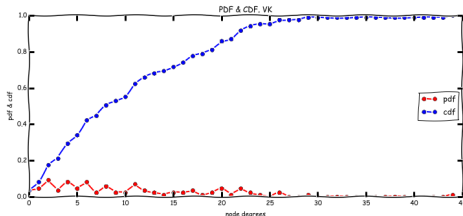
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parameter	average degree	diameter	average path	average clustering
str160	float64	int32	float64	float64
value	10.66	8.00	21.25	0.59

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## Deduction:

- ▶ *Common Friend*: a male from a economic science department of NRU HSE, who hides a relationship status and is busy enough to make posts and hand out a lot of «likes».
- ▶ *Node Degree Distribution*: while social network is supposed to be classified as scale-free network, which means node degree distribution should follow power law, this tendency does not hold ( $85 \ll \infty$ ).
- ▶ *Average Path*: the average path as well as the diameter of the graph is much more than 6  $\rightarrow$  the network of my vk friends does not supports the theory of 6 handshakes.
- ▶ *Cluster Coefficient*: although this coefficient should be similar to 1 for social network, it is not; there is no strong tendency for clusters distinguishing.

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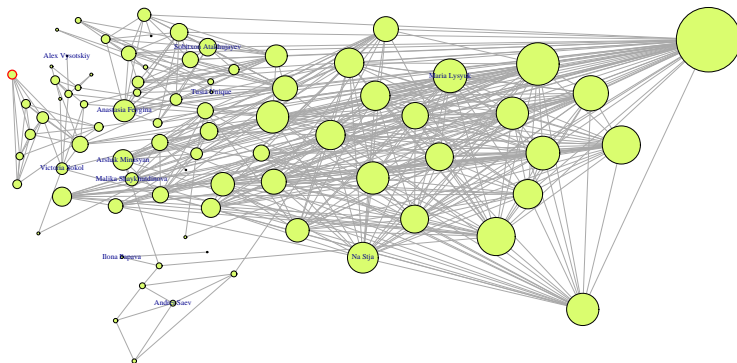
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# Betweenness Centrality

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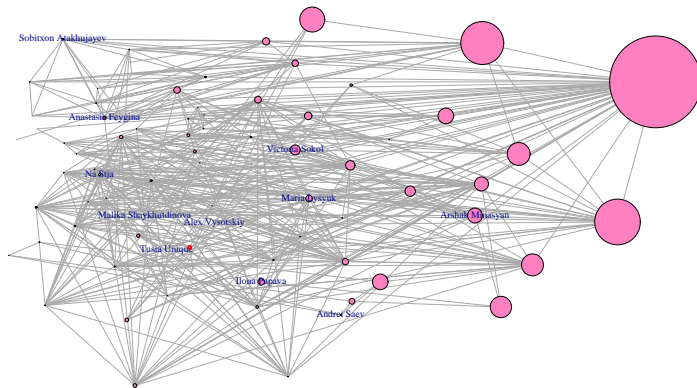
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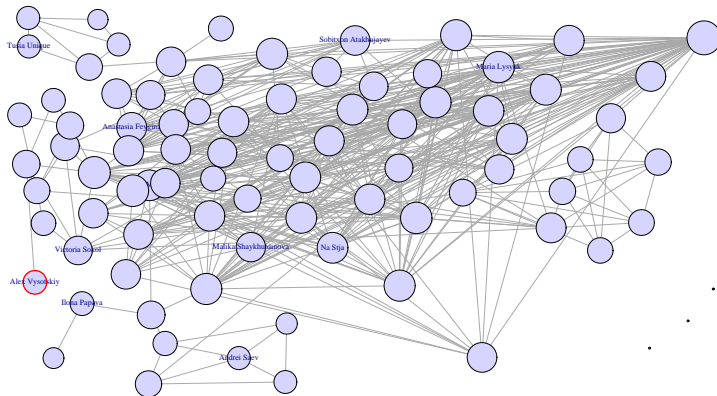
The End



