COMMUNITY TALKS

GOING GREEN TRAININGS

Integrating open dataset & AI models for textile sorting

6 June 2024 • 10:30-11:30 • Online

REGIO GREEN TEX

Webinar Procedures

The webinar is recorded and will be shared - in parts or entirely – with all consortium partners. By staying connected you agree to this. If you would not like to appear on the recording, please keep your camera and microphone off at all times.

Mute your microphone

Disconnect video

Type questions in the chat

Raise your hand when you wish to speak

When you are invited to speak, unmute mic and show video (if possible)

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Agenda

Introduction
Charlotte Denis, Textile ETP

Integrating open dataset & AI models for textile sorting
Farrukh Nauman, RISE

Q&A

Conclusion
Charlotte Denis, Textile ETP

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COMMUNITY TALKS

GOING GREEN TRAININGS

Online animation activities play a pivotal role in sustaining the engagement of SMEs within the digital ecosystem. To stimulate interaction, the RegioGreenTex Community Talks **promote the latest progresses and results of the project, and well as encouraging dialogue and knowledge sharing in the textile sector.**

The 'Going Green Trainings', a component of the RegioGreenTex Community Talks, offer advisory green support to SMEs in the textile sector, carefully tailored to address sustainability concerns. Led by experts from RISE, these webinars provide practical training across six distinct areas of sustainability.

The Going Green Trainings are part of WP4 (T4.2 Green advice/advisory support to SMEs) and are managed by RISE, with support from OVAM, Euramaterials, Citeve, Eurofins, Ateval, AEI Textils, CS-Pointex, NTT, EURATEX, and Textile ETP.

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Integrating open dataset & AI models for textile sorting

Farrukh Nauman, Digital Systems division, RISE

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AI in circular fashion

Farrukh Nauman

Agenda

- Overview
- Fashion value chain
- Data
- AI Models
- Conclusions

RI.
SE

1-slide summary

Second-hand fashion industry ~100% manual.

AI can prove game changing.

Domain-specific datasets are essential.

Our dataset is about post-consumer textiles

RISE

- ~3500 employees
- Spread all over Sweden
- Public Research Organization
- Headquarters: Borås

RISE's strategy for sustainable growth 2022-2026 is based on five prioritised societal challenges in the Swedish Research Bill.

Climate and environment +

Health and welfare +

Digitalisation +

Talent management and working life +

A strong, democratic society +

AI at RISE
(nearly 500 AI researchers/developers)

Center for applied AI	Computer vision	Advanced data analysis	Cyber security	Digital innovation	Transport and mobility	Energy systems	Materials and production
Deep learning	Natural language processing	Planning and scheduling	Digital ethics		Telecom	Healthcare	ICE data center
AI platforms and edge	Automated reasoning	Knowledge representa-tion	Education	Industrial automation	AI agenda	Built environment	ToD: Cyber Range
Policy innovation	Interaction design	Software engineering	Climate change	Food and agriculture	Chemistry and pharma	ToD: AstaZero	ToD: 5G/Edge

- Technology areas
- Synergistic areas
- Application areas
- Test & Demo
- Special projects

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Overview

What is AI?

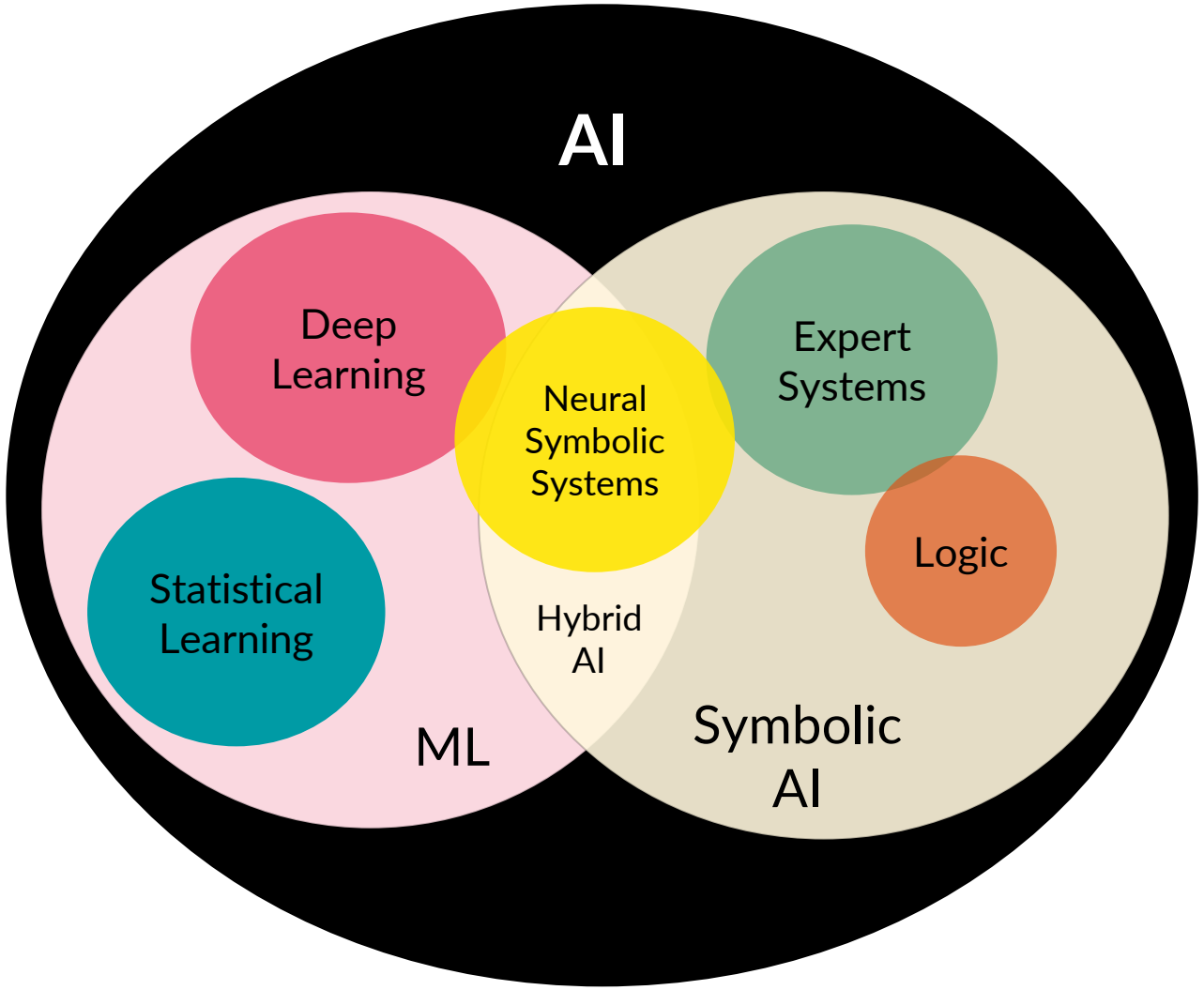

Illustration Inspired by:

