Tutorial on

Human-Centered and Sustainable Recommender Systems

https://giuspillo.github.io/umap25_sustainable_recsys_tutorial/

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Tutorial Outline

1. Introduction to Sustainability in Recommender Systems
2. Recommender Systems for Sustainability
3. Sustainability of Recommender Systems
4. Discussion and Closing Remarks

Motivation

What is sustainable development?

“Development that meets the needs of the present without compromising the ability of future generations to meet their own needs”

the globally accepted definition adopted in 1987 at the World Commission on Environment and Development

Motivation

The 2030 agenda for sustainable development

It contains the **17 Sustainable Development Goals (SDGs)**, which are an urgent call for action by all countries - developed and developing - in a global partnership.

https://sdgs.un.org/2030agenda

Motivation


WHAT DOES
SUSTAINABILITY
MEAN?

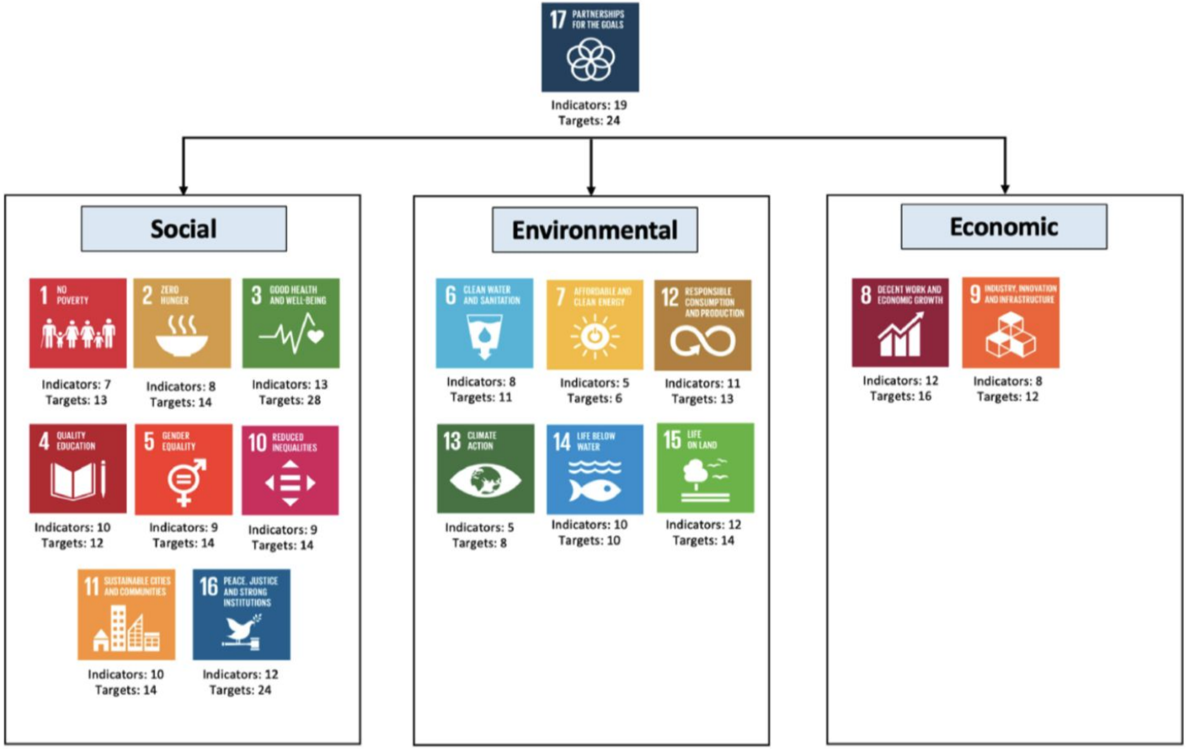

AGENDA
2030


Three pillars of
Sustainability
Social
Meeting the needs of people today and future generations
Environmental
Protecting the well-being of the environment and our resources
Economic
Ensuring financial stability and growth for now and the future

Motivation

https://sdgs.un.org/goals

Motivation



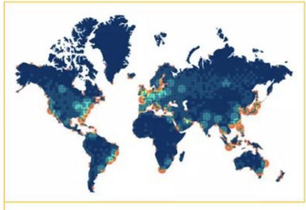
M. Regona, et al. **Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry.** SCS, page 105499, 2024.

Motivation

It is misleading to consider the pillars in isolation, as each Sustainable Development Goal **often impacts multiple pillars simultaneously**.

Motivation

AI4SDGs Cooperation Network



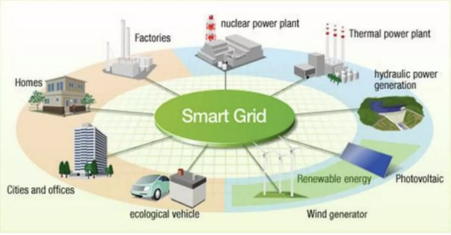
Satellite images analytics and Agro-meteorological monitoring

Predictive Healthcare

(analyzes historical data to prevent future target events)

Personalized Learning

- **Smart renewable energy grids**



Is AI always an accelerator for the Sustainable Development Goals?

Our Vision

Van Wynsberghe, A. "Sustainable AI: AI for sustainability and the sustainability of AI." *AI and Ethics* 1.3 (2021): 213-218

Our Vision

Which can be the connection with Sustainability and **Recommender systems**?

Why Recommender Systems?

Recommender Systems (RS) are AI technologies that:

- handle the information overload by providing **personalized item lists**
- support the everyday **decision-making process**

Recommender systems have always been designed to influence choices.

Now, **sustainability goals** indicate how to **guide these choices**.

Why Recommender Systems?

RS can be very effective in **actively promoting sustainable behaviors** and societal good

RS for tailored healthy food recommendations

3 GOOD HEALTH AND WELL-BEING

Tourism RS for Sustainable City Trips

11 SUSTAINABLE CITIES AND COMMUNITIES

RS for Personalised Learning Experiences

4 QUALITY EDUCATION

RS for Promoting Virtuous Energy Consumption Behaviors

7 AFFORDABLE AND CLEAN ENERGY

ECONOMIC

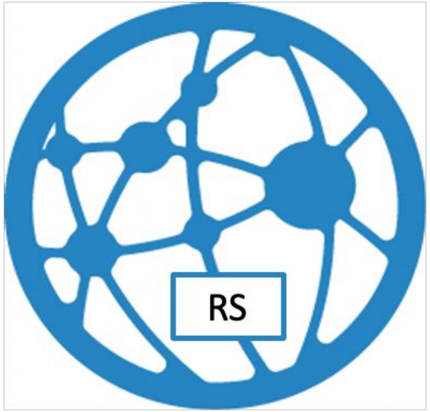
ENVIRONMENTAL

SOCIAL

Our Vision for RS

RS for Sustainability

A wide range of applications already exists



Our Vision for RS

De Filippo et al., ***Recommender Systems and Sustainability: a Dual Perspective***, submitted to Computer Science Review Journal

Our Vision for RS

What are we doing in this research direction?

- **First International Workshop on** «Recommender Systems for Sustainability and Social Good», co-located with RecSys 2024

- Contribution to the current literature:
  - **published volume** on «Recommender Systems for Sustainability and Social Good» (Springer, CCIS Series)
  - **published (and under review) papers** on different techniques to reduce the environmental and social impact of RS

RecSoGood Workshop

UMAP25 NYC

RecSoGood

First International Workshop on Recommender Systems for Sustainability and Social Good

co-located with RecSys 2024

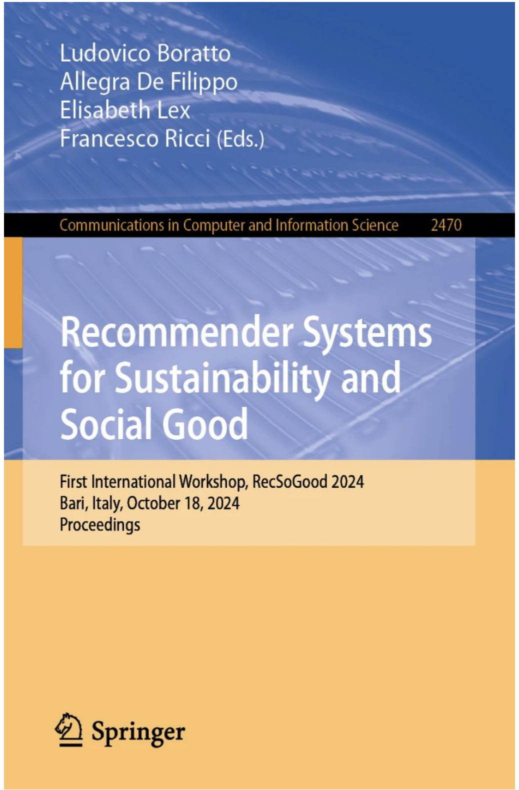
The ACM Conference Series on **Recommender Systems**

SCAN ME!

Next Edition

RecSys 2025

RecSoGood Volume



Our current works on RS and Sustainability

1. G. Spillo, A. De Filippo, et al. Training Green and Sustainable Recommendation Models: Introducing **Carbon Footprint Data into Early Stopping Criteria**. In ACM **UMAP, 2025**.

2. G. Spillo, A. De Filippo, et al. Towards green recommender systems: Investigating the impact of **data reduction on carbon footprint** and algorithm performances. In ACM **RecSys, 2024**.

3. G. Balloccu, L. Boratto, et al. Knowledge Data Modeling in Food Recommendation: A **Case Study on Nutritional Values**. In **Springer RecSoGood** volume, **2024**.

4. G. Spillo, A. De Filippo, et al. RecSys CarbonAtor: **Predicting Carbon Footprint of Recommendation** System Models. In **Springer RecSoGood** volume, **2024**.

5. L. Boratto, et al. Practical perspectives of consumer **fairness** in recommendation. **Information Processing & Management**, 60(2):103208, **2023**.

6. G. Spillo, A. De Filippo, et al. Towards sustainability-aware recommender systems: analyzing the **trade-off between algorithms performance and carbon footprint**. In ACM **RecSys, 2023**.

What will we learn today?

1. RS for Sustainability

How can recommender systems be designed to not just reflect user preferences, but **to actively promote sustainable behaviors and societal good**?

2. Sustainability of RS

What are the hidden **environmental and ethical costs** of deploying large-scale recommender systems, and how can we redesign them to **align with sustainability principles**?

3. The Dual Perspective

Can we envision a future where recommender systems **both enable sustainable choices and are themselves sustainable**, without compromising performance or user experience?

