Towards Recommendations for Value Sensitive Sustainable Consumption

Dr. Thomas Asikis
thomas.asikis@uzh.ch

Behavioral Game Theory
University of Zurich

NEURAL INFORMATION PROCESSING SYSTEMS

Climate Change AI

University of Zurich[UZH]

National Centre of Competence in Research Automation

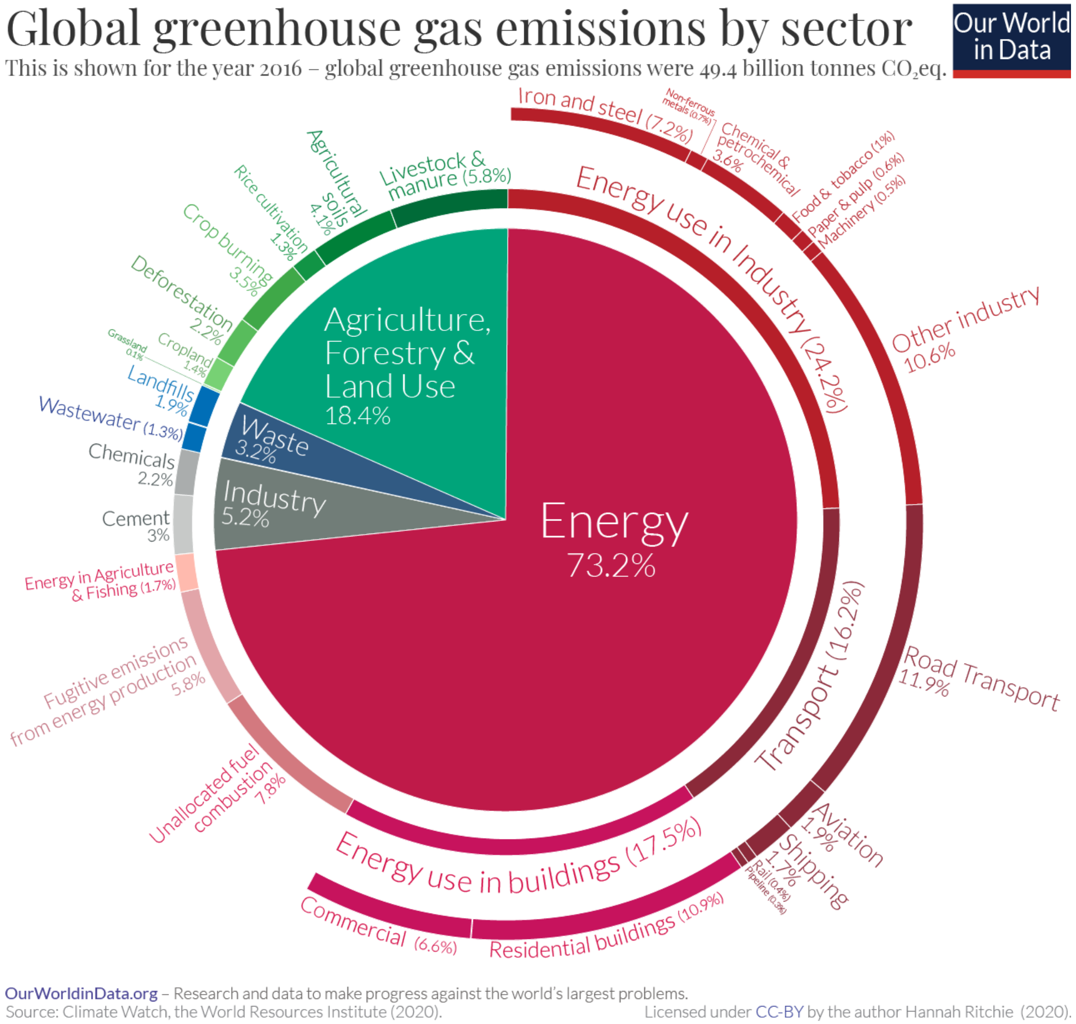
ETH zürich

CoCi

Consumption and Emissions

Source: United Nations
https://sdgs.un.org/goals

Pradhan, Prajal, et al. "A systematic study of sustainable development goal (SDG) interactions." *Earth's Future* 5.11 (2017): 1169-1179.



