

Symulacje złożonych systemów społecznych

modelowanie zachowania ludzkiego

@ GMUM, Faculty of Mathematics and Computer Science, Jagiellonian University, Kraków

Rafał Kucharski

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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**



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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**

past²: 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 in computers



Optimisation

finding optimal value

Problem

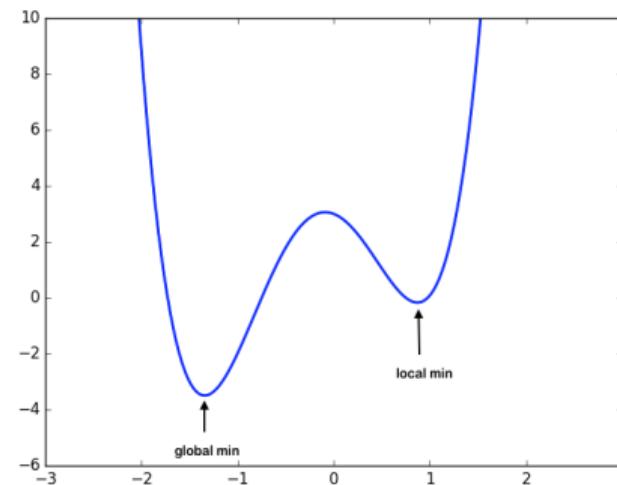
What is the minimal value of the function?

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

where

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

both are **deterministic**.



Optimisation

finding optimal value

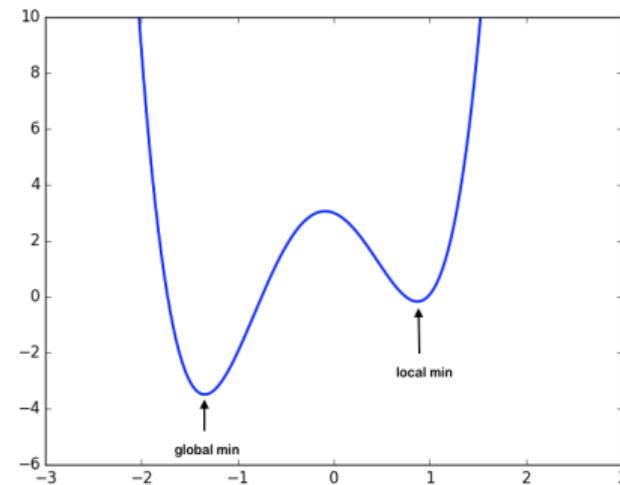
Optimisation

can be:

- policy criterial: $x \rightarrow x, y, \dots,$
- 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

finding optimal value

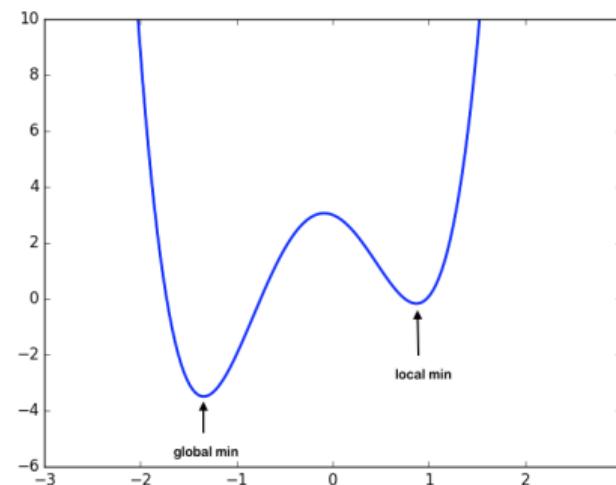
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Computer Science

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Discrete Choice

Path choice

Problem

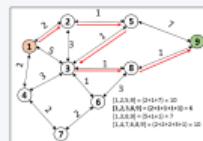
Given a weighted network $G(N, A)$ find a path (sequence of nodes $n \in N$) from origin o to destination d

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 τ :

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

Discrete Choice

Path choice

Problem

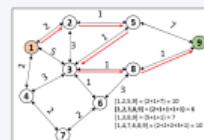
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Behaviour