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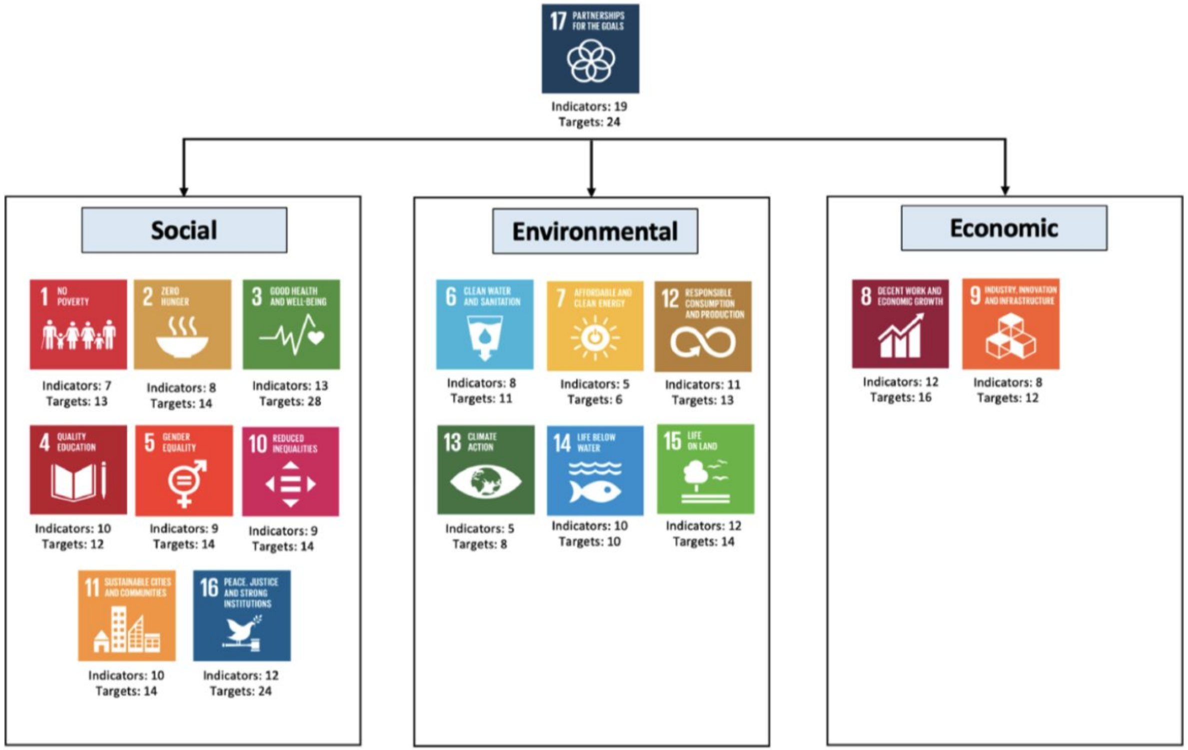
1. RS for Sustainability

How can recommender systems be designed to not just reflect user preferences, but **to actively promote sustainable behaviors and societal good**?

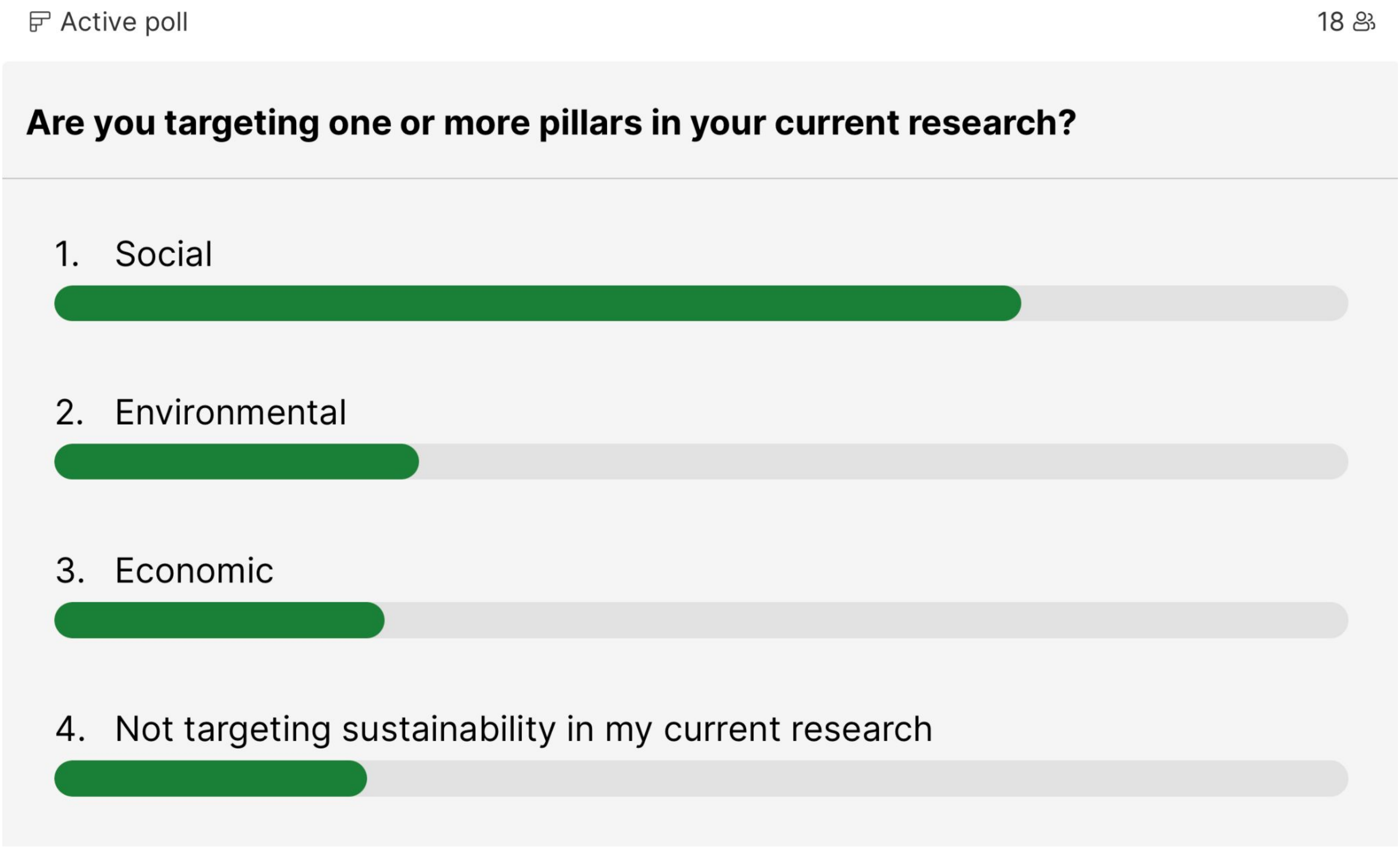
SDGs and the Three Pillars



M. Regona, et al. **Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry.** SCS, page 105499, 2024.

Question time!

Are you targeting one or more pillars in your current research?


Active poll
18
Are you targeting one or more pillars in your current research?
1. Social
2. Environmental
3. Economic
4. Not targeting sustainability in my current research

Social pillar

01	Equity and inclusivity	5 GENDER EQUALITY; 10 REDUCED INEQUALITIES
02	Well-being	3 GOOD HEALTH AND WELL-BEING
03	Education and Empowerment	4 QUALITY EDUCATION
04	Poverty and Hunger	1 NO POVERTY; 2 ZERO HUNGER
05	Urban Inclusion	11 SUSTAINABLE CITIES AND COMMUNITIES
06	Justice and Institutions	16 PEACE, JUSTICE AND STRONG INSTITUTIONS

Environmental pillar

UMAP25 NYC

01	Resource preservation	6 CLEAN WATER AND SANITATION; 7 AFFORDABLE AND CLEAN ENERGY; 12 RESPONSIBLE CONSUMPTION AND PRODUCTION
02	Ecological footprint reduction	7 AFFORDABLE AND CLEAN ENERGY; 12 RESPONSIBLE CONSUMPTION AND PRODUCTION
03	Climate change mitigation	13 CLIMATE ACTION
04	Marine ecosystem protection	14 LIFE BELOW WATER
05	Terrestrial biodiversity	15 LIFE ON LAND

Economic pillar

01	Economic growth and employment	8 DECENT WORK AND ECONOMIC GROWTH
02	Industrial innovation	9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
03	Efficiency in production/consumption	9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

RS for Sustainability

Refers to systems designed to **support SDGs through recommendation**

Actionability → **Individual and organizational levels**

External impact → **Behaviors and decisions**

Alignment with the broader vision of “AI for Sustainability”

RS for Social Sustainability

Social pillar targets	• Equity • Well-being • Access to resources
Decision support by RS	• Poverty • Health • Education
Impact	• Gender equality • Inclusive cities

De Filippo et al., ***Recommender Systems and Sustainability: a Dual Perspective***, submitted to Computer Science Review Journal

Examples of RS for Social Sustainability

SDG 1 — **Poverty**

Export diversification via RS supporting latent competitiveness

SDG 2 — **Hunger**

RS aid crop disease detection and food rescue logistics.

SDG 3 — **Health**

Health communication and well-being recommendations

N. Che. Intelligent export diversification: An export recommendation system with machine learning. IMF Working Paper, 2020.

A. Ahmad, et al. A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. Smart Agricultural Technology, 3:100083, 2023

Z. Shi, et al. Predicting and presenting task difficulty for crowdsourcing food rescue platforms. In ACM Web Conf., pages 4686–4696, 2024

J.N. Cappella, et al. Critical considerations for using cultural targeting and tailoring in health communication interventions. Health Communication, pages 1–12, 2024

Examples of RS for Social Sustainability

SDG 4 — **Education**

Adaptive learning paths via AI personalization

SDG 5/10 — **Equity**

Reduce bias in job recruitment and lending

SDG 11 — **Urban Inclusion**

Guide tourists and planners toward sustainable options

SDG 16 — **Justice**

Aid legal analysis and misinformation prevention

A.Y. Huang, et al. ***Effects of artificial intelligence–enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom***. Computers & Education, 2023

C. Meng, et al. ***Dfrp: A dual-track feedback recommendation system for educational resources***. In IJCAI, 2024

T. Bogers, et al. ***Fourth workshop on recommender systems for human resources (recsys in hr 2024)***. In ACM RecSys, 2024

K. Sivamayilvelan, et al. ***Flexible recommendation for optimizing the debt collection process based on customer risk using deep reinforcement learning.*** Expert Systems with Applications, 2024

A. Banerjee. ***Fairness and sustainability in multistakeholder tourism recommender systems***. In ACM UMAP, 2023

P. Merinov. ***Sustainability-oriented recommender systems***. In ACM UMAP, 2023

J. Dhanani, et al. ***Legal document recommendation system: A cluster based pairwise similarity computation.*** Journal of Intelligent & Fuzzy Systems, 2021

D. Sallami, et al. ***Trust-based recommender system for fake news mitigation.*** In ACM UMAP, 2023

Case study
Health and Well-being Recommendations

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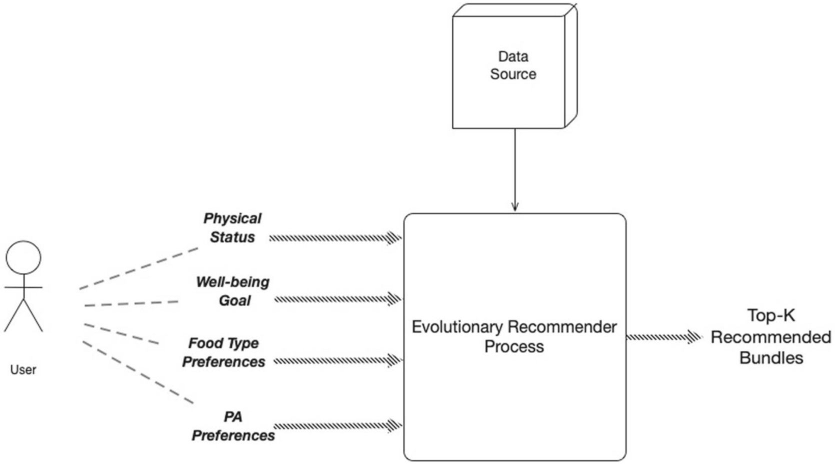
EvoRecSys

- RS for personalized health support
- Evolutionary algorithms for healthy lifestyle choices
- Balances individual preferences with public health objectives (SDG 3)
- Nudge sustainable behaviors