Digitalized Transformation Guides vol. 2, Loughborough University

Jerod Santo, “Disentangling AI, machine learning, and deep learning”, Changelog news, 2021-04-29

Calegari, R., Ciatto, G., Denti, E., & Omicini, A. (2020). Logic-based technologies for intelligent systems: State of the art and perspectives. *Information*, *11*(3), 167.

How to Represent An Image?





→ class

- Domain knowledge required
- But what's next?

→ edge → class

→ edge → orientation → class

→ edge → orientation → histogram → class

→ edge → orientation → histogram → clusters → class

deeper

Kaiming He, Deep Learning Bootcamp, MIT Schwarzman College of Computing

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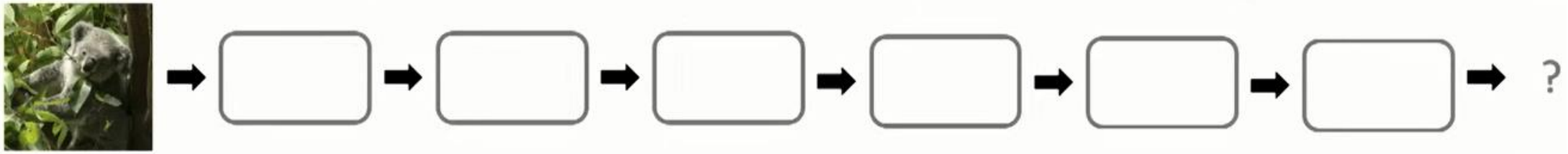
Deep Learning

general modules (instead of specialized features)



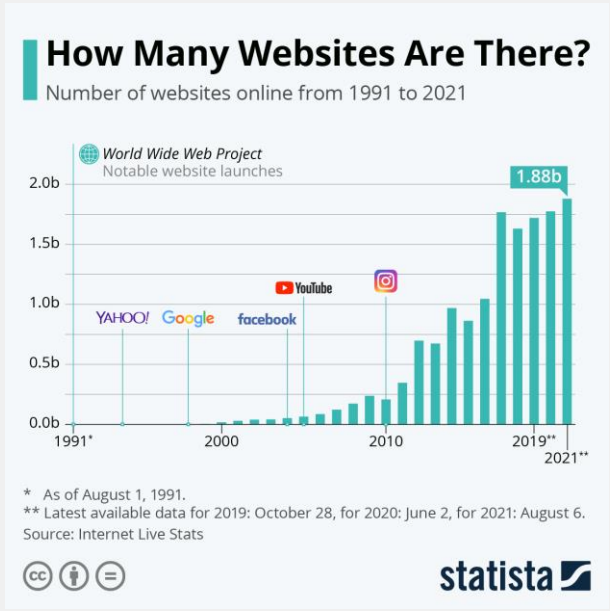
compose simple modules into complex functions

- build multiple levels of abstractions
- learn by back-prop
- learn from data
- reduce domain knowledge and feature engineering

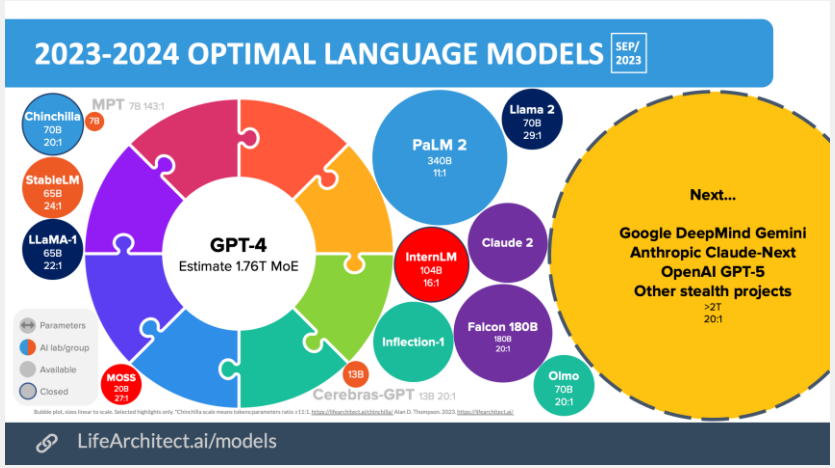
Kaiming He, Deep Learning Bootcamp, MIT Schwarzman College of Computing

Why now?