Additionally:

- Water footprint
- Land use
- Acidification
- Eutrophication

Possible Solution?
From Environmental to Personal Values

A suggestion

Diet with non-animal products, which can reduce by:
~ **76%** land use.
~ **49%** GHG Emissions.
~ **50%** acidification.
~ **49%** eutrophication.
~ **19%** scarcity-weighted freshwater withdrawals.

Personal Values

- Nutrition and budget constraints
- Taste preferences
- Willingness to avoid different foods

A recommender system

- Automation: Recommendation of whole baskets
- Direct personalization: Ability to collect value priorities via surveys.

Poore, Joseph, and Thomas Nemecek. "Reducing food’s environmental impacts through producers and consumers." *Science* 360.6392 (2018): 987-992.
Kurzgesagt: Can YOU Fix Climate Change? https://www.youtube.com/watch?v=yiw6_JakZFc

Experimental Setting

Synthetic dataset:

- Dunnhumby Retailer: Preprocessed the Great Journey
  - 500 households, 82 weeks, 28’400 intended baskets in total.
- Nutrition: FAO Food Balance Sheets
- Environmental Impact: Poore et al 2018.

Simulation:

- Intended vs Recommended baskets:
  - Intended = Historically purchased basket
  - Recommended: Proposed on historically purchased basket.
- Randomly replace 1 out of 4 intended baskets with a recommended one.

Finding “Good” Recommendations

Multi-Objective Mixed Integer Programming

A basket x, of integers (product units)