H. Alcaraz-Herrera, J. Cartlidge, Z. Toumpakari, et al. ***Evorecsys: Evolutionary framework for health and well-being recommender systems.*** UMUAI, 32(5):883–921, 2022

RS for Environmental Sustainability

Environmental pillar targets	• Preservation • Sustainable resource use
Decision support by RS	• Energy and water savings • Reduce waste • Support biodiversity
Impact	• Responsible habits • Local environmental action

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Examples of RS for Environmental Sustainability

UMAP25 NYC

SDG 6 — **Water**
Sanitation planning and personalized water use

SDG 7 — **Energy**
Energy-saving tips, tailored to user profiles

SDG 12 — **Consumption**
Promote green fashion and circular reuse

F. Magalhaes Filho, et al. ***Sustainable sanitation management tool for decision making in isolated areas in brazil.*** IJRPH, 16(7):1118, 2019

D. Arsene, et al. ***Decision support strategies for household water consumption behaviors based on advanced recommender systems.*** water 2023, 15, 2550, 2023

V. Riabchuk, et al. ***Utility-based context- aware multi-agent recommendation system for energy efficiency in residential buildings.*** Information Fusion, 112:102559, 2024

S.Yuksel, e tal. ***An Integrated Expert Recommender system approach to environmental service priorities in renewable energy.*** Env. Research Communications, 6(9):095001, 2024

A. Cossatin, et al. ***Promoting green fashion con- sumption through digital nudges in recommender systems.*** IEEE Access, 2024

G. van Capelleveen, et al. ***Toward building recommender systems for the circular economy: Exploring the perils of the european waste catalogue***. Journal of env. man., 277:111430, 2021

Examples of RS for Environmental Sustainability

SDG 13 — **Climate**

Reduce emissions via local energy clustering and VR-based awareness tools

SDG 14 — **Marine ecosystems**

RS for aquaculture and illegal fishing alerts

SDG 15 — **Terrestrial biodiversity**

RS-based anti-poaching systems

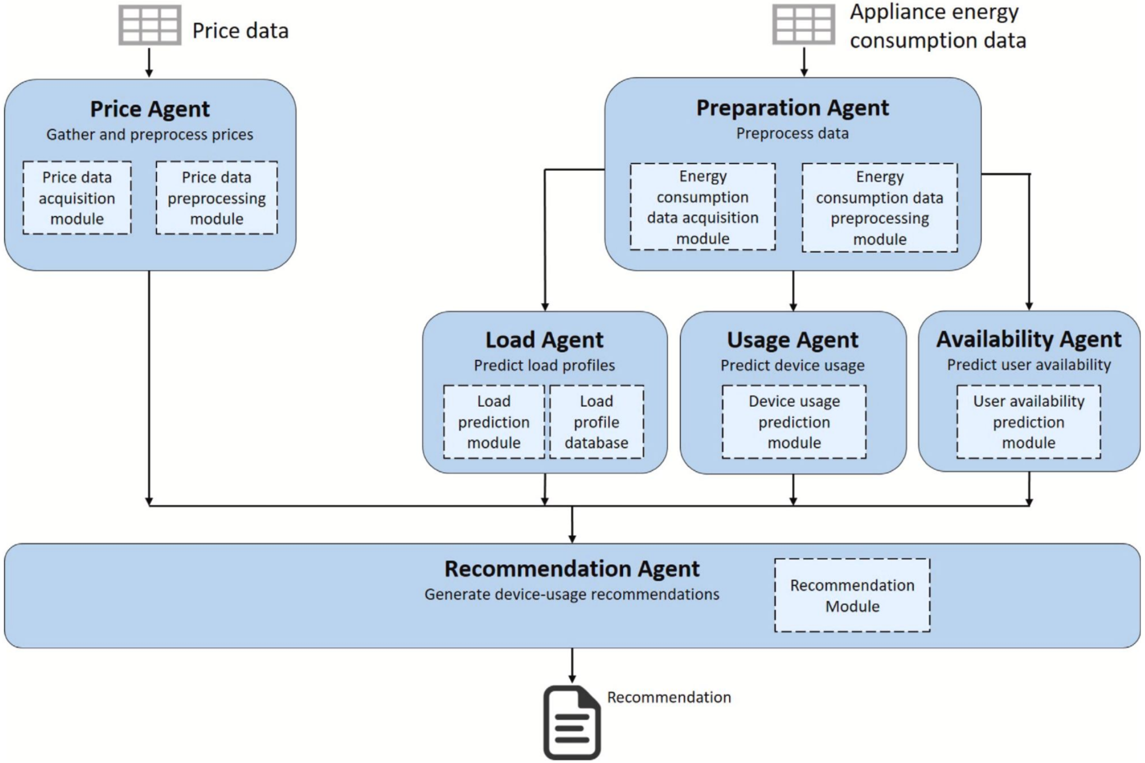
S. Zhang, et al. ***Personalized recommendation algorithm based on electricity users' usage behavior portrait.*** In IET, number 21, pages 89–98. IET, 2024

A. Clocchiatti, et al. ***Vr4green-walk through the (visual) effects of climate change.*** In SIGCHI, pages 1–3, 2023

M. Praba, et al. ***Smart fish farming recommendation system using k-means algorithm.*** In Confluence, pages 333–338. IEEE, 2023

P. Mitra, et al. ***Info-wild: Knowledge extraction and management for wildlife conservation.*** In CIKM, pages 5281–5284, 2023

Case study
Personalized Energy Efficiency



Multi-agent, context-aware RS for SDG 7

Household data analysis for tailored energy-saving actions

Context-awareness for sustainable behavior at scale

V. Riabchuk, et al ***Utility-based context-aware multi-agent recommendation system for energy efficiency in residential buildings.*** Information Fusion, 2024

RS for Economic Sustainability

Economic pillar targets	• Work • Innovation • Sustainable production
Decision support by RS	• Identify jobs • Match skills • Foster industry innovation
Impact	• Sustainable consumption choices

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Examples of RS for Economic Sustainability

SDG 8

Jobs and Innovation

RS support open innovation and workforce collaboration

SDG 9

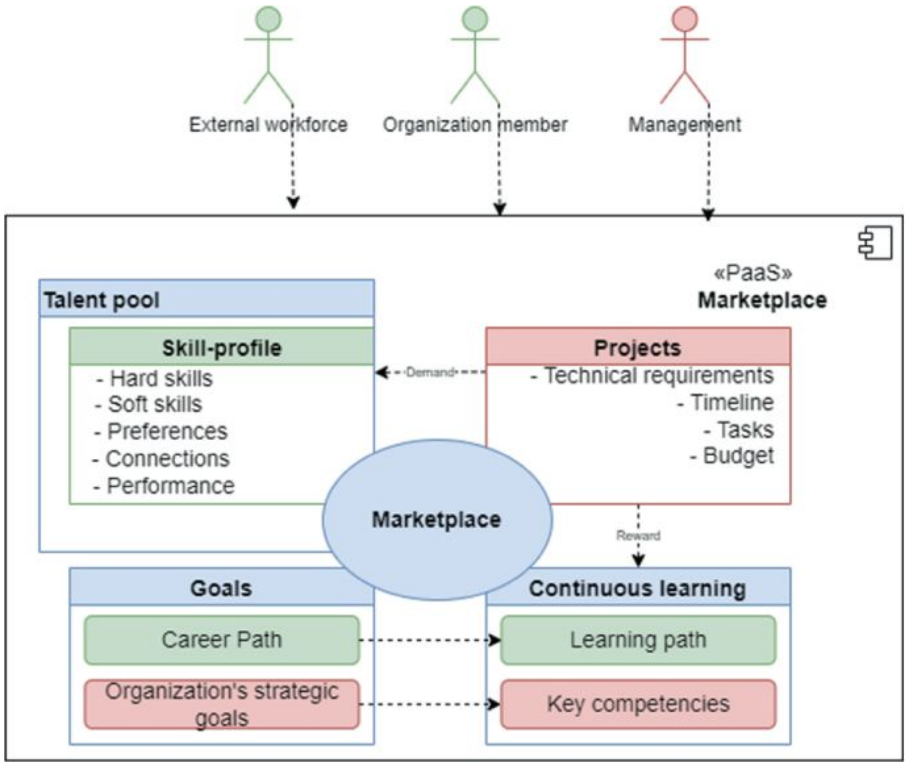
Industry

RS help industries reduce impact and close skill gaps

J. Konstan, et al. ***Recwork: Workshop on recommender systems for the future of work***. In ACM RecSys, pages 675–677, 2022.

E.L. Zickler, et al. ***A recommender system to close skill gaps and drive organisations' success.*** In IBICA, pages 806–815. Springer, 2022

Case study
RS for Sustainable Innovation in Industry



RS to support industrial sustainability (SDG 8)

Open innovation by matching companies w/sustainable solutions

Aligns operational needs with global sustainability goals

H. Fayed and V. Wohlgemuth. ***Design of a recommender system to improve the environmental impact of companies based on their material and energy balances.*** EnviroInfo, 2023

Toward Cross-Pillar RS

SG3 +	SG12 →	Healthy and sustainable food recommendation
SG7 +	SG11 →	Inclusive and low carbon footprint tourism recommendation

A. Petruzzelli, et al. ***Recommending healthy and sustainable meals exploiting food retrieval and large language models.*** In ACM RecSys, page 1057–1061, 2024

Open Issues and Limitations

1	Lack of real-world deployment
2	How do RS impact SDGs?
3	Need stronger interdisciplinary validation
4	Better evaluation frameworks

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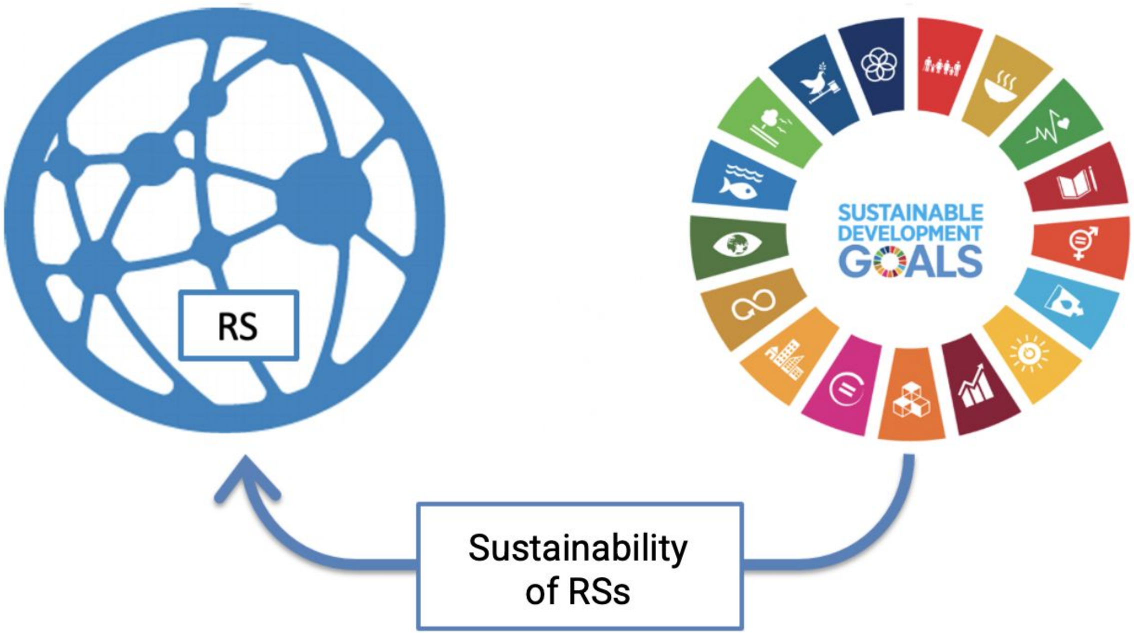
Sustainability of RS