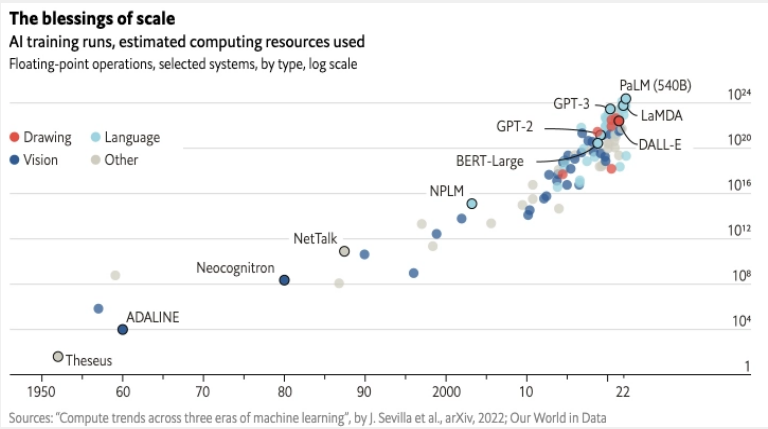
Data



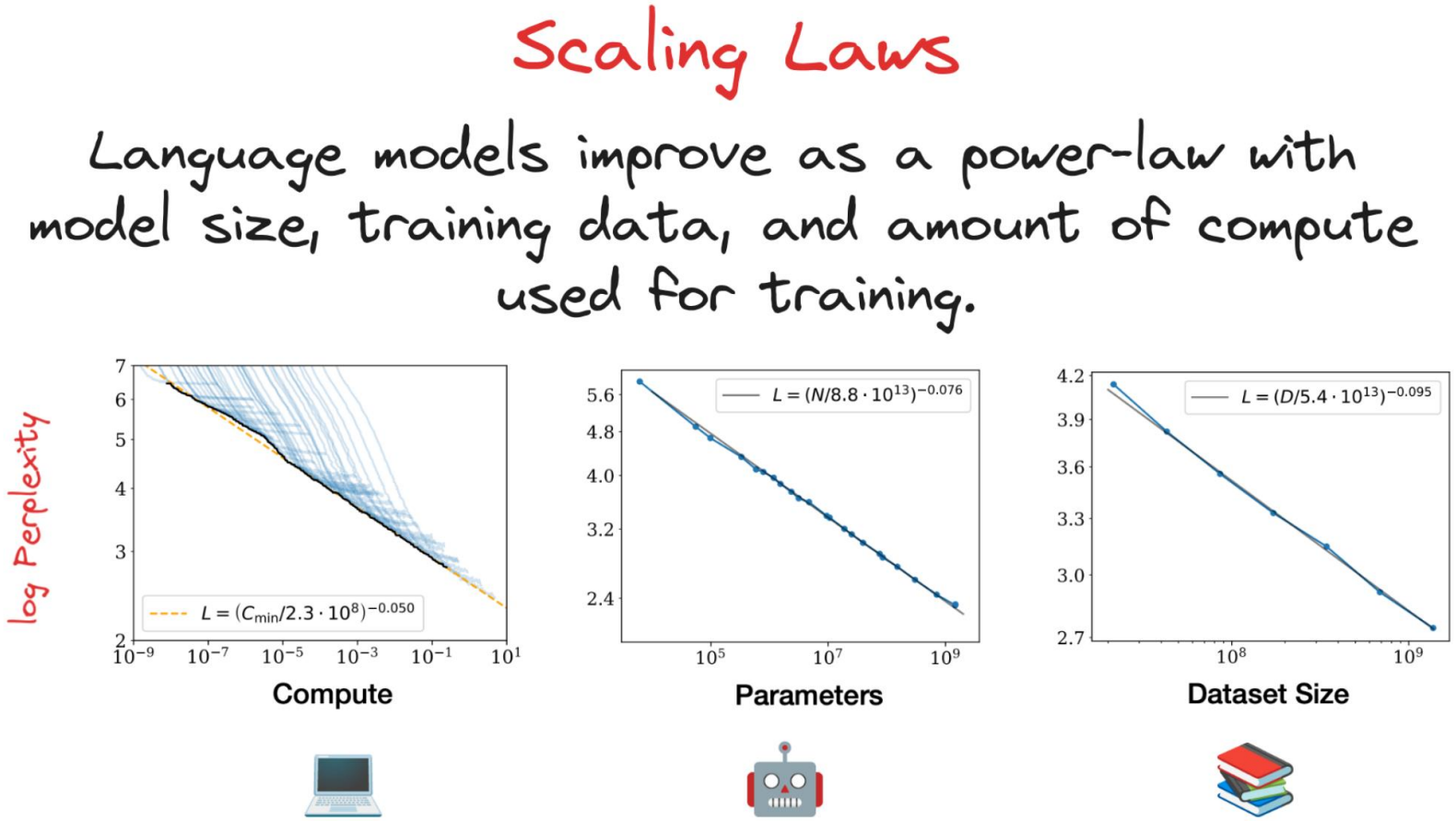
Model architecture



Computing power



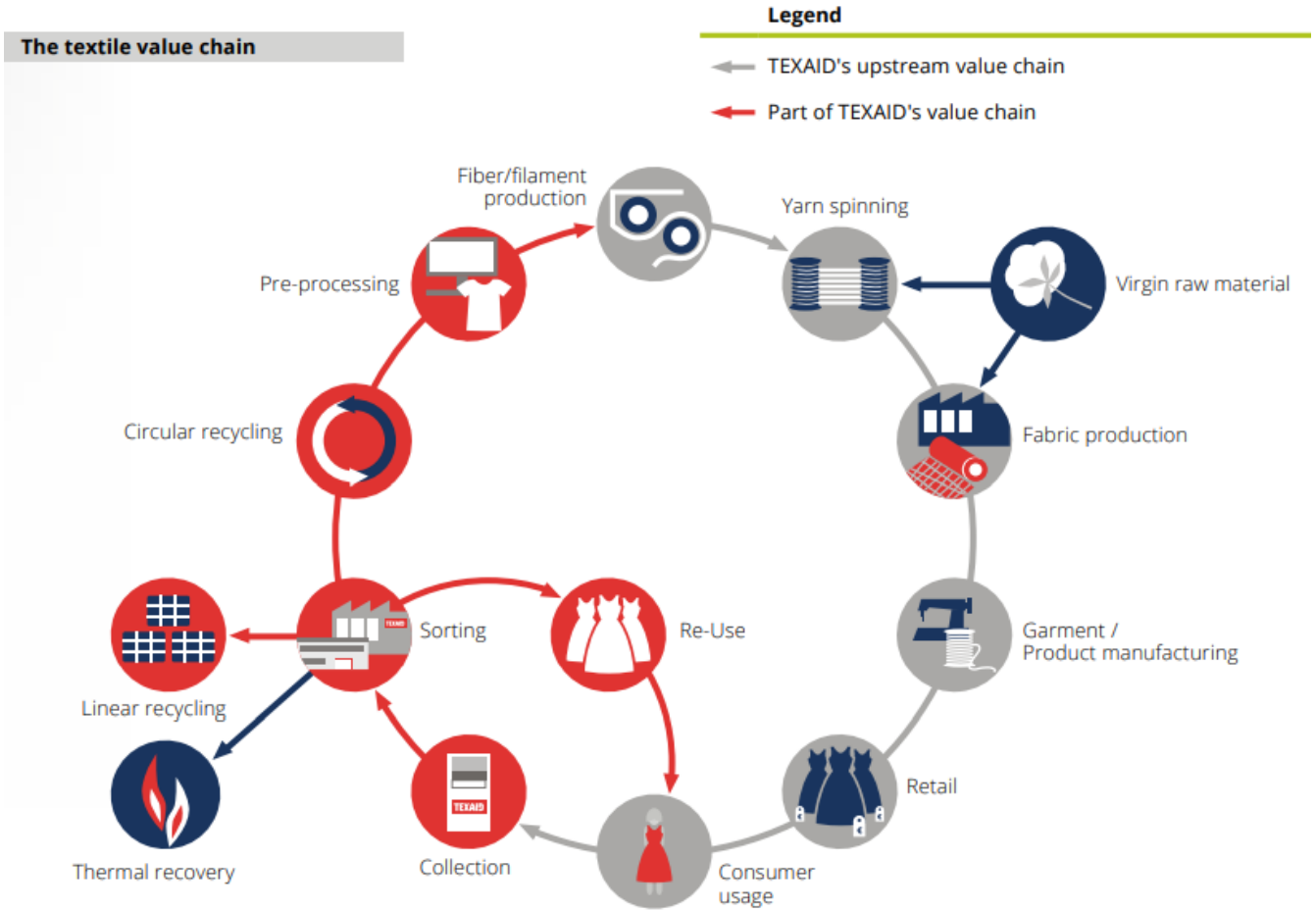
Scaling



Sasha Rush, LLMs in 5 formulas

Fashion

Fashion value chain



Texaid report 2021

