

# Symulacje złożonych systemów społecznych

## modelowanie zachowania ludzkiego

@ GMUM, Faculty of Mathematics and Computer Science, Jagiellonian University, Kraków  
Rafał Kucharski  
rafal.kucharski@uj.edu.pl  
<https://rafal-kucharski.u.matinf.uj.edu.pl/>





# Agenda

## this talk

### Idea

- 1 What computers (and Computer Scientists) usually do? **optimization**
- 2 What human individuals usually do? **decisions**
- 3 What groups of humans (society) usually do? **society**.

### Cases

- discrete choice models - **Multinomial Logit Model**
- social networks - **Behavioural Profiling**
- traffic flow models - **Traffic Microsimulation**

### Leitmotif

While **CS** is purely **STEM**, now the big-data is also in **social science**, opening widely for novel and exciting **CS** applications

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# myself

Rafał Kucharski

**now:** associate. prof, Jagiellonian University, Faculty of Math. and CompSci, **GMUM**, prof. Jacek Tabor

**2023-2028** ERC Starting Grant - **COeXISTENCE** 3 PhDs + PostDoc; **Reinforcement Learning**

**2023-2026** Horizon Europe - **SUM** 2 PhDs + PostDoc; **Transport Planning**

**2021-2024** NCN OPUS - **Post-corona shared mobility** 2 PhDs + PostDoc; **Network Science+Optimisation**

**past:** PostDoc @ **TU Delft** working in Critical MaaS **ERC Starting Grant**

- shared rides algorithms **ExMAS**
- agent based model **MaasSim**

**past<sup>2</sup>:** assist. prof @ **Politechnika Krakowska**, prof. Andrzej Szarata

**PhD:** DTA, La Sapienza Rome, prof. Guido Gentile

- outside academia:**
- R&D software developer (PTV SISTeMA, Rome)
  - transport modeller (models for Kraków, Warsaw and more)
  - data scientist, ML engineer (NorthGravity)





# Humans and computers



# Optimisation

finding optimal value

## Problem

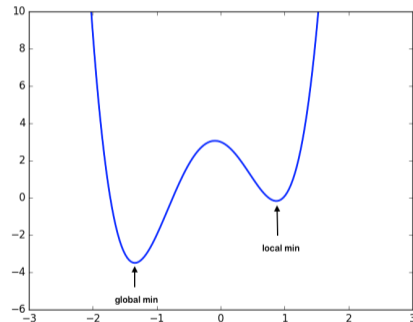
What is the minimal value of the function?

$$\arg \min_x f(x) \quad (1)$$

where

- $x$  is the vector of decision variables,
- $f(x)$  is the objective function to be minimized.

both are **deterministic**.



# Optimisation

finding optimal value

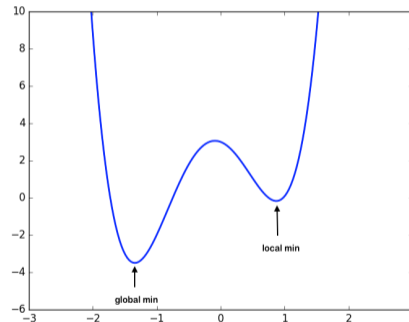
## Optimisation

can be:

- polycriterial:  $x \rightarrow x, y, \dots$ ,
- stochastic:  $f(x) \rightarrow f(x + \epsilon)$ ,
- multivariate:  $f(x) \rightarrow f(x, y, \dots)$ ,
- black-box (like neural network)

## Computer Science

We can reduce bigger part of CS to solving optimization problems.



# Optimisation

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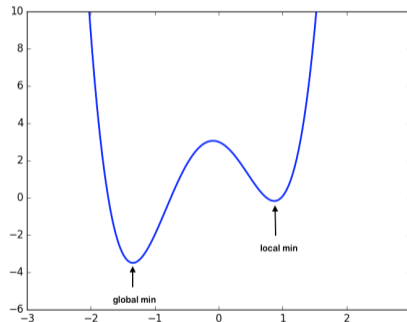
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# Discrete Choice

## Path choice

### Problem

Given a weighted network  $G(N, A)$  find a path (sequence of nodes  $n \in N$ ) from origin  $o$  to destination  $d$

## Computers

### Shortest Path Choice

Define objective function (e.g. distance or more generically a cost  $c(a)$  :  $a \in A$ ) and propose an algorithm to find a solution.

e.g. **Dijkstra** - which deterministically and reliably outputs an **optimal** path.



## Humans

### Discrete Choice

Each agent  $i$  **selects** the **optimal** path  $k$  from her origin  $o_i$  to destination  $d_i$  at her departure time  $\tau$ :

$$k_{od,i} = \arg \min_{k \in K_{od}} \sum_{a \in k} c_{a,i} \quad (2)$$



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# Behaviour



# Discrete Choice

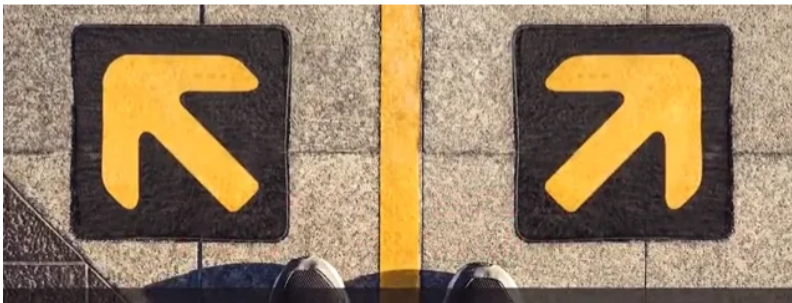
## Example

### Problem

There are two products.