Sustainability of RS

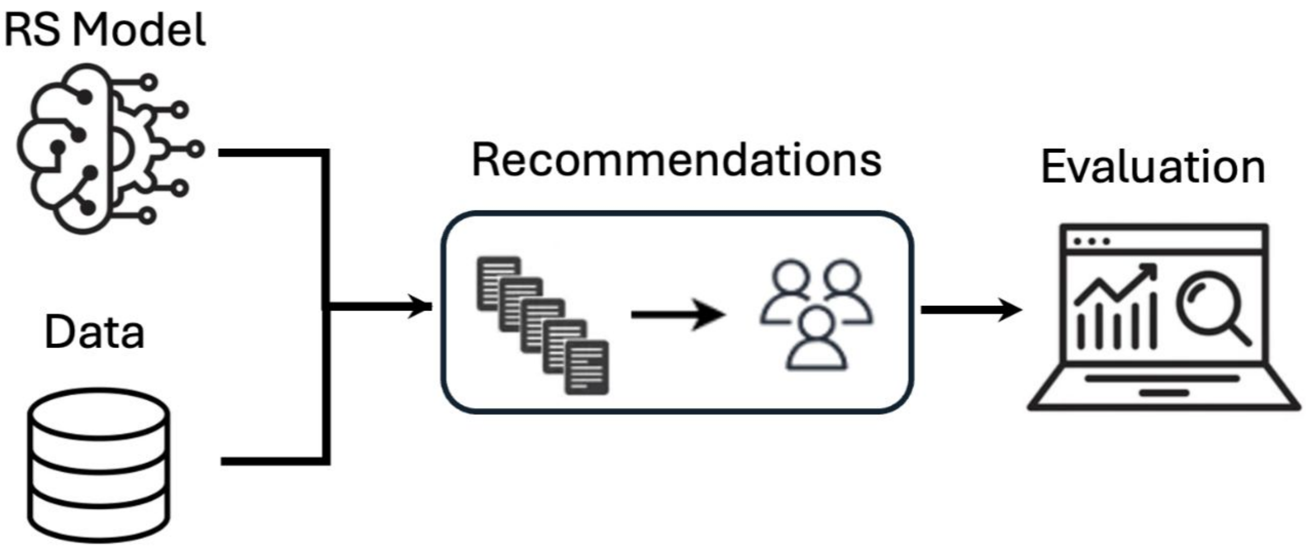
Can SDGs support the design and the development of Recommender Systems?

Sustainability of RS

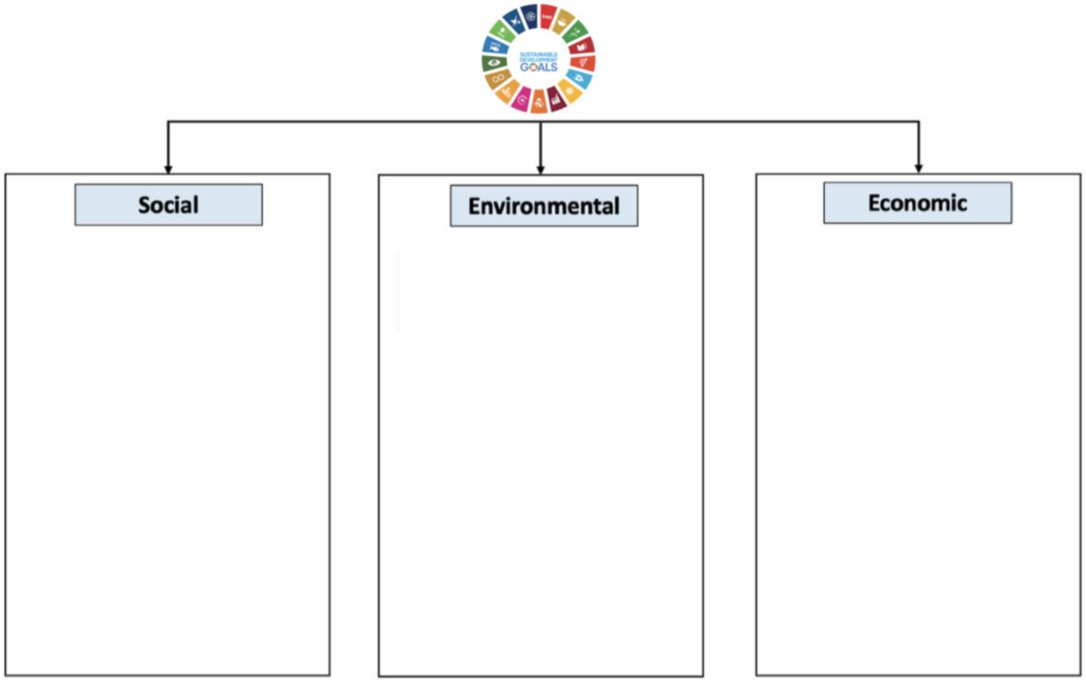
- Designing and developing of **RSs should follow the SGDs** as well *(Van Wynsbergh)*

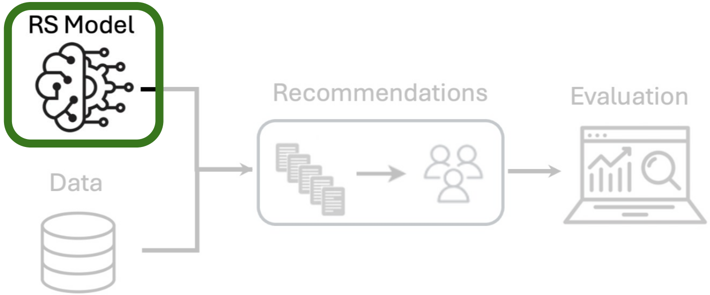
- We focus **not only on accuracy**, but also on **beyond-accuracy** *(Kaminskas et al.)*
  - diversity, fairness, transparency, environmental impact

Sustainable RS lifecycle

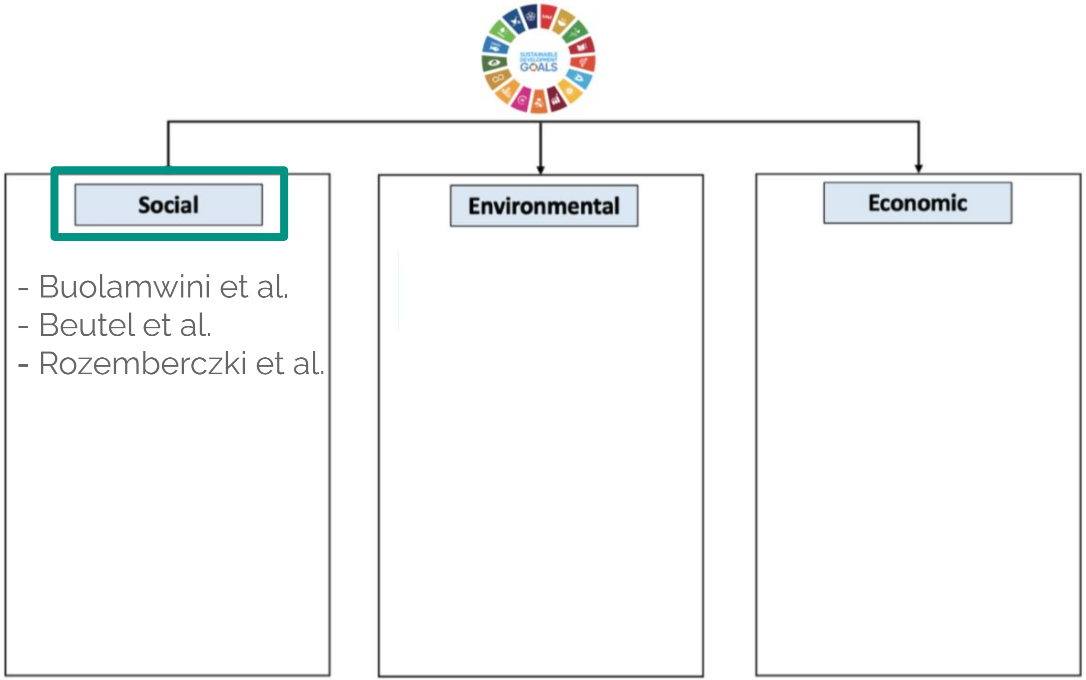


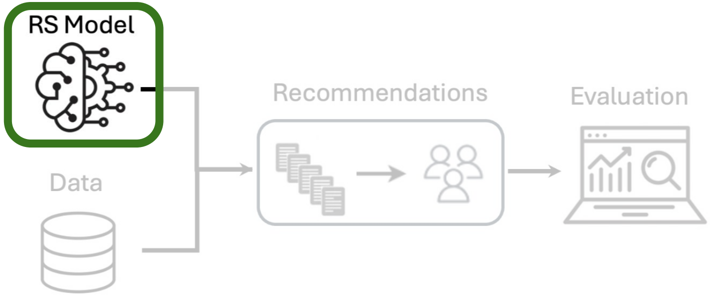
Design of RS models





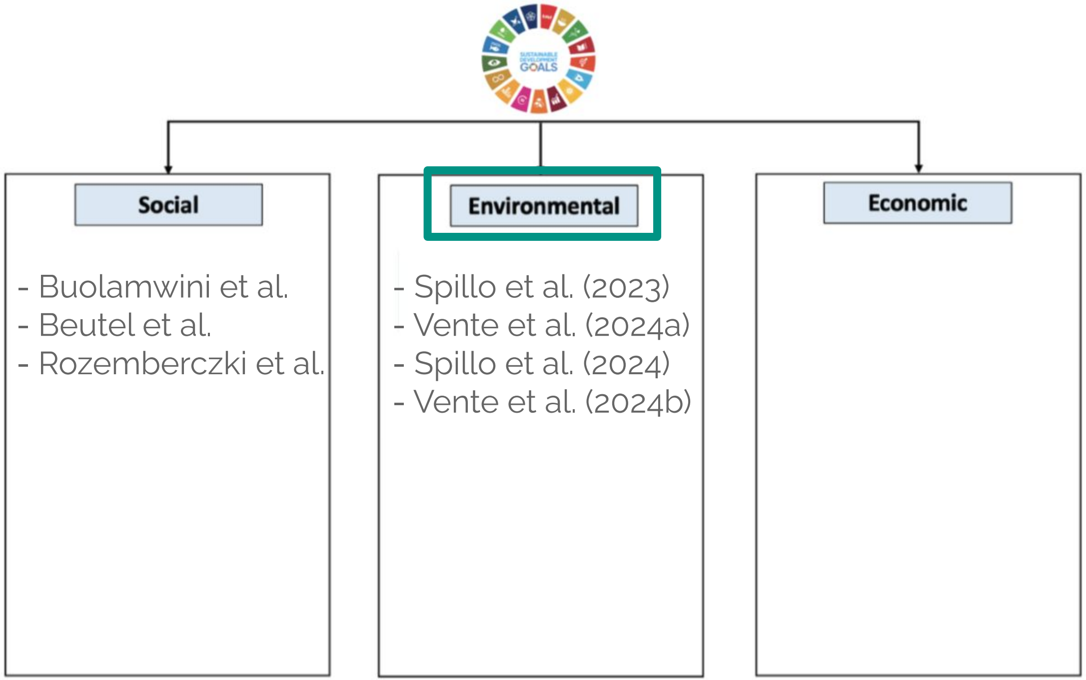
Design of RS models

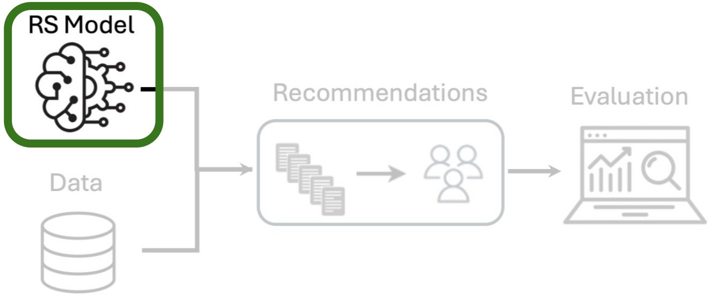




- Loss function tweaks to reduce the correlation between sensitive attributes and predicted ratings
    - *Buolamwini et al.*
    - *Beutel et al.*
- Maximize diversity in item exposure
    - *Rozemberczki et al.*