CISUTAC

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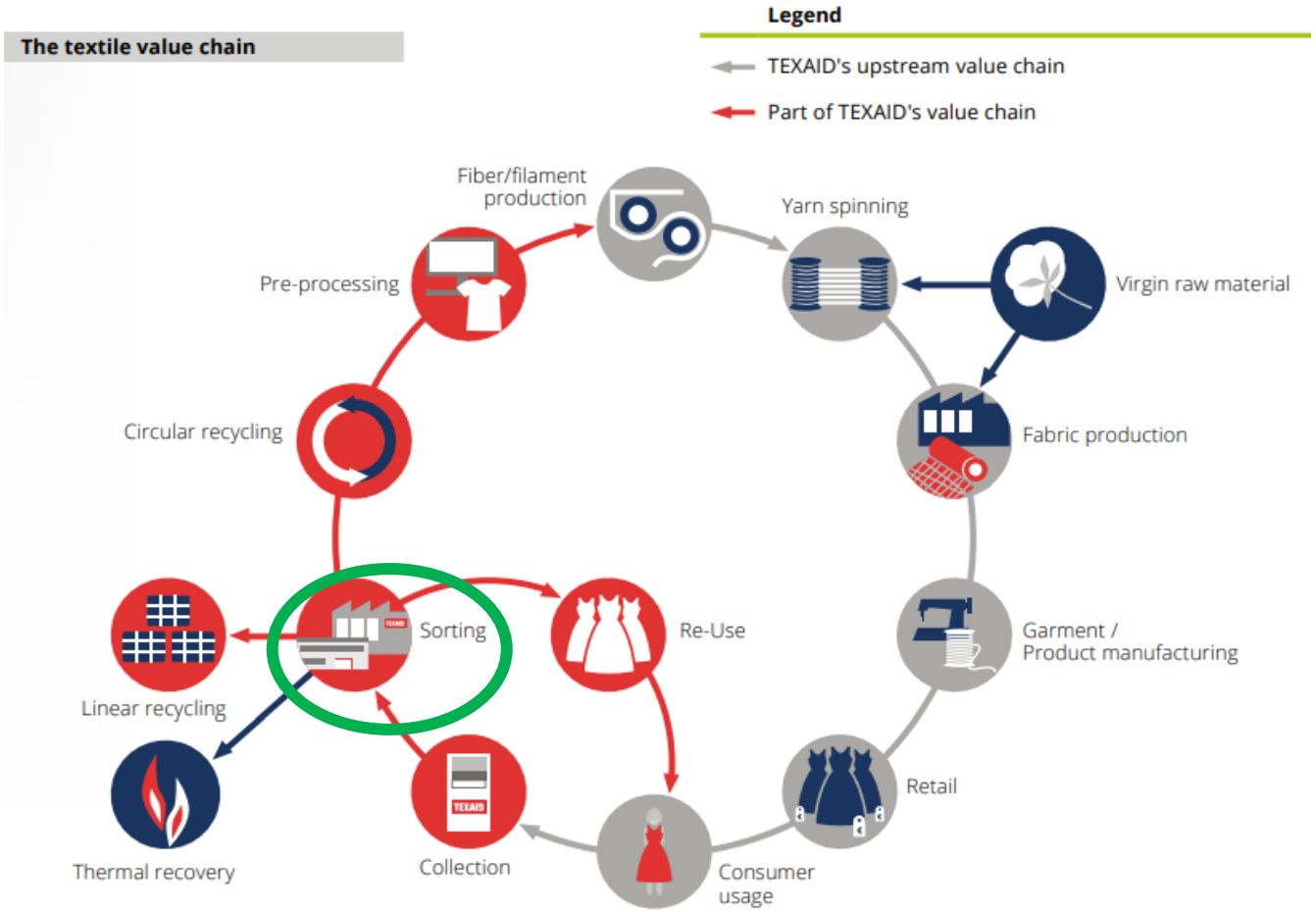
Fashion value chain



Texaid report 2021

CISUTAC

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Fashion AI and datasets work is focused on first-hand fashion