# Closeness Centrality

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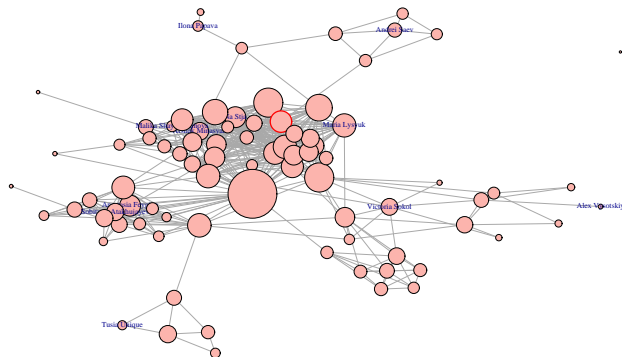
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degree centrality	closeness centrality	betweenness centrality	pagerank
str576	str576	str576	str608
Sasha Kuznetsova	Sasha Kuznetsova	Sasha Kuznetsova	Sasha Kuznetsova
Andrey Zubanov	Tatyana Ramazanova	Tatyana Ramazanova	Tatyana Ramazanova
Darya Bykovskaya	Andrey Zubanov	Anya Muratova	Andrey Zubanov
Daniil Gerchik	Masha Gerasimenko	Karina Melnik	Daniil Gerchik
Kesha Kozlov	Maria Lysyuk	Alexander Ushakov	Darya Bykovskaya
Ksyusha Vasilyeva	Yulia Kazakovtseva	Alexey Uzhegov	Danil Fyodorovykh
Maria Lysyuk	Daniil Gerchik	Lev Feofanov	Kesha Kozlov
Masha Gerasimenko	Ksyusha Vasilyeva	Anastasia Pestova	Maria Lysyuk
Yulia Kazakovtseva	Danil Fyodorovykh	Dima Karpov	Anya Muratova
Danil Fyodorovykh	Kesha Kozlov	Arshak Minasyan	Ksyusha Vasilyeva
Tatyana Ramazanova	Anya Muratova	Daniil Gerchik	Anastasia Manokhina
Na Stja	Yana Myachenkova	Alyona Lukashenko	Masha Gerasimenko
Anton Votinov	Vova Menshikov	Victoria Sokol	Yulia Kazakovtseva
Pasha Lukashkin	Na Stja	Danil Fyodorovykh	Alexey Uzhegov
Alexey Uzhegov	Pavel Yakovenko	Elina Khakimova	Na Stja

## Part I

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assortativity	degree	sex	relation	graduation	faculty_name	university_name	post_number	likes_num_net	group_num
str160	float64	float64	float64	float64	float64	float64	float64	float64	float64
value	0.248	-0.029	0.010	0.084	0.164	0.090	-0.021	-0.019	-0.007

## *Enough Evident Results:*

Assortative mixing takes place according to

- ▶ degree
- ▶ graduation
- ▶ name of the University
- ▶ name of the Faculty

## *It can be interesting:*

While graph is disassortative regarding to sex it at the same time assortative to relationship status

Disassortative mixing takes place according to

- ▶ number of posts on the wall
- ▶ amount of getting «likes»
- ▶ number of groups

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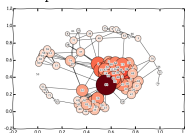


# The closest random graph model or how Nastya plays with parameters

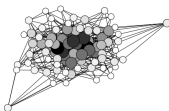
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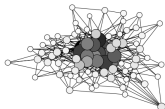
Graph of vk friends



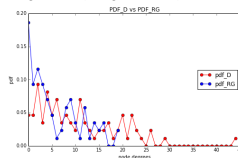
Random Graph



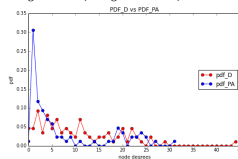
Preferential attachment



Random Graph,  
 $n_0 = 28, m_0 = 166, m = 5$



Preferential attachment,  
 $n_0 = 20, m_0 = 400, m = 4$



	AvND	NoEd	AvCl
Real Graph	10.66	454	0.59
RG	10.6	456	0.18
PA	10.5	446	0.31

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# Cliques search

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There are 179 cliques with size ranging from 3 to 12.