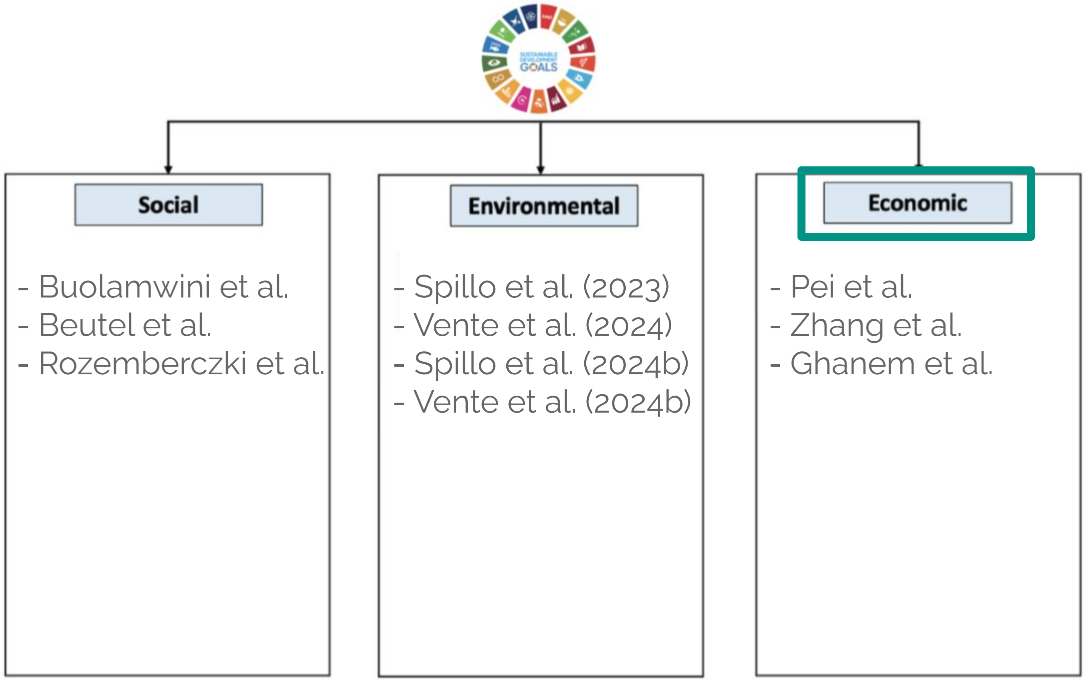
Design of RS models

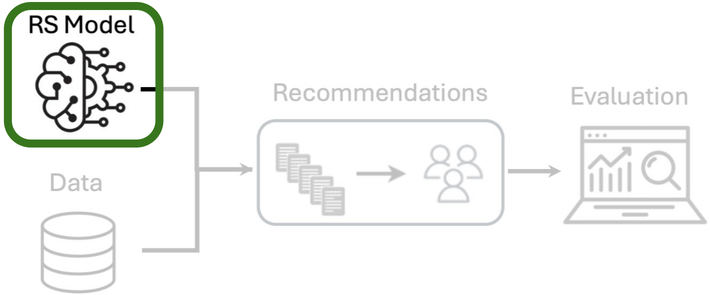




- Benchmark environmental impact of RSs
  - *Spillo et al. (2023)*
  - *Vente et al. (2024a)*
- Use efficient hardware
  - *Vente et al. (2024b)*
- Predict RS carbon footprint
  - *Spillo et al. (2024)*

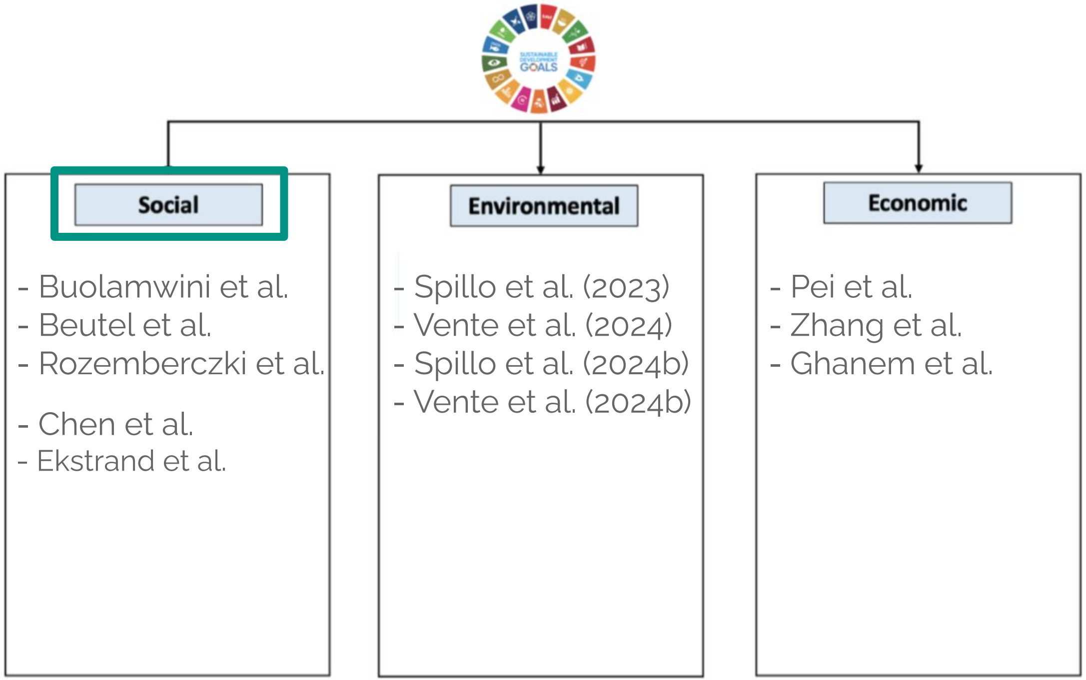
Design of RS models





- Profit maximization
  - *Pei et al.*
- Satisfaction maximization
  - *Zhang et al.*
- Balance consumer utility and profitability provide the highest long-term benefits
  - *Ghanem et al.*

Dataset processing



- Reduce biases in the dataset by resampling or augmentation
  - *Chen et al.*
  - *Ekstrand et. al*

Dataset processing

Social

- Buolamwini et al.
- Beutel et al.
- Rozemberczki et al.

- Chen et al.
- Ekstrand et al.

Environmental

- Spillo et al. (2023)
- Vente et al. (2024)
- Spillo et al. (2024)
- Vente et al. (2024b)

- Spillo et al. (2024b)
- Baumgart et al.

Economic

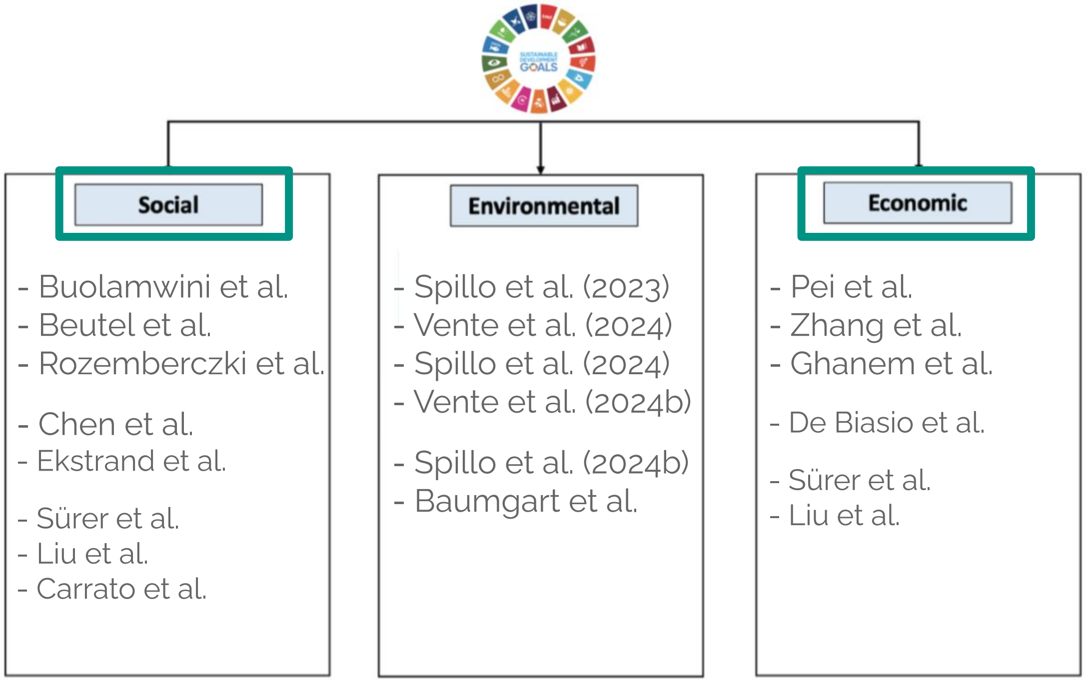
- Pei et al.
- Zhang et al.
- Ghanem et al.

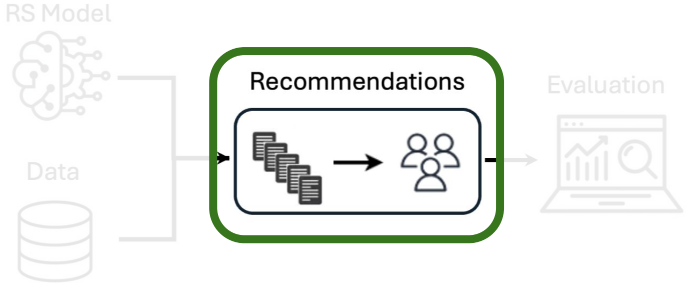
- De Biasio et al.

- Training the model on a smaller set of data
  - *Spillo et al.*
  - *Baumgart et al.*

- Identification of economically valuable item feature
  - *De Biasio et al.*

Recommendation list processing





- Improve item coverage and guarantee minimum item exposure
  - *Sürer et al.*
  - *Carraro et al.*
- Users inclined to some items are more exposed to that type
  - *Liu et al.*
- **No works on environmental pillar**

Evaluation

Social

- Buolamwini et al.
- Beutel et al.
- Rozemberczki et al.

- Chen et al.
- Ekstrand et al.

- Sürer et al.
- Carrato et al.
- Liu et al.

- Dinnissen et al.

Environmental

- Spillo et al. (2023)
- Vente et al.
- Spillo et al. (2024)
- Arabzadeh et al.