DeepFashion: https://mmlab.ie.cuhk.edu.hk/projects/DeepFashion.html

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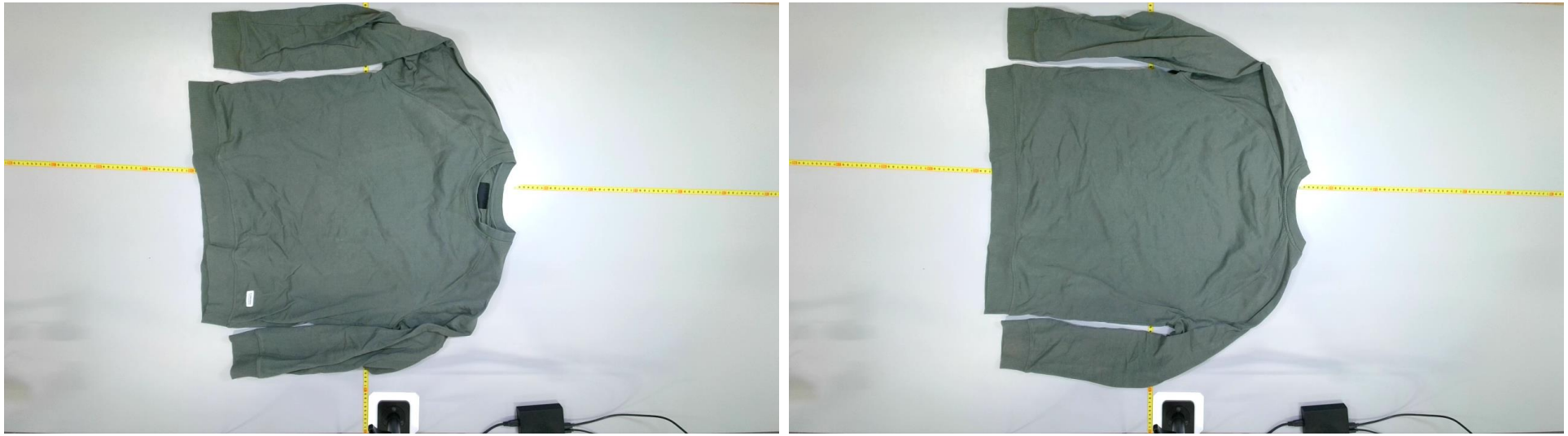
Data

Data

30,000 x 3 images + extensive set of labels describing attributes such as price, condition, trend, stains, damage

Wargön Innovation



Lager 157, Ladies, Sweater, XXL, Green, Price: 50-100 SEK, Use: Export,
Trend: None, Cut: C-collar, Plain, Material: 100% cotton
Holes: None, **Stains: Yes**, **Pilling: 4, Condition: 3**

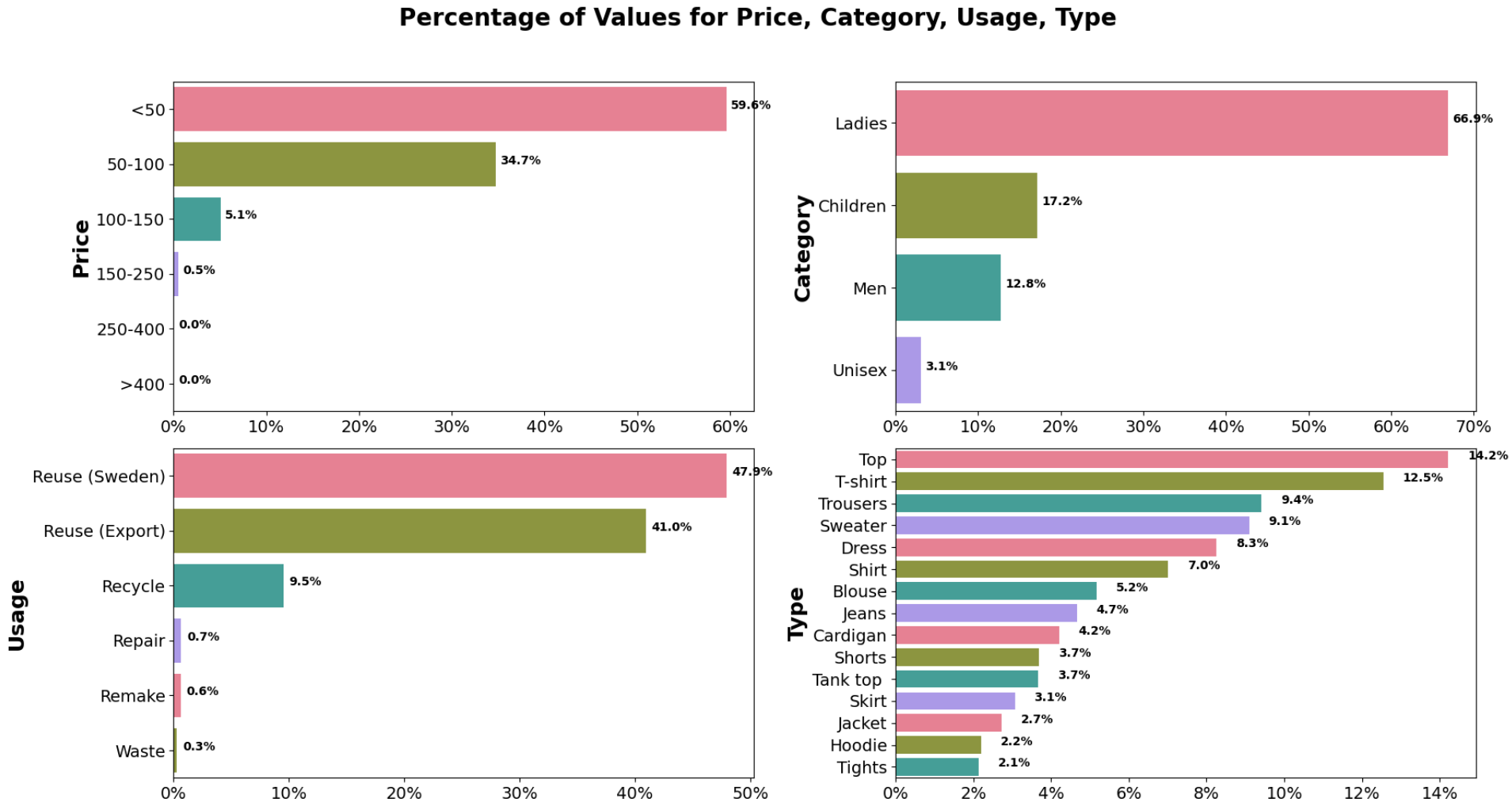
Data

30,000 x 3 images + extensive set of labels describing attributes such as price, condition, trend, stains, damage

Myrorna

Mywear (Ica), Ladies, Cardigan, XL, Beige, Price: 50-100 SEK, Use: Reuse,
Trend: None, Material: 77% viscose, 23% polyester
Holes: None, Stains: No, Pilling: 4, Condition: 4

Data


Percentage of Values for Price, Category, Usage, Type
Price
<50
50-100
100-150
150-250
250-400
>400
59.6%
34.7%
5.1%
0.5%
0.0%
0.0%
0%
10%
20%
30%
40%
50%
60%
Category
Ladies
Children
Men
Unisex
66.9%
17.2%
12.8%
3.1%
0%
10%
20%
30%
40%
50%
60%
70%
Usage
Reuse (Sweden)
Reuse (Export)
Recycle
Repair
Remake
Waste
47.9%
41.0%
9.5%
0.7%
0.6%
0.3%
0%
10%
20%
30%
40%
50%
Type
Top
T-shirt
Trousers
Sweater
Dress
Shirt
Blouse
Jeans
Cardigan
Shorts
Tank top
Skirt
Jacket
Hoodie
Tights
14.2%
12.5%
9.4%
9.1%
8.3%
7.0%
5.2%
4.7%
4.2%
3.7%
3.7%
3.1%
2.7%
2.2%
2.1%
0%
2%
4%
6%
8%
10%
12%
14%

Images containing human hands, faces, sometimes bags/laptops
(not shown here to respect privacy)

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Improving Annotations

(Quality and Diversity)

Annotations

- Agreement rate differs a lot across different topics; ranging from 0.96 on violence/gory to 0.25 on personal topics.
- Agreement rates are higher on “extreme” and “benign” conversations, given four label options marking “benign”, “debatable”, “moderate” to “extreme”.