Discrete Choice

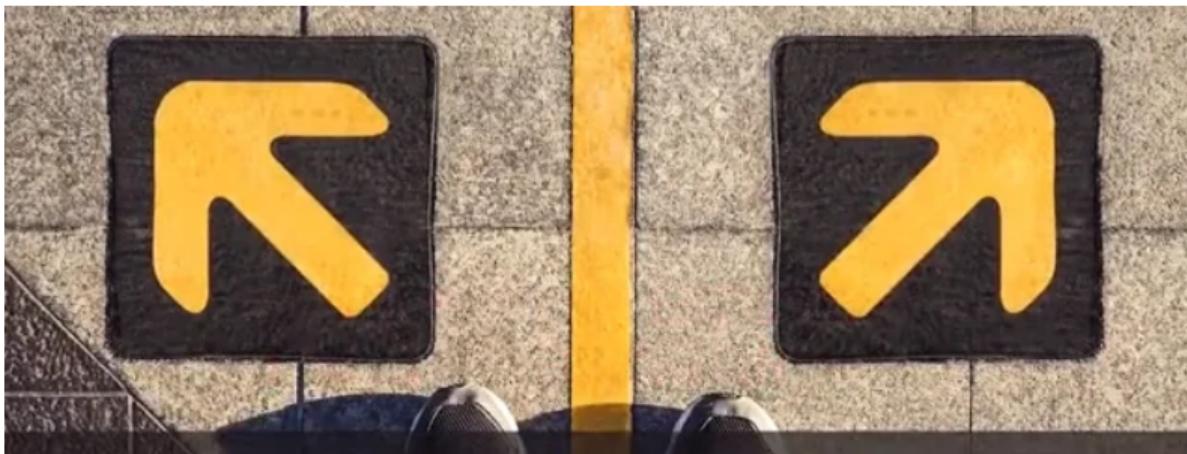
Example

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**

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

β_0 alternative-specific constant, i.e. taste variation, i.e. sentiment

ε random term

β_t value of time (10€/h)

β_c value of money

Rational utility maximisers

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β_c value of money

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

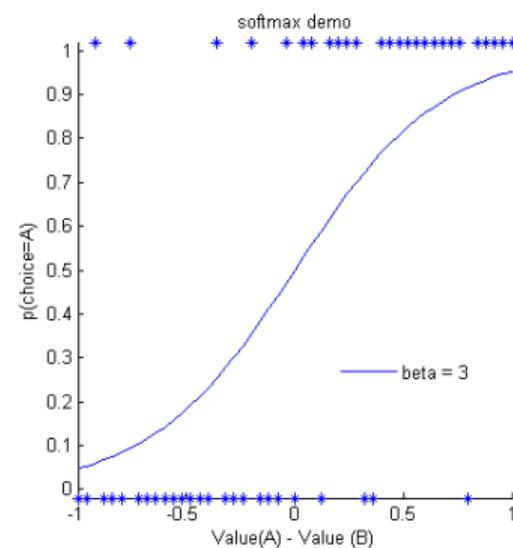
We are different, each of us has its' own:

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

ε 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.

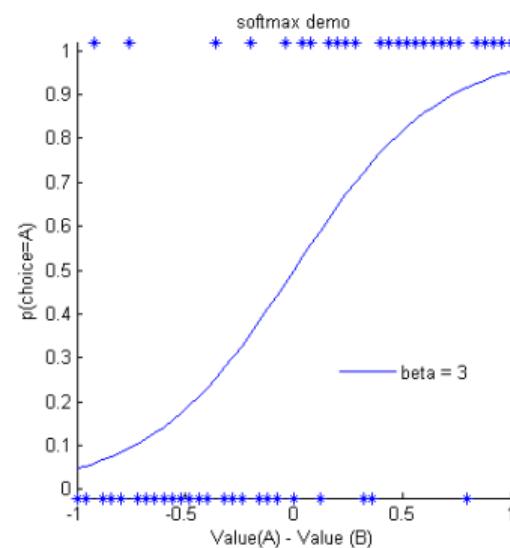
Logit model

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	wttWalk	wttBike	wttCar	wttTransit	odtWalk	odtBike	odtCar	odtTransit	costWalk	costBike	costCar	costTransit	betaWalk	betaBike
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	-0.62497903	-1.119626123
3	1	3	3	0	0	56	65	145	63	1	16	0	0	3	1	-0.643188316	-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	-0.846659563
6	1	6	3	0	0	41	35	48	39	8	22	0	0	3	3	-0.229752721	-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	-0.369889557	-1.261493142
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	-0.63559085
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	-0.491108347	-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	-0.6172338817	-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	-1.014582059
18	2	8	3	0	0	51	51	84	37	0	16	0	0	6	1	-0.433200047	-1.418909935
19	2	9	4	0	0	44	35	531	177	5	15	0	0	9	3	-0.524877465	-0.971677976