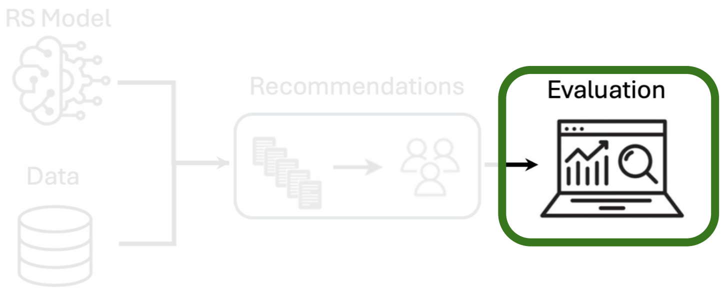
- Spillo et al. (2024b)
- Baumgart et al.

Economic

- Pei et al.
- Zhang et al.
- Ghanem et al.

- De Biasio et al.

- Sürer et al.
- Liu et al.



- Diversification, novelty, transparency, explanations
  - *Dinnissen et al.*
- Carbon footprint
  - *Spillo et al.*
  - *Vente et al.*
- Customer/Provider satisfaction, and how to balance them
  - *Ghanem et al.*

Resources (1/2)

Buolamwini, J., Gebru, T., Friedler, S. A., & Wilson, C. (2018). Proceedings of the 1st Conference on Fairness, Accountability and Transparency. PMLR, 81, 77-79.
Beutel, A., Chen, J., Zhao, Z., & Chi, E. H. (2017). Data decisions and theoretical implications when adversarially learning fair representations. arXiv preprint arXiv:1707.00075.
Rozemberczki, B., Kiss, O., & Sarkar, R. (2020). Proceedings of the 29th ACM International Conference on Information and Knowledge Management (CIKM'20).
Pei, C., Yang, X., Cui, Q., Lin, X., Sun, F., Jiang, P., ... & Zhang, Y. (2019, May). Value-aware recommendation based on reinforcement profit maximization. In The World Wide Web Conference (pp. 3123-3129).
Zhang, X., Xu, B., Yang, L., Li, C., Ma, F., Liu, H., & Lin, H. (2022, July). Price does matter! modeling price and interest preferences in session-based recommendation. In Proceedings of the 45th international ACM SIGIR conference on research and development in information retrieval (pp. 1684-1693).
Ghanem, N., Leitner, S., & Jannach, D. (2022). Balancing consumer and business value of recommender systems: A simulation-based analysis. Electronic Commerce Research and Applications, 55, 101195.
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Resources (2/2)

Spillo, G., De Filippo, A., Musto, C., Milano, M., & Semeraro, G. (2024, October). Towards green recommender systems: Investigating the impact of data reduction on carbon footprint and algorithm performances. In Proceedings of the 18th ACM Conference on Recommender Systems (pp. 866-871).
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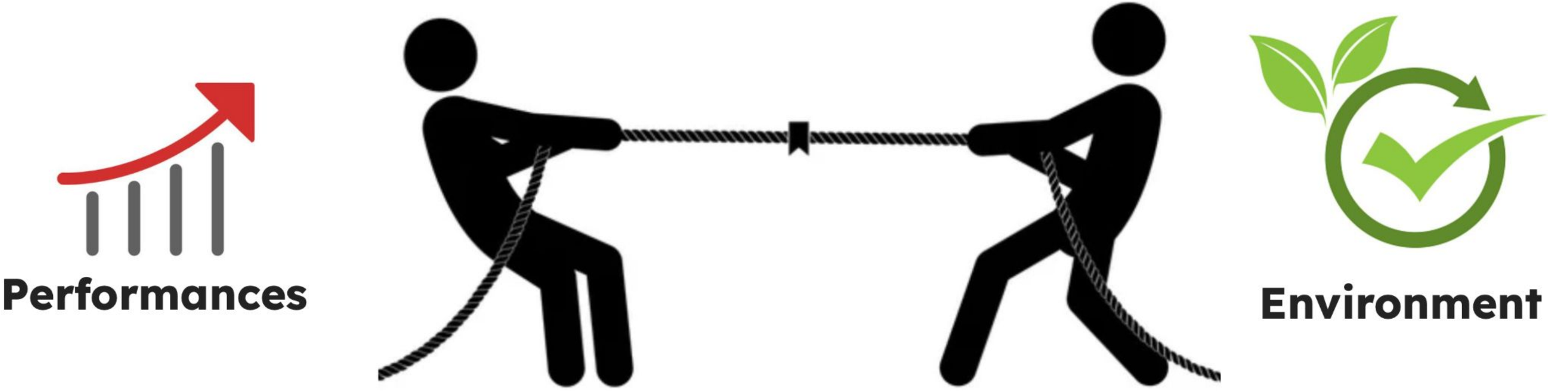
What about our research?

1. Benchmarking RS models' carbon footprint

Accuracy and carbon footprint Trade-off analysis

Do more complex recommendation models show (**accuracy-based**) higher **performances** that justify their higher **carbon footprint**?



How to measure Carbon Footprint?

A measure used to express the total **warming impact** of various greenhouse gases **in terms of carbon dioxide (CO2)**

Energy source mix used for the computation (i.e., coal, gas, nuclear, etc.)

$$Emissions(CO_2 - eq.) = carbonIntensity * powerConsumption$$

Electrical power required by the computation (read from the hardware during the training)

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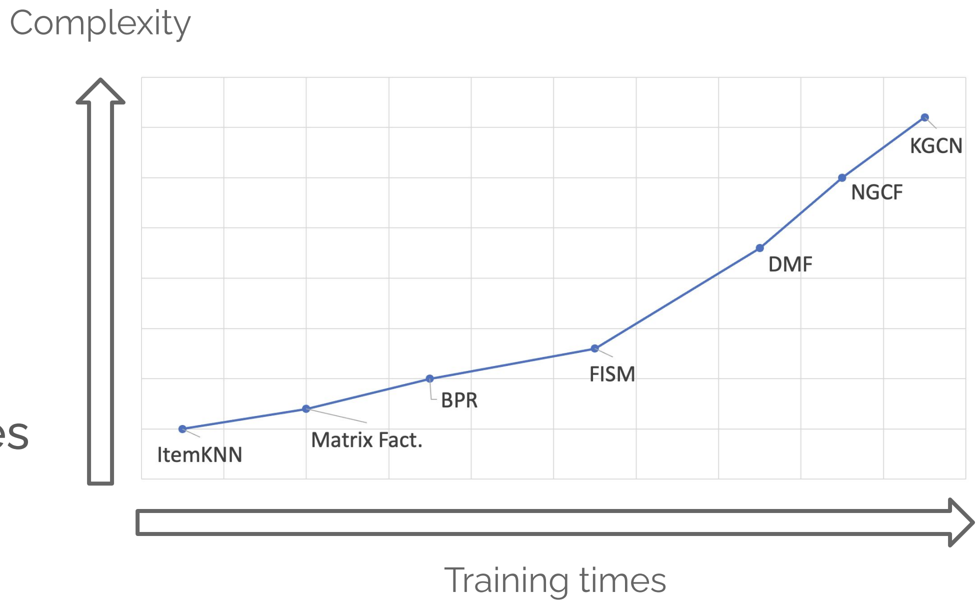
A simple use-case scenario

Let's just track the emissions of a simple BPR model on the ML-100K dataset (default on RecBole)

```python
from recbole.quick_start import run_recbole
from codecarbon import EmissionsTracker

# init the tracker
tracker = EmissionsTracker()

# start the emission tracking
tracker.start()

# train the model
run_recbole(model='BPR', dataset='ml-100k')

# stop the tracker
tracker.stop()

print(f'The computation emitted {tracker.final_emissions} KGs of CO2-eq')
```

Experimental Setting

- We considered models available in RecBole:
  - distance-based
  - matrix factorization
  - graph-based
  - content-based and KARS
- Trained with default parameter values
- We used different domains: Movies, Books, News.
  - **MovieLens-1M**, Amazon Books, Mind



What do we expect?

Let us suppose we train the following models:

- ItemKNN
- LightGCN
- NGCF
- DGCF

What do we expect? Which is the most effective? Which is the most sustainable?

Question time!

Which model do you think shows the best trade-off?

Active poll 16

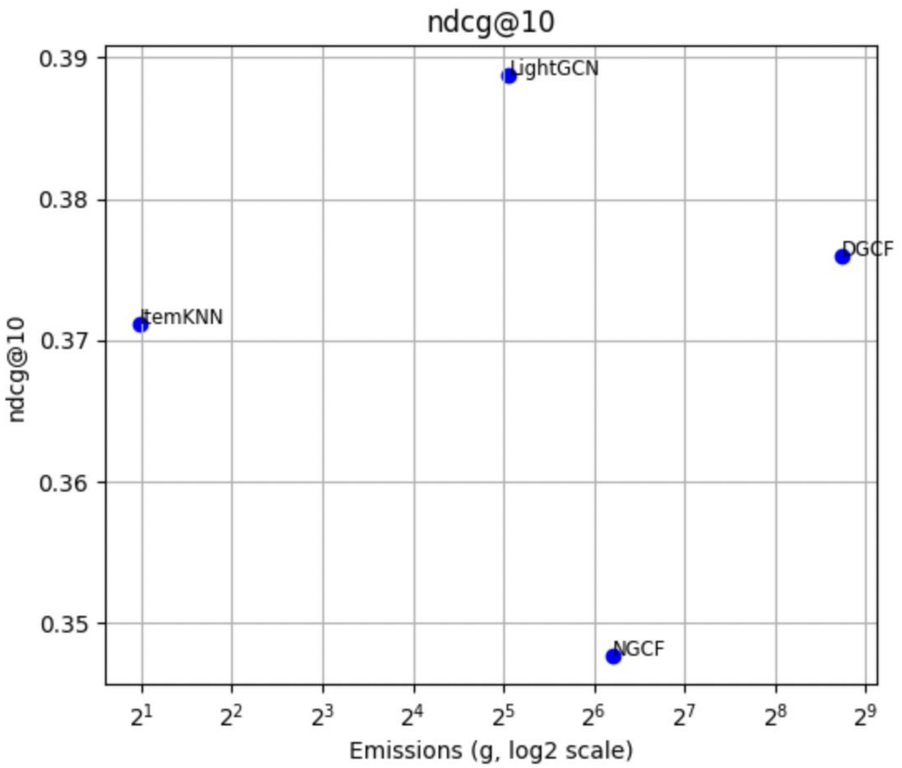
Which model do you think shows the best trade-off?