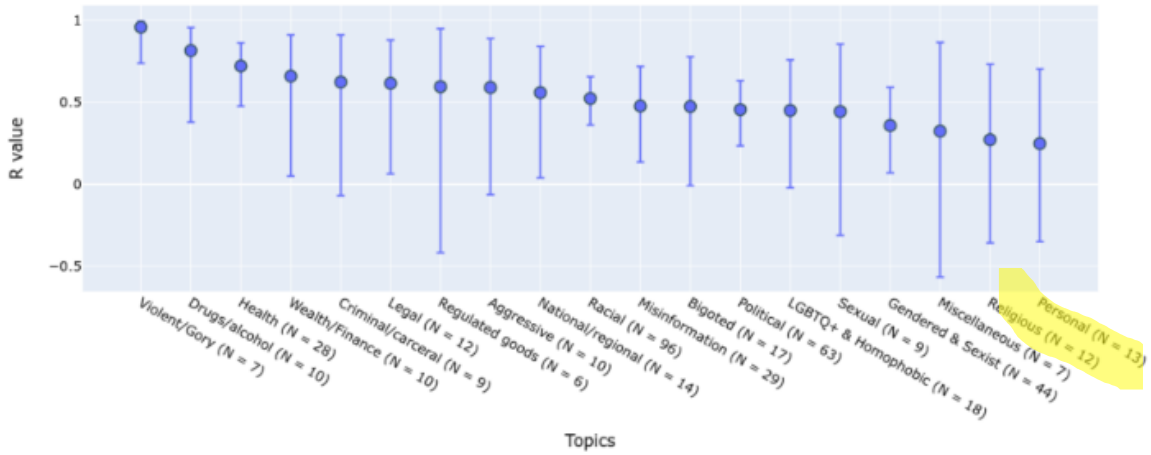

Fig. 4. Correlations between non-expert and expert annotations vary a lot across topics. (Image source: Wang et al. 2023)

Weng, Lilian. (Feb 2024). “Thinking about High-Quality Human Data”. Lil’Log.

Myth One: *One Truth*
Most data collection efforts assume that there is one correct interpretation for every input example.

Myth Two: *Disagreement Is Bad*
To increase the quality of annotation data, disagreement among the annotators should be avoided or reduced.

Myth Three: *Detailed Guidelines Help*
When specific cases continuously cause disagreement, more instructions are added to limit interpretations.

Myth Four: *One Is Enough*
Most annotated examples are evaluated by one person.

Myth Five: *Experts Are Better*
Human annotators with domain knowledge provide better annotated data.

Myth Six: *All Examples Are Created Equal*
The mathematics of using ground truth treats every example the same; either you match the correct result or not.

Myth Seven: *Once Done, Forever Valid*
Once human annotated data is collected for a task, it is used over and over with no update. New annotated data is not aligned with previous data.

Aroyo, L., & Welty, C. (2015). Truth Is a Lie: Crowd Truth and the Seven Myths of Human Annotation. *AI Magazine*, *36*(1), 15-24.

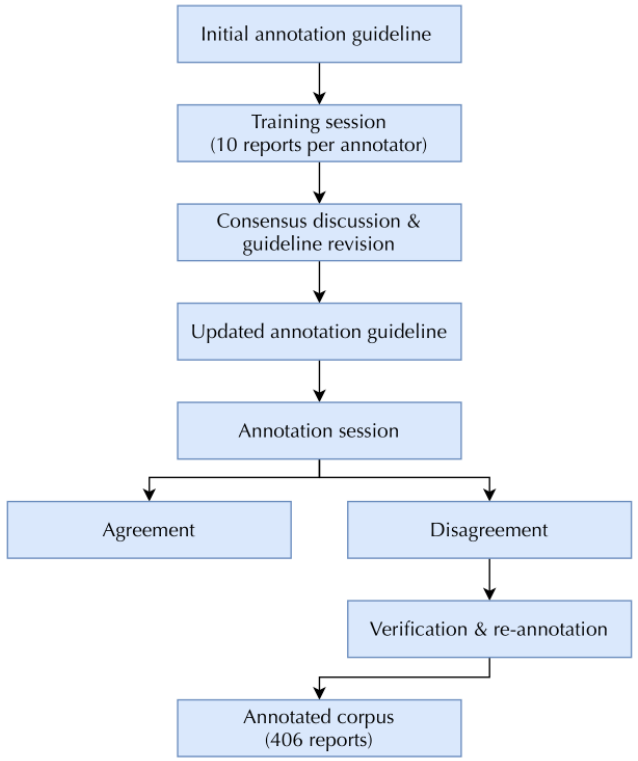

Figure 2: Flowchart describing CXR-LT gold standard dataset annotation.

"A set of **451** radiology reports were randomly sampled from the CXR-LT challenge test set, and each report was **annotated by at least two annotators**."