## The Largest Clique



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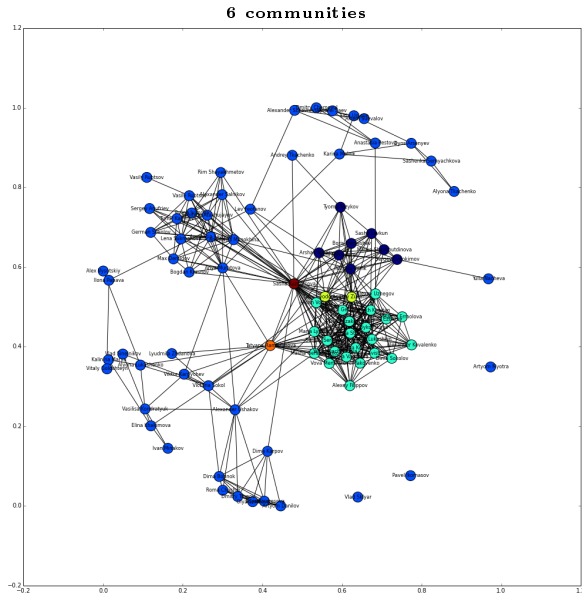
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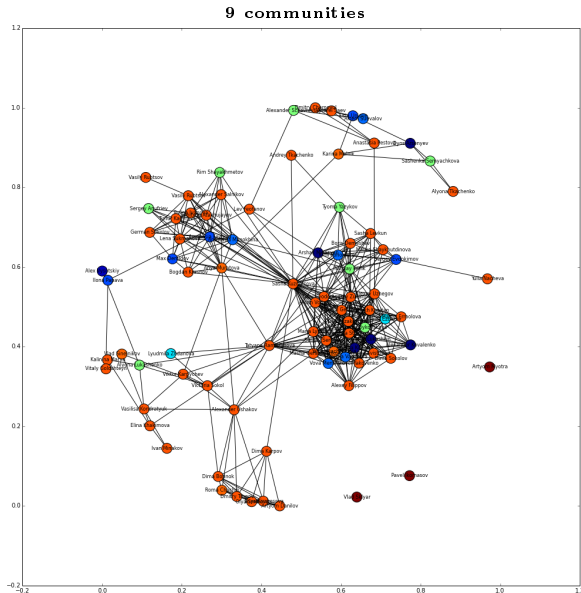
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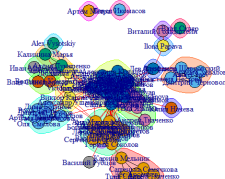
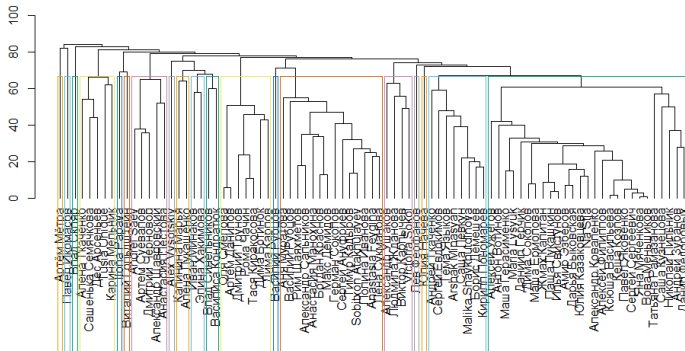
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19 communities, modularity = 0.39



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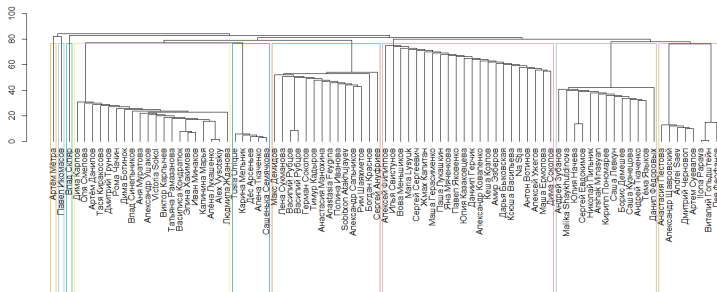
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9 communities, modularity = 0.45



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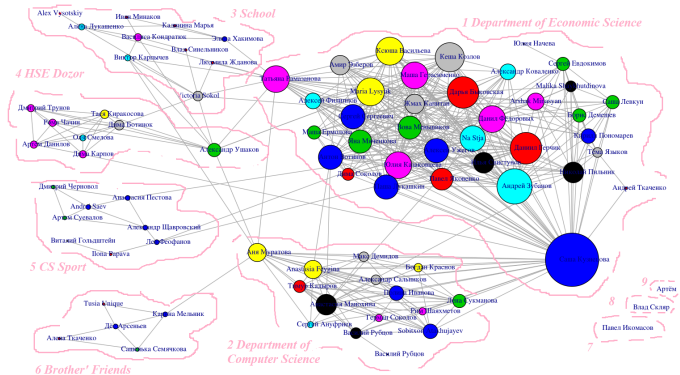
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# True Communities

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Fastgreedy Method provides the best results both in modularity and closeness to the true communities' partition terms

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That is all :)

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Thanks for your attention!

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The most frequent words occurring in posts of students studying at computer science department



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