Binary classifier

Predict the binary (0/1 value)

Machine Learning

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



Humans in computers
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Behaviour
oooooo

Predict behaviour from digital traces
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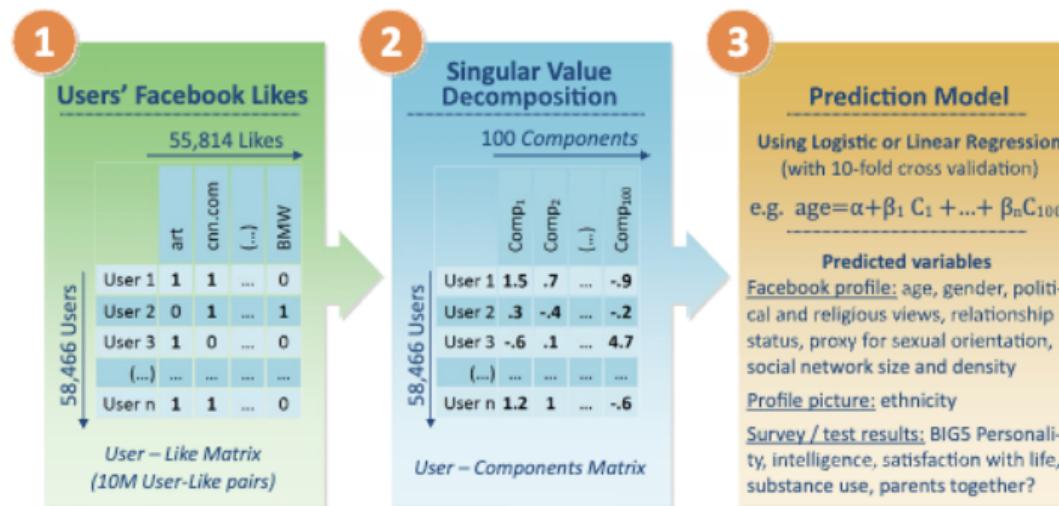
Traffic flow
oooooo

Predict behaviour from digital traces



Internet privacy

What Facebook likes tell about us?¹



¹ 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(1), 5802-5805.

Internet privacy

What Facebook likes tell about us?²

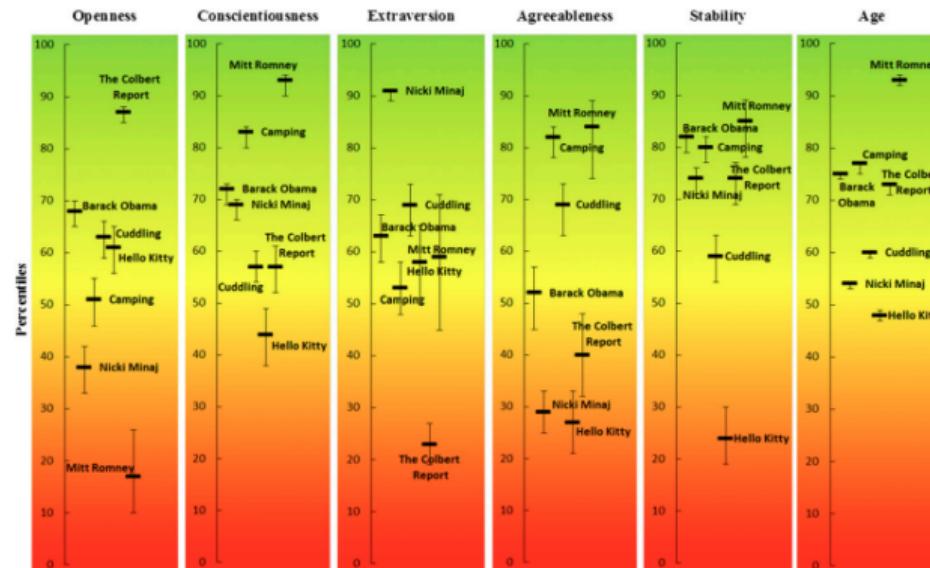


Fig. S1. Average levels of five personality traits and age of the users associated with selected Likes presented on the percentile scale. For example, the average extraversion of users associated with "The Colbert Report" was relatively low: it was lower only for 23% of other Likes in the sample. Error bars signify 95% confidence intervals of the mean.