Towards long-tailed, multi-label disease classification from chest X-ray: Overview of the CXR-LT challenge
arxiv.org/abs/2310.16112

Gold dataset

100 clothing items

Two annotators:
Wargön
Myrorna

Human (Wargön)

- Mens
- T-shirt
- Plain
- Reuse
- Condition: 5

Human (Myrorna)

- Mens
- T-shirt
- Plain
- Reuse
- **Condition: 4**

AI (GPT-4 Vision)

- Mens
- T-shirt
- Plain
- **Export/Reuse outside Sweden**
- Condition: 5

AI Models

AI developments

- 2021:
  Open-world Image Classification
- 2022-:
  Diffusion models (Dall-E 2/3, SD)
- Nov. 2022: ChatGPT
- 2023:
  Open-world Detection/Segmentation

Our plan

- 2021-2022:
  Predict Use, Attributes using front image (and brand?)
- 2022-2024:
  Damage detection (region level)
  Generative AI for synthetic data

Image recognition

New clothes

Vinnova project

Used clothes

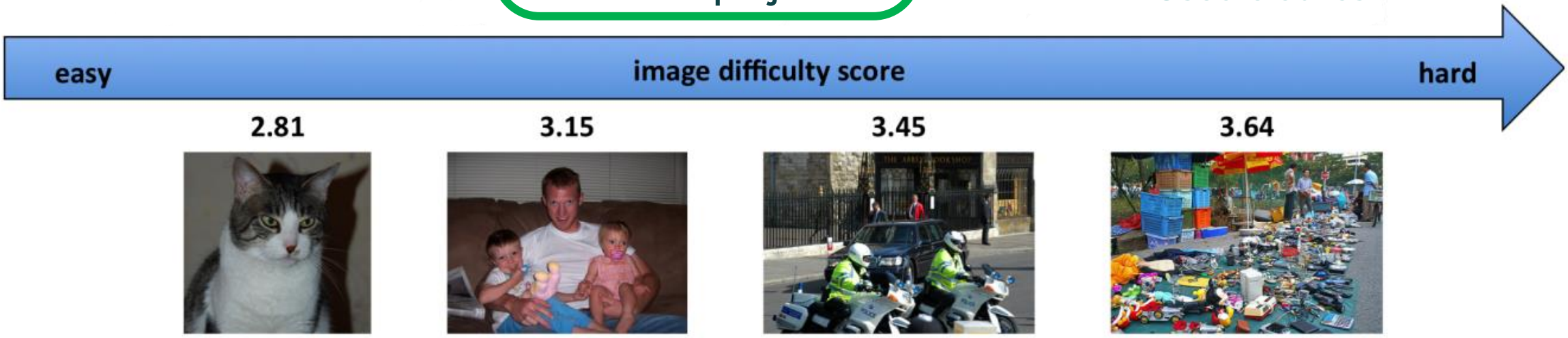

Figure 1. Images with difficulty scores predicted by our system in increasing order of their difficulty.

CISUTAC

R. Ionescu, et al., "How Hard Can It Be? Estimating the Difficulty of Visual Search in an Image," CVPR 2016

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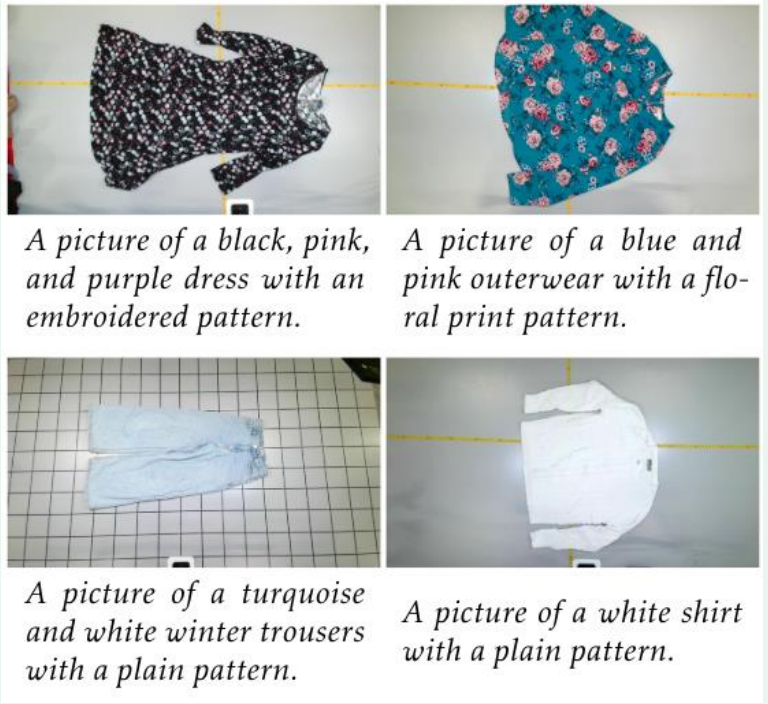
Image embeddings & Classification
(S. Hermansson 2023; LiU)

- SOTA CLIP for creating embeddings and image search
- Use prediction:
  Poor results
- Price prediction:
  Poor results
- 3000 samples