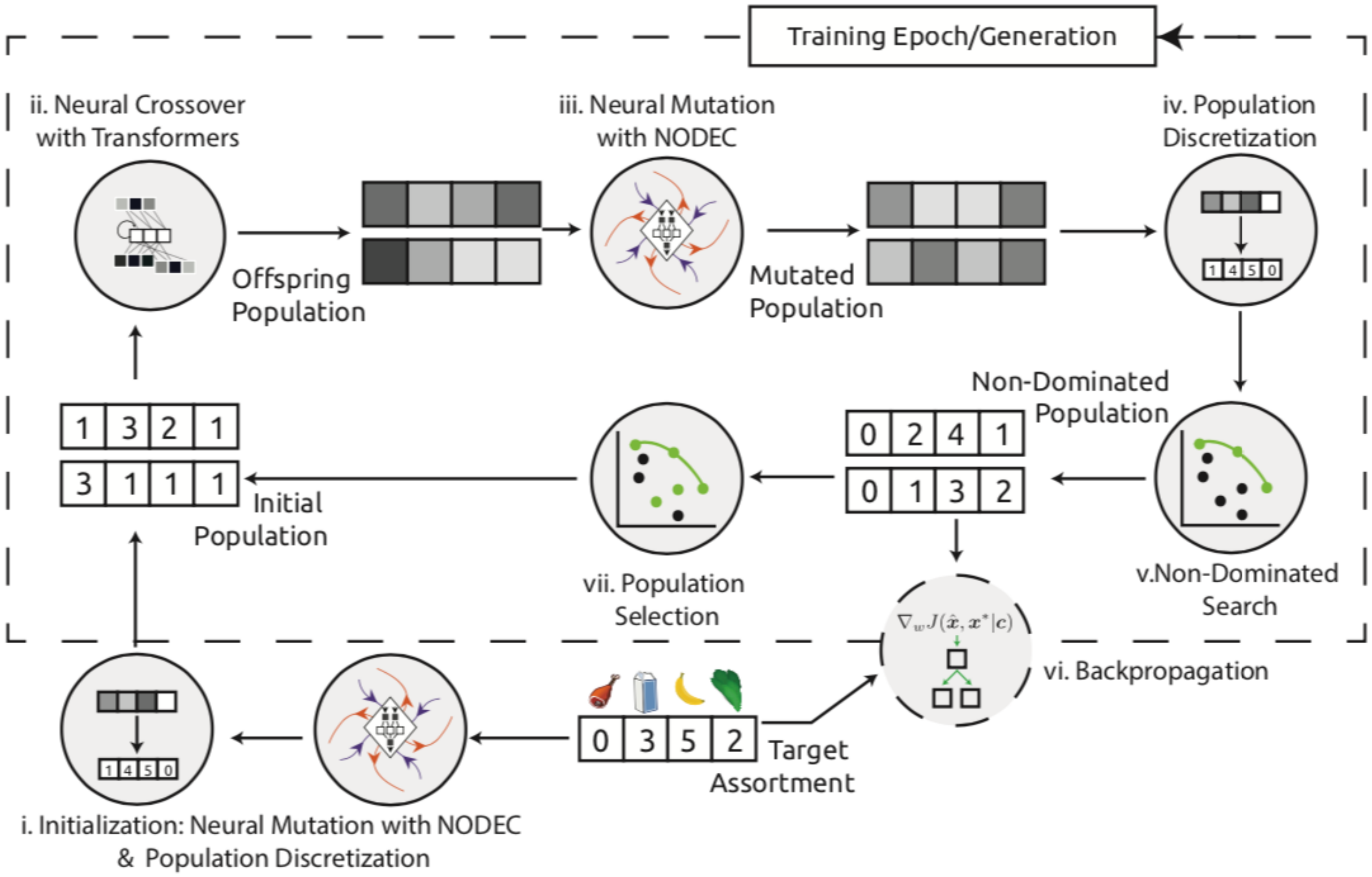
$$x = [3, \ 1, \ 0]$$

Ratio $\rho(x, x^*)$ of recommended basket x value $v(x)$ over intended basket x^* value. $v(x^*)$. Basket values measure:

- calories of recommended basket vs intended basket.
- CO_2 emissions of recommended basket vs intended basket.

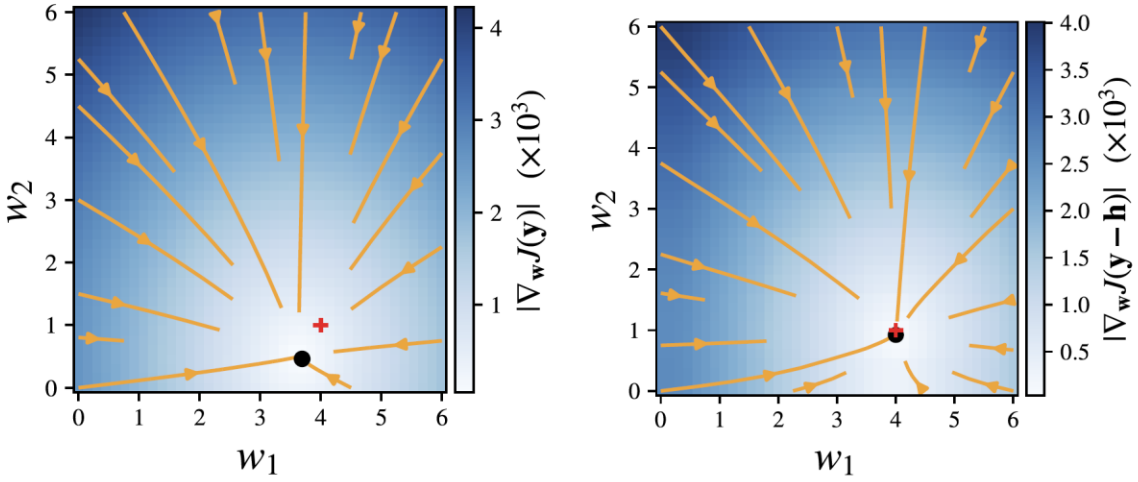
Scope	Feature	Unit	Min. Objective
Taste	Cosine similarity	-	$J_{sim} = 1 - \frac{x^T x^*}{\lVert x \rVert \lVert x^* \rVert}$
	Cost	Dollars (\$)	$J_{cost} = \rho_{cost}(x, x^*)$
Nutrition	Energy	kCal	$J_{nutr} = \left(1 - \rho_{nutr}(x, x^*)\right)^2$
	Protein	grams (g)	
	Fat		
Environmental Impact	GHG emissions	CO_2 kg eq.	$J_{\mathrm{env}} = \rho_{\mathrm{env}}(x, x^*)$
	Acidification	SO_2 kg eq.	
	Eutrophication	PO_4^{3-} kg eq.	
	Land use	m^2	
	Water usage	L	
	Str. Water usage		