1. LightGCN
2. ItemKNN
3. NGCF
4. DGCF

Accuracy

- ItemKNN
  - low emissions
  - medium accuracy
- LightGCN
  - medium emissions
  - high accuracy

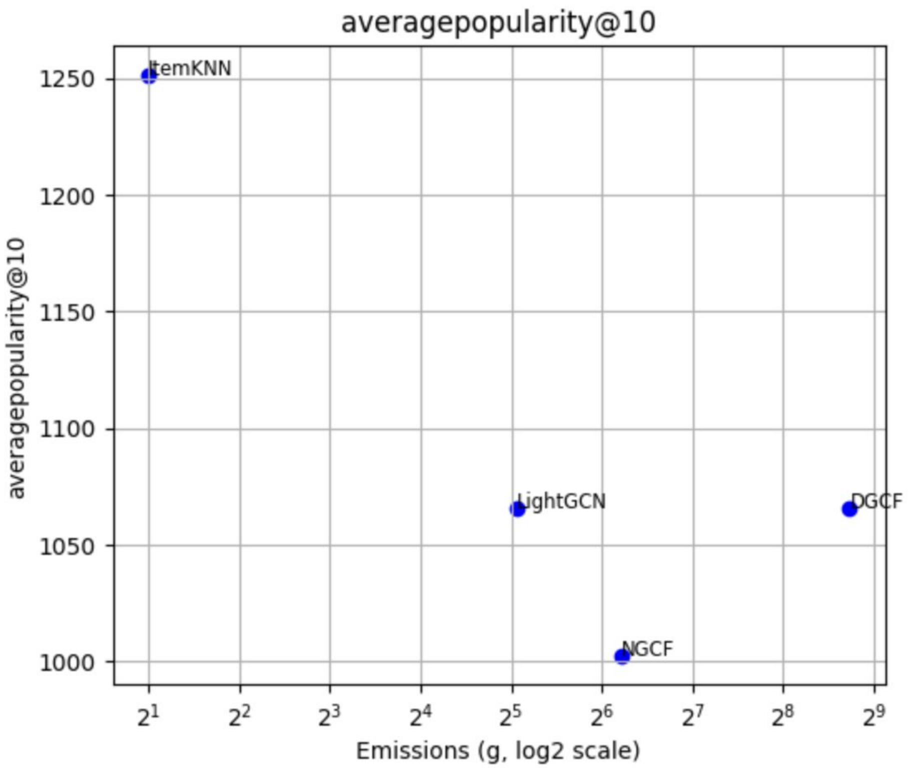
- LightGCN shows the best trade-off
  - Confirmed by *Vente et al. (2024)*



Beyond-accuracy

- ItemKNN
  - low emissions
  - high biased
- LightGCN
  - medium emissions
  - less biased accuracy

LightGCN confirms its good trade-off between performance and carbon footprint



More resources

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Spillo, G., De Filippo, A., Musto, C., Milano, M., & Semeraro, G. (2023, September). **Towards sustainability-aware recommender systems: analyzing the trade-off between algorithms performance and carbon footprint**. In *Proceedings of the 17th ACM Conference on Recommender Systems* (pp. 856-862).

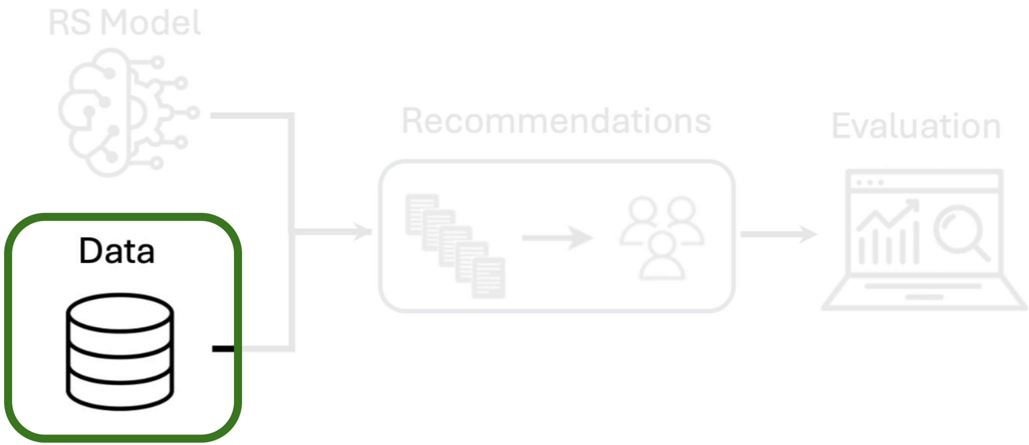
Our Colab Notebook, **do try** this at home to replicate our results!

https://shorturl.at/WtIka

What about our research?

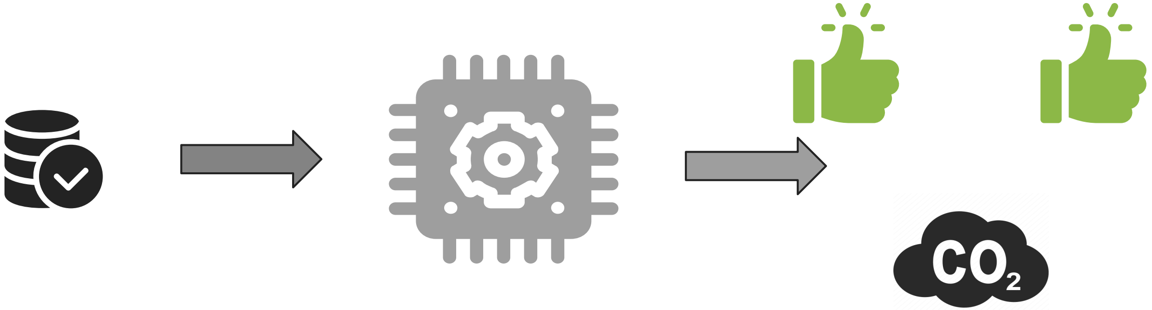
1. Benchmarking RS models' carbon footprint

2. Data reduction strategies to improve the trade-off between accuracy and carbon footprint



Data Reduction Strategies for Green Training

- RSs typically require lots of training data
- Data-intensive technology: the more the data
  - The better the performances



Data Reduction Strategies for Green Training

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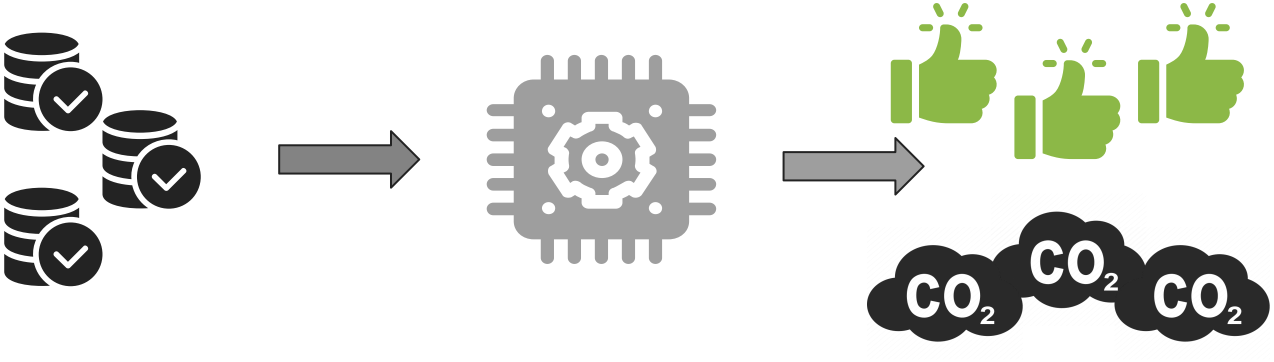
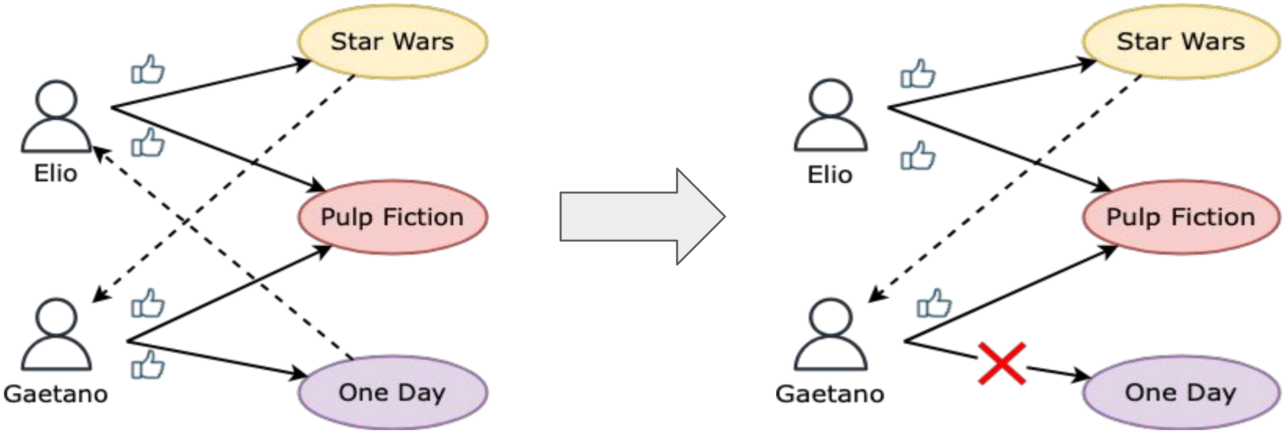


Data Reduction Strategies for Green Training

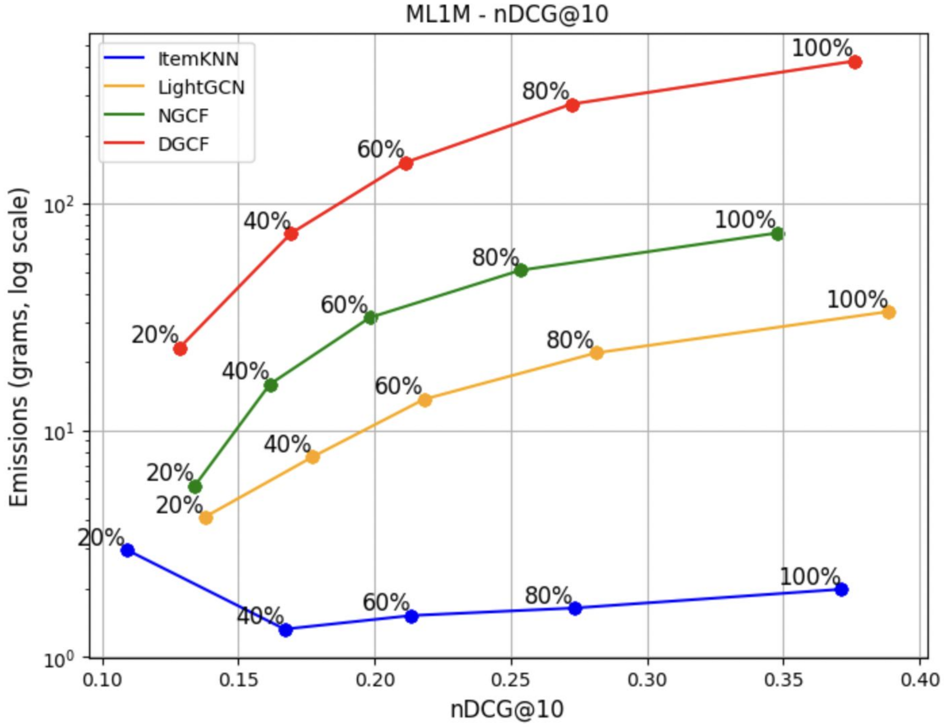
How do **data reduction** strategies **affect** the trade-off between recommendation model **performance** and **carbon footprint?**



Accuracy

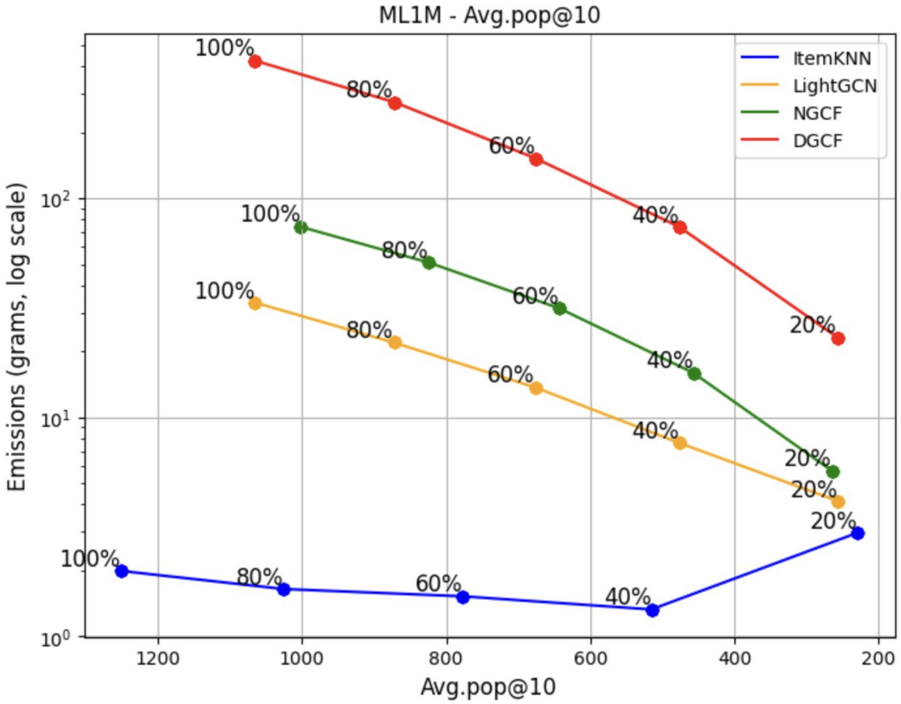
We observe **drops** in terms of **both accuracy and carbon footprint**, as expected.