- 1 cheap, nice and low quality
- 2 expensive, ugly and high quality

which is optimal?





# Rational utility maximisers

in path choice

## Rational

Let's assume all humans are rational:

$$\Pr(k|od, i) = \Pr\left(c_{k,i} = \min_{k' \in K_{od}} c_{k',i}\right)$$

i.e. we take the **best** option.

## Costs

Each path candidate has a given:

- length
- travel time
- cost (fare)
- comfort factor
- ...

## Perceived costs

### utility

length and travel time are **physical**  
cost is **subjective**, in discrete choice called **Utility**

$$U_{k,i} = \beta_{0,i} + \beta_{t,i}t_k + \beta_{c,i}c_k + \dots + \varepsilon$$

$\beta_0$  alternative-specific constant, i.e. taste variation, i.e. sentiment

$\varepsilon$  random term

$\beta_t$  value of time (10€/h)

$\beta_c$  value of money



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# Discrete choice theory

## Key concepts

### Non-determinism

we can reasonably well **predict** the probability of selecting an option  $a$  by individual  $i$ , yet there is always non-determinism. Probabilities only asymptotically approach to 0 and 1.

### Heterogeneity

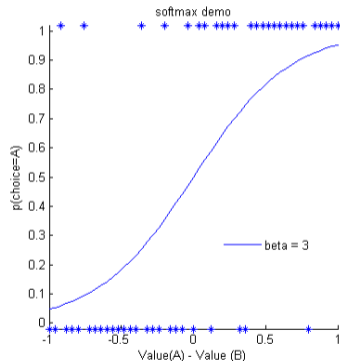
We are different, each of us has its' own:

$\beta_{0,i}$  alternative-specific constant, i.e. taste variation, i.e. sentiment

$\varepsilon$  random term

$\beta_{t,i}$  value of time

$\beta_{c,i}$  value of money



# Discrete choice theory

Nobel prize

Daniel McFadden won the Nobel prize in 2000 for his pioneering work in developing the theoretical basis for discrete choice.

## Discrete choice theory

Discrete choice models statistically relate the choice made by each person to the attributes of the person and the attributes of the alternatives available to the person.

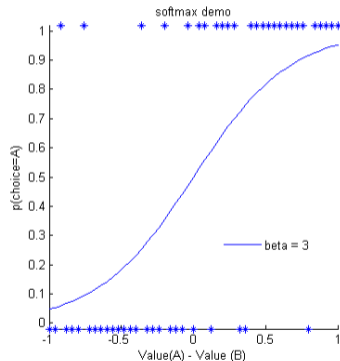
## Logit model

assumption:

$\varepsilon \approx \text{Gumbel}(0, \sigma)$ , yields

Probability of selecting option  $a$  in the choice set  $C$  by individual  $i$  is:

$$p_{a,i} = \frac{\exp \mu U_{a,i}}{\sum_{a' \in C} \exp \mu U_{a',i}}$$



# Estimation

## Bigdata

### Datasets

obsID	personID	panelID	choice	costWalk	costBike	costCar	costTransit	costWalk	costBike	costCar	costTransit	betaWalk	betaBike	betaCar	betaTransit		
1	1	1	3	0	0	58	72	96	109	10	12	0	0	5	1	-0.371273721	-1.066419469
2	1	2	3	0	0	38	42	166	55	0	15	0	0	7	3	-0.62497503	-1.119626125
3	1	3	3	0	0	56	65	145	63	1	16	0	0	3	1	-0.641188316	-1.174059586
4	1	4	3	0	0	19	20	106	37	9	15	0	0	4	1	-0.438671827	-1.24832442
5	1	5	3	0	0	54	81	185	41	2	19	0	0	5	3	-0.287124529	-0.864659563
6	1	6	3	0	0	41	35	48	30	8	22	0	0	3	3	-0.257752721	-0.55035108
7	1	7	3	0	0	27	33	106	25	3	13	0	0	2	0	-0.569873118	-0.764597732
8	1	8	4	0	0	18	21	163	41	8	12	0	0	6	1	-0.369689557	-1.261403142
9	1	9	3	0	0	24	22	66	42	10	16	0	0	3	3	-0.096837917	-1.025072048
10	1	10	3	0	0	14	17	35	27	5	24	0	0	3	2	-0.191661813	-0.63550085
11	2	1	1	0	0	13	11	0	0	4	19	0	0	1	2	-0.02980754	-0.399523895
12	2	2	3	0	0	43	49	135	31	4	14	0	0	4	4	-0.22930545	-0.915244977
13	2	3	4	0	0	50	42	1142	84	9	11	0	0	6	1	-0.491108147	-0.627612196
14	2	4	1	0	0	22	23	18	20	6	21	0	0	5	2	-0.484219256	-0.889211994
15	2	5	3	0	0	18	18	61	29	2	13	0	0	4	0	-0.617233817	-1.441170191
16	2	6	2	0	0	17	21	167	21	10	15	0	0	3	1	-0.136576508	-0.828506671
17	2	7	3	0	0	34	42	179	63	3	19	0	0	5	2	-0.427847708	-1.014582039
18	2	8	3	0	0	51	51	84	37	0	16	0	0	6	1	-0.432000047	-1.418900935
19	2	9	4	0	0	44	35	531	137	5	15	0	0	9	3	-0.524877465	-0.971677976