Model: Multi-objective Optimization with NNs and Evolutionary Algorithms



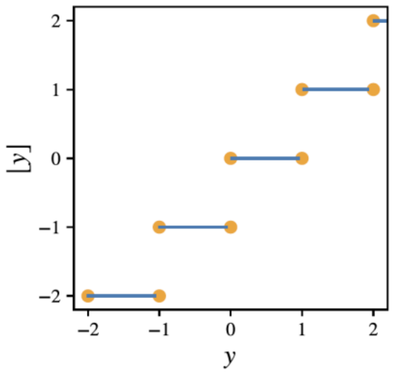
**NODEC: Neural ODE Control*

Fractional Decoupling: A straight-through estimator for integer outputs.



(a) Continuous gradient. (b) Fractional decoupling gradient.

FIGURE C.2: Gradient direction (orange lines), optimal solution (red cross) and lowest gradient norm point (black disk).



$$f(\boldsymbol{x};\boldsymbol{w}) = \boldsymbol{y} - \boldsymbol{h}$$

$$h_i = y_i - \lfloor y_i \rfloor$$

Bengio, Yoshua, Nicholas Léonard, and Aaron Courville. "Estimating or propagating gradients through stochastic neurons for conditional computation." *arXiv preprint arXiv:1308.3432* (2013).

Böttcher, Lucas, Thomas Asikis, and Ioannis Fragkos. "Control of Dual-Sourcing Inventory Systems Using Recurrent Neural Networks." *INFORMS Journal on Computing* (2023).

Why Gradient Guided Genetic Algorithms (G3A)?

- Flexibility and modularity of NNs
  - Backpropagation through optimization instances (e.g. optimize in time).
  - Generalize to unknown samples.
- Extend NNs to MIP efficiently
  - one could also use Gumbel-softmax, but then unbounded problems may be more difficult to tackle.
- Tune gradients with preferences, e.g. scale gradients from each objective proportionally to a preference score from a user.

Similar “non-NN” benchmarks:

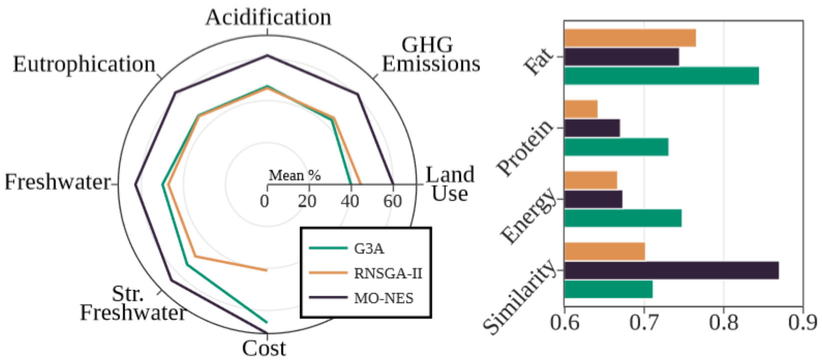
1. MO-NES
(Glasmachers, Tobias, Tom Schaul, and Jürgen Schmidhuber. "A natural evolution strategy for multi-objective optimization." *International Conference on Parallel Problem Solving from Nature*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010.)

2. RNSGA-II
(Deb, Kalyanmoy, and J. Sundar. "Reference point based multi-objective optimization using evolutionary algorithms." *Proceedings of the 8th annual conference on Genetic and evolutionary computation*. 2006.)