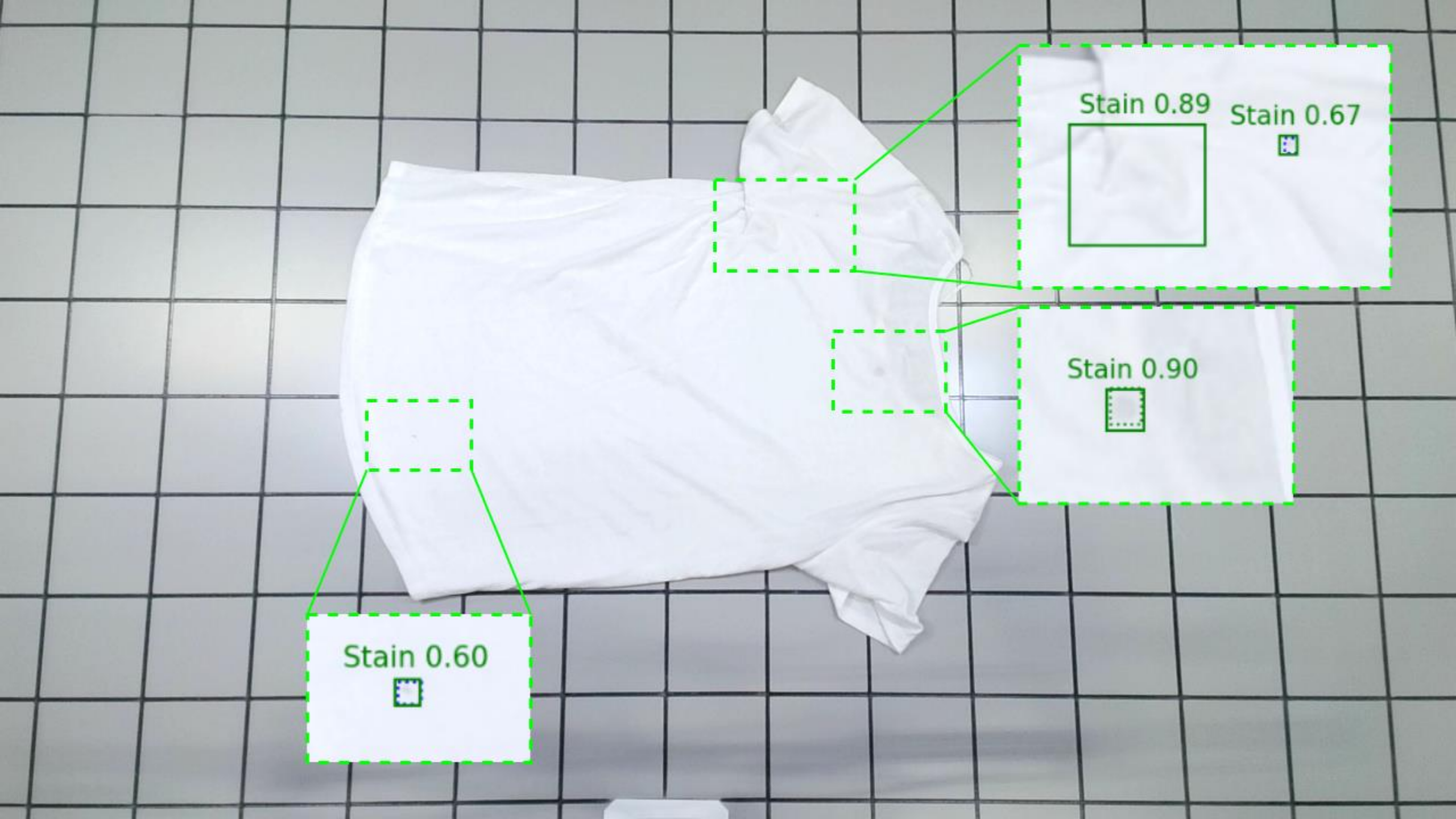
CLIP: Caption Generation



Damage detection (L. Norblad 2024; LiU)

- Annotate various types of damage: holes, stains, etc.
- **Challenges:**
  Small size and poor lighting.
  Annotations done post-data collection

Object detection


Stain 0.89
Stain 0.67
Stain 0.90
Stain 0.60

Gen. AI for synthetic data

(S. Jonsson 2024; LiU)

- Generate damage for undamaged clothes; Remove damage for damaged ones.
- **Challenge:**
  Generative AI is extremely stochastic; hard to make it do what we want.
  End-end Automation is hard!

Remove stain

Discolor

Ongoing: Multi-task/target classification

Goal: Predict usage (reuse/recycling), condition (1-5) + first-hand fashion attributes (category, pattern, etc.)

Challenges

- Correlated targets (usage, condition) make learning heard.
- Need “much” larger networks for effective multi-task learning.
- Tasks learn at different rates/Gradients scales are different.

Negative transfer: Sometimes independent networks work the best.

Multi-Task CIFAR-100

	% accuracy	
task specific, 1-fc (Rosenbaum et al., 2018)	42	} multi-head architectures
task specific, all-fc (Rosenbaum et al., 2018)	49	} multi-head architectures
cross stitch, all-fc (Misra et al., 2016b)	53	} cross-stitch architecture
independent	67.7	} independent training

(Yu et al. Gradient Surgery for Multi-Task Learning. 2020)

Source: Chelsea Finn, Stanford CS330

Evaluations

First-hand (pattern, cut, category)
vs
Second-hand (wear and tear)

Evaluations

First-hand vs Second-hand

Foundation model bias: 1st hand fashion.
Finetuning bias: 1st hand fashion.
(Existing work: ViT, CLIP, ConvNext)

Apples to Oranges:

Pink stained T-shirt vs Black pant with holes.

Apples to Apples

Remove stain

Discolor

Evaluations

Next steps (Now until April 30th, 2024)

Data:

- Real: Take a clothing item and wash x100, put stains, holes, etc.
- **Synthetic: Generative AI.**

Models: Image-level vs Region-level

- Object detection/Segmentation + annotations (or zero-shot: SAM & variants)
- Multi-modal: GPT-4V?

Apples to Apples

Remove stain

Discolor

Unsolved challenges

- Multiple pricing models:
  by weight,
  fixed for all garments,
  first-hand fashion like pricing like Sellpy ,etc.
- Robot arms to replace initial manual handling.
- Smell detection.
- Recycling:
  - Direct integration with Infrared Sensors for material detection.
  - Support for mixed materials and multi-layered clothes.

Conclusions

- ***Open*** **Dataset:**

  30,000 clothing items with detailed annotations (damage).

  Version 1: https://zenodo.org/records/8386668

- **Evaluations:**

  Models must distinguish between different degrees of damage.

- **Comparison to existing work:**

  Most existing AI work is really solving first-hand fashion problems.

Pitch

OPEN Dataset

We are curating an open dataset of **30,000** clothing items, each meticulously annotated by expert sorters.
Specialized datasets are necessary to fully leverage the potential of foundation and multimodal AI models in specific industries, such as second-hand clothing.

User-friendly AI models

Since many extensive sorting facilities are **non-profit organizations** run by volunteers with little training in sorting and AI, user-friendly models are not just desirable but essential.

Sustainability Impact

Our project aligns closely with the goals of the **European Waste Directive 2025**.

It promotes longer consumer benefits from high-quality, affordable textiles and the widespread availability of economically profitable re-use and repair services.

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Us vs Them

Data	Models	Evaluations
• Scraped / No wear & tear • Either too curated; or completely wild (C2C websites)	• Off-the-shelf foundation models for classification. • No region level annotations.	• No First-hand vs Second-hand (New vs Used) • Results are generally laughably poor.

Q&A

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Thank you

For more information about the RegioGreenTex Community Talks, contact: charlotte.denis@textile-platform.eu

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COMMUNITY TALKS

Building value chains for mixed textile waste with the RegioGreenTex Lowlands Hub

Introduction to the Hub, Interregional Focus Group and Presentations of SMEs

27 June 2024 • 10:30-11:30 • Online

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COMMUNITY TALKS

GOING GREEN TRAININGS

Understanding the tools for systemic change

Green Kaizen & Waste Flow Mapping

14 November 2024 • 10:30-11:30 • Online

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