### Binary classifier

Predict the binary (0/1 value)

**d6922a778401**

### Machine Learning

Lately, instead of classical methods (like BIOGEME's max **log-likelihood**) neural networks are used to classify choices - still in infancy.

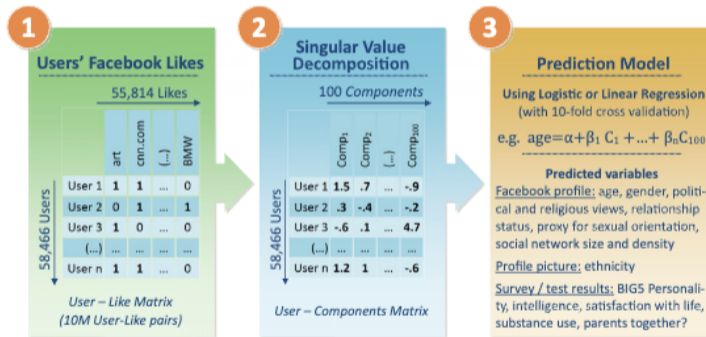


# Predict behaviour from digital traces



# Internet privacy

What Facebook likes tell about us?<sup>1</sup>



<sup>1</sup> Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behaviour. Proceedings of the national academy of sciences, 110(15), 5802-5805.

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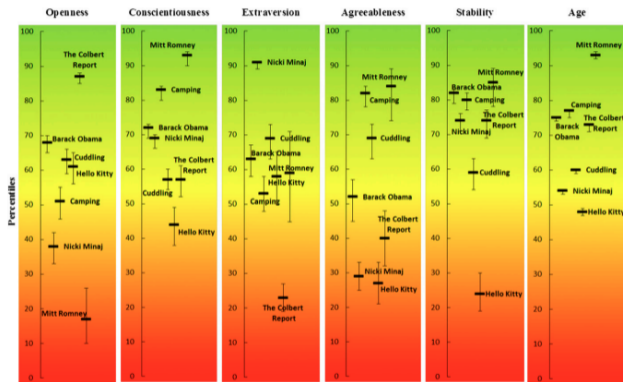


Fig. 51. Average levels of five personality traits and age of the users associated with selected Likes presented on the percentile scale. For example, the average extraversion of users associated with “The Colbert Report” was relatively low: it was lower only for 23% of other Likes in the sample. Error bars signify 95% confidence intervals of the mean.

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# Traffic flow



# Phantom jam

Let's drive around the circle at constant speed



# Phantom jam

Let's drive around the circle at constant speed



## Video

<https://youtu.be/FW9VkoibWDw?si=a0qexb-zSMxPxLwY&t=25>

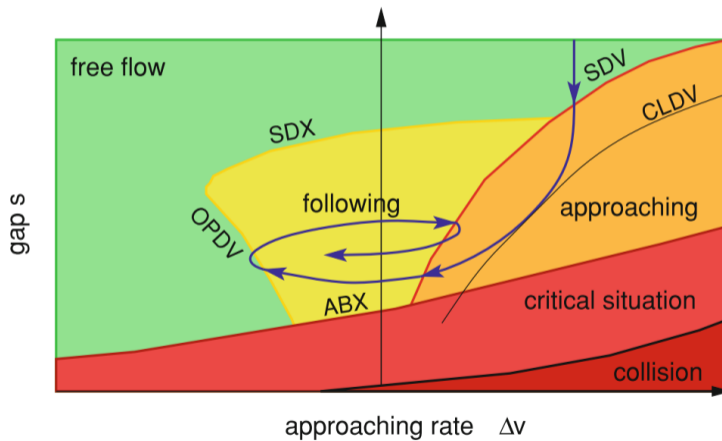
## What can go wrong?

Why there was a **traffic breakdown**?

Why we couldn't do such an easy task and led to the **phantom jam**?

# Car following Model

Wiedemann



# Microsimulation

PTV Vissim, SUMO, Aimsun, ...



<https://www.youtube.com/watch?v=bqF-Hyovg9E&t=3s>

# Thank you!

Thank you for your attention,  
welcome to discuss

Rafał Kucharski

[rafal.kucharski@uj.edu.pl](mailto:rafal.kucharski@uj.edu.pl)

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