Results

- G3A: Better Land Use and nutrition, competitive in most environmental impact categories.
- RNSGA-II: Better Freshwater Usages and Cost, competitive in most environmental impact categories.
- MO-NES: Best Similarity

(a) The mean ratio of quantities between recommended and intended basket.



(b) What do I sacrifice?

Personal Impact: G3A (Intended)	
Cost	35.2 (38.7)
Fat (g)	698 (726)
Protein (g)	911 (971)
Energy (kCal)	25400 (27100)
Added (%)	21
Removed (%)	54

(c) How much do we save?

G3A Environmental Impact	
Land Use (km^2)	1.02
GHG Emissions (kt)	0.35
Acidification (t)	1.16
Eutrophication (t)	1.24
Freshwater (10^7L)	22.8
Str. Freshwater (10^9L)	1.06

Model	Runtime seconds	Emissions kg CO_2 eq.	Mean / Min Improv. kg CO_2 eq.	Mean Optimality (CI) %
G3A (GPU)	1.89 ± 1.22	$(2.07 \pm 1.44)10^{-8}$	31.49 / 0.46	98.0 (97.9, 98.1)
MO-NES (CPU)	0.20 ± 0.01	$(2.16 \pm 0.14)10^{-9}$	21.03 / 0.41	94.8 (94.6, 94.9)
RNSGA-II (CPU)	0.46 ± 0.06	$(6.95 \pm 2.41)10^{-10}$	34.04 / 0.45	98.6 (98.5, 98.6)

Conclusions

- Multi-objective optimization recommendations can assist in decreasing environmental impact of consumption.
  - ➢ Focus on respecting personal preferences.
- Relative, low-medium adaption (25%) could yield considerable improvements, across various benchmarks.
  - ➢ Different benchmarks - different “best” solution profiles.

Steps forward: improve dataset, perform field-tests, improve benchmarks.

Looking forward to discussions!

References

- Tomkins, S., Isley, S., London, B. & Getoor, L. Sustainability at scale: towards bridging the intention-behavior gap with sustainable recommendations. In Proceedings of the 12th ACM Conference on Recommender Systems, 214–218 (ACM, 2018).
- Tobias Glasmachers, Tom Schaul, and Jürgen Schmidhuber. “A natural evolution strategy for multi-objective optimization”. In: International Conference on Parallel Problem Solving from Nature. Springer. 2010, pp. 627–636.
- Deb, Kalyanmoy, and J. Sundar. "Reference point based multi-objective optimization using evolutionary algorithms." Proceedings of the 8th annual conference on Genetic and evolutionary computation. 2006.
- Ricardo Abejón et al. “Multi-Objective Optimization of Nutritional, Environmental and Eco-nomic Aspects of Diets Applied to the Spanish Context”. In: Foods 9.11 (2020), p. 1677.
- Hui Lu et al. “The effects of using chaotic map on improving the performance of multiobjective evolutionary algorithms”. In: Mathematical Problems in Engineering 2014 (2014).
- Poore, Joseph, and Thomas Nemecek. "Reducing food’s environmental impacts through producers and consumers." *Science* 360.6392 (2018): 987-992.
- Asikis, Thomas, Lucas Böttcher, and Nino Antulov-Fantulin. "Neural ordinary differential equation control of dynamics on graphs." *Physical Review Research* 4.1 (2022): 013221.
- Böttcher, Lucas, Thomas Asikis, and Ioannis Fragkos. "Control of Dual-Sourcing Inventory Systems Using Recurrent Neural Networks." *INFORMS Journal on Computing* (2023).
- Bengio, Yoshua, Nicholas Léonard, and Aaron Courville. "Estimating or propagating gradients through stochastic neurons for conditional computation." *arXiv preprint arXiv:1308.3432* (2013).
- Pradhan, Prajal, et al. "A systematic study of sustainable development goal (SDG) interactions." *Earth's Future* 5.11 (2017): 1169-1179.