Again, LightGCN seems the best trade-off solution model



Beyond-accuracy

On the other hand, we observed **improvements** in the **average popularity** of the recommendation lists!



More resources

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What about our research?

1. Benchmarking RS models' carbon footprint

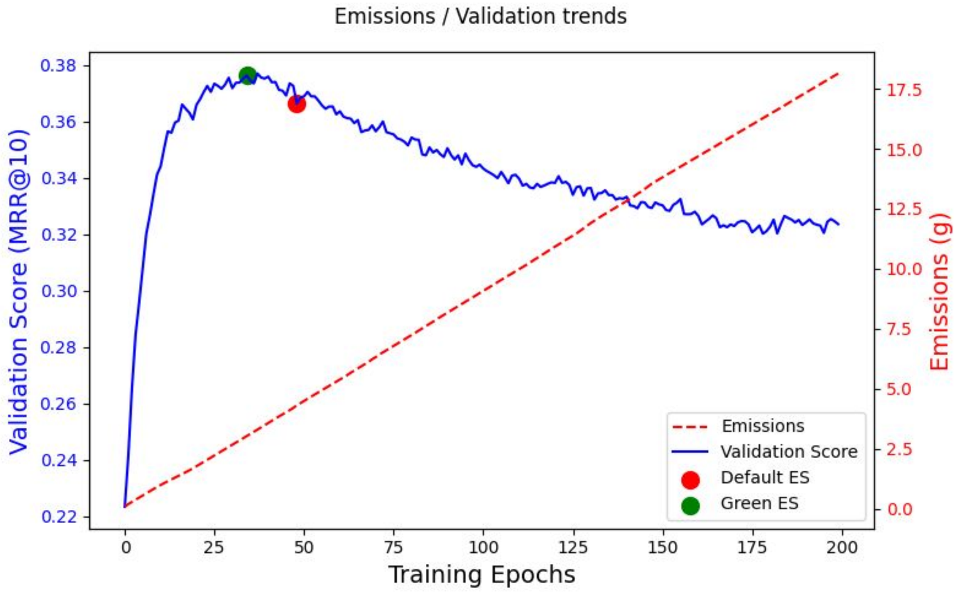
2. Data reduction strategies to improve the trade-off between accuracy and carbon footprint

3. Green Early-Stop (GES) criterion for environmental sustainable training

GES for Sustainable Training

How to make the training of a RS model ***aware*** of the **carbon footprint**?

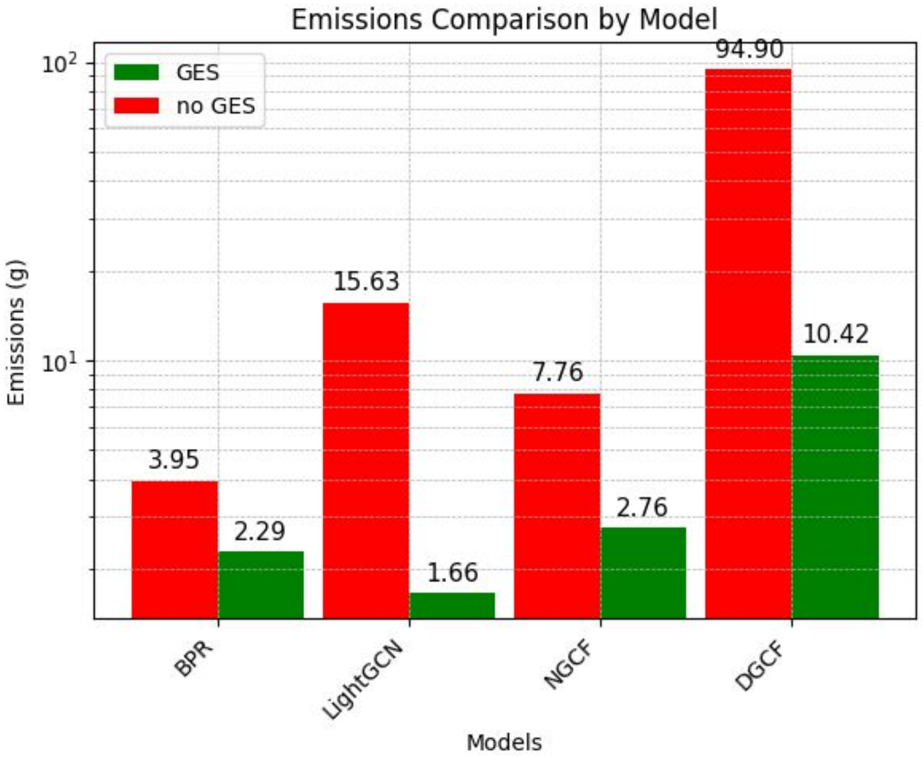
Can we design a **Green Early-Stop (GES)** criterion, that stops the training when too much CO2 has been emitted?



GES for Sustainable Training

We observe **huge reduction** in the **carbon footprint** of ***all*** the considered RS models.

Check this out tomorrow, during the poster session!

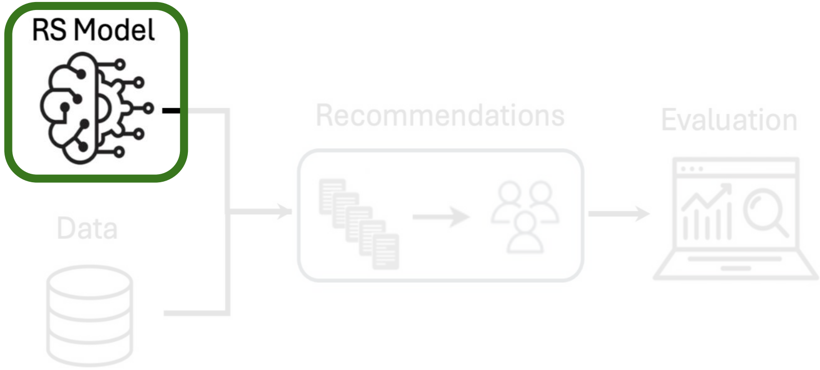


Check-out our paper!

Spillo, G., De Filippo, A., Fontana, E., Milano, M., & Semeraro, G. (2025, June). **Training Green and Sustainable Recommendation Models: Introducing Carbon Footprint Data into Early Stopping Criteria**. *In Proceedings of the 33rd ACM Conference on User Modeling, Adaptation and Personalization (pp. 341-346).*

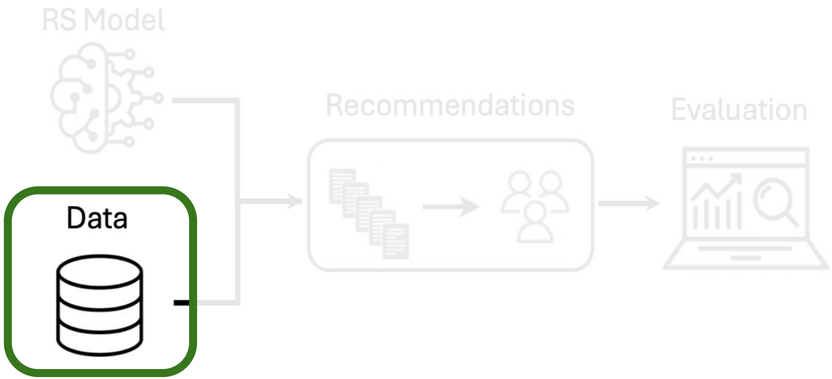
Take-home messages

- Carefully choose the recommendation algorithm
  - Which is the current task? What is the target performance?



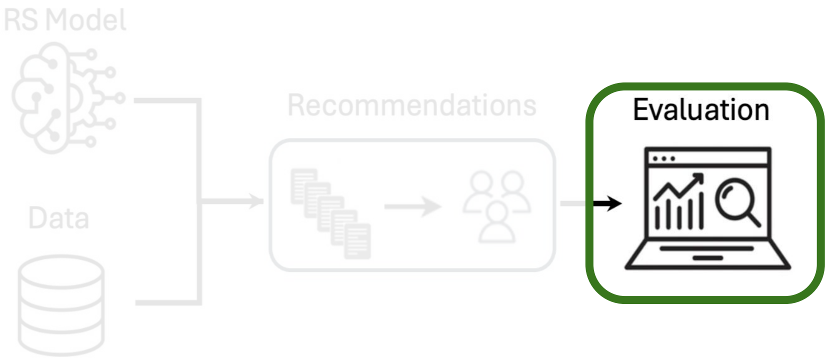
Take-home messages

- Carefully choose the recommendation algorithm
- Evaluation at scale: RSs are typically trained from scratch daily
  - Do I need to train my model more often?
  - Do I need the whole training data?
  - Can I stop my training process in advance?



Take-home messages

- Carefully choose the recommendation algorithm
- Evaluation at scale: RSs are typically trained from scratch daily
- Adopt Multi-objective Approaches
    - Balancing business goals with sustainability requires algorithms that optimize fairness, emissions, and accuracy



Discussion

3. The Dual Perspective

Can we envision a future where recommender systems **both enable sustainable choices and are themselves sustainable**, without compromising performance or user experience?

Question time!

Which of the following research directions do you find most promising, are already working on, or would like to explore regarding the integration of Sustainability and RS?

Discussion

Research Direction	SoTA Maturity	Current Practices	Main Gaps
Developing **Multi-Pillar** RS Applications	Low	Some systems address 2 pillars (e.g., health + environment)	Rarely address all three pillars (environmental, social, economic) simultaneously
Designing **Multi-Objective** RS	Medium	Growing interest in balancing fairness and accuracy	Lack of frameworks that also balance environmental and economic objectives concurrently
Designing **Evaluation** Frameworks **Beyond Accuracy**	Low	Some systems use fairness metrics or carbon footprint separately	Evaluations are mostly isolated; no integrated multi-pillar evaluation protocols
Establishing **Cross Disciplinary Collaborations**	Low	Few cases involve stakeholders beyond computer science	Missing practical, interdisciplinary teams including economists, environmentalists, policymaker

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SCAN ME!

Thank you!

Allegra De Filippo, Ludovico Boratto and Giuseppe Spillo

https://giuspillo.github.io/umap25_sustainable_recsys_tutorial/