²Kosinski, 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.

Humans in computers
oooo

Behaviour
oooooo

Predict behaviour from digital traces
ooo

Traffic flow
●ooooo

Traffic flow



Humans in computers

oooo

Behaviour

oooooo

Predict behaviour from digital traces

ooo

Traffic flow

o●oooo

Phantom jam

Let's drive around the circle at constant speed



European Research Council
Financing for the European Union

Phantom jam

Let's drive around the circle at constant speed



Video

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

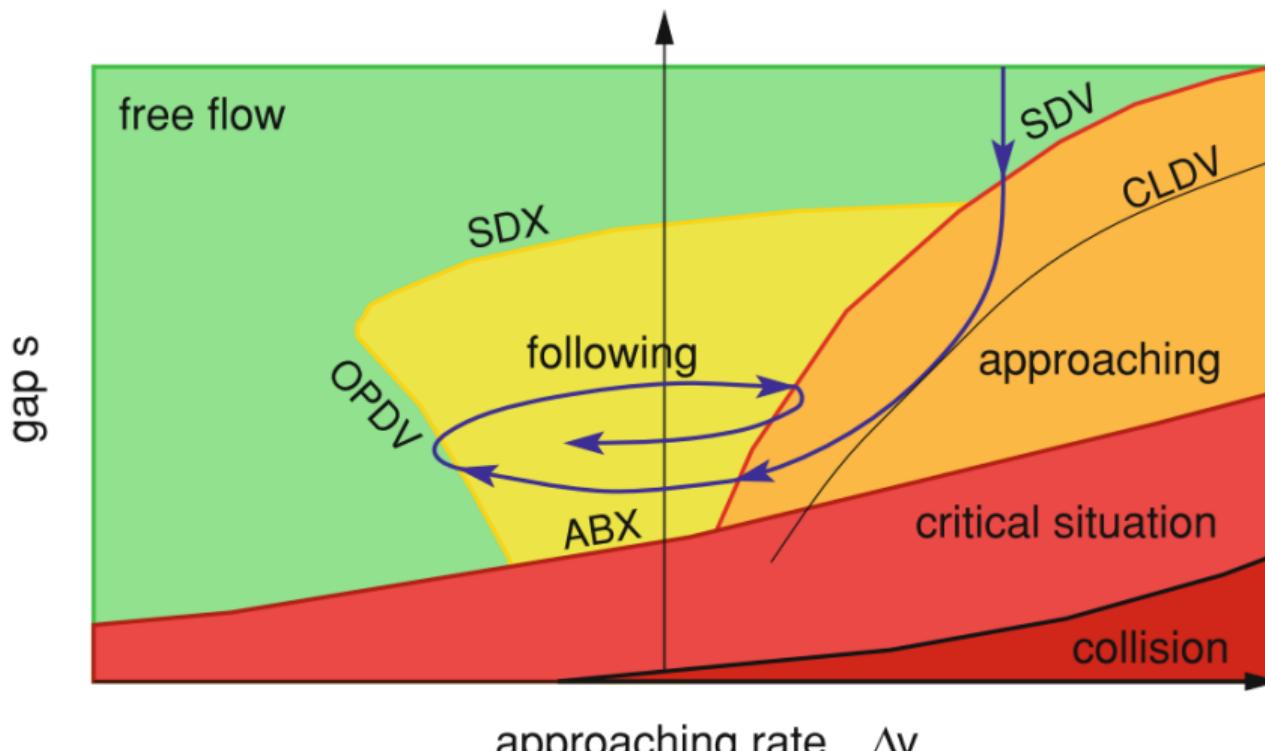
What can go wrong?

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



Humans in computers

oooo

Behaviour

oooooo

Predict behaviour from digital traces

ooo

Traffic flow

oooo●○

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

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