LORE: Mapping Subjective Experience Without Guessing Its Dimensions

Vivek Anand[1], Alec Helbling[1], Mark A. Davenport[1], Gordon Berman[2], Sankaraleengam Alagapan[1] & Christopher J. Rozell[1]

[1]Georgia Institute of Technology

[2]Emory University

Measure subjective experience with comparisons, not ratings

Absolute rating

rating



How bright is this image?

1 2 3 4 5 **6** 7 8 9 10

Ratings shift with each person and with what they saw before [1]

Relative comparison

comparison



Which is closer in brightness to A: B or C?

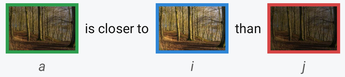
B | C

Comparisons are consistent within and across observers, with no scale to calibrate

Comparisons become a perceptual map

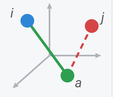
Human feedback

one triplet



Ordinal embedding algorithm

Perceptual map



What the map gives

- **Predicts comparisons** never asked
- **A distance** between any two percepts
- **Axes are discovered,** not assumed

Brightness

dimension known



d = 1 dimension

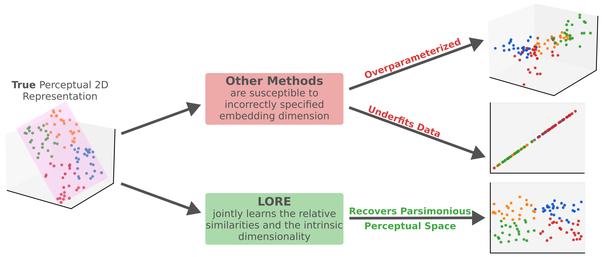
Materials, effort

dimensions unknown



d = ? dimensions

But every existing method makes you guess the dimension



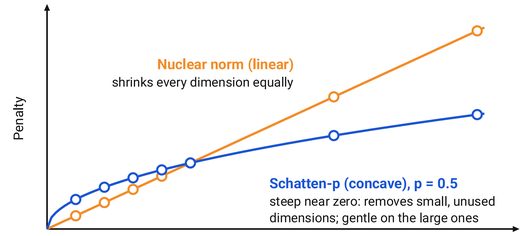
Guess too high and the map fits noise; too low and it distorts. LORE learns the dimension from the data.

LORE: fit the comparisons, pay for every dimension used

$$\min_{Z} \Psi(Z) = \sum_{(a,i,j)\in T} \log\left(1+\exp\left(1+d\left(Z_{a,:},Z_{i,:}\right)-d\left(Z_{a,:},Z_{j,:}\right)\right)\right) + \lambda \sum_{i=1}^{\min\{N,d'\}} \sigma_i(Z)^p$$

Fit the comparisons
Softplus triplet loss: the map respects each choice (a is closer to i than j)

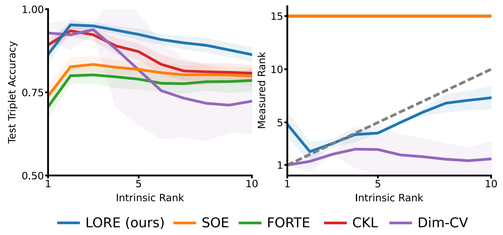
Penalize space
Schatten-p quasi-norm of the embedding (0 < p < 1)



Singular value: how much a dimension is used

- **Unused dimensions are driven to zero,** so the data decide how many survive
- Provably converges to a stationary point [2]
- One setting, λ = 0.01, works across noise levels, item counts and true dimensions
- Seconds per fit; open source in the cblearn Python package

In simulation, LORE recovers the true dimension



Accuracy matches the best baselines; only LORE tracks the true dimension.

To read more

Paper
arxiv.org/abs/2602.04192

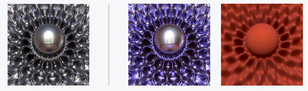
Code (also in cblearn)
github.com/vivek2000anand/lore_iclr

Contact
vivek-anand.xyz

Material appearance has two perceptual dimensions

Example query

Which is more similar to the reference?

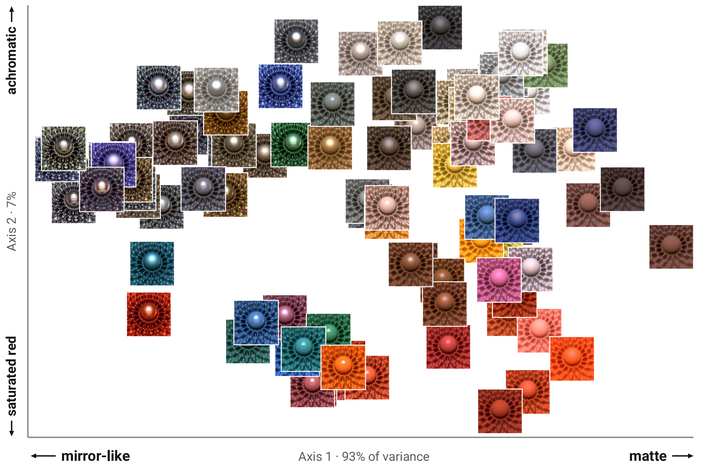


- **100 materials** (MERL), rendered as images [3]
- **92,892 crowdsourced answers** on 22,801 triplets
- **LORE sees only the answers,** never the images

Materials [3] · held-out triplet accuracy

Method	Test acc. %	Rank	Time (s)
LORE	84.1	**2.2**	5.8
SOE	81.9	**15**	35.5
FORTE	79.4	**15**	3.7
t-STE	83.4	**15**	27.2
CKL	83.9	**15**	14.8
Dim-CV hypothesis test	78.1	**1.0**	1,429

15 dimensions offered to every method · mean of30 runs



LORE embedding of 100 material images from human triplet judgements (best of 30 runs, rank 2), shown on its principal axes; axis 2 is stretched 2.4× for legibility. Axis names are our reading of the ordering, not an output of the method. Stimuli: [3].

LORE needs about 2 dimensions where every other method uses all 15, at the same accuracy. The two it finds read as gloss and colour, with no labels given.

Application: what makes an action effortful?

Motivation is a cost–benefit decision

We act when a reward seems worth the effort. What counts is effort as it is perceived, not the work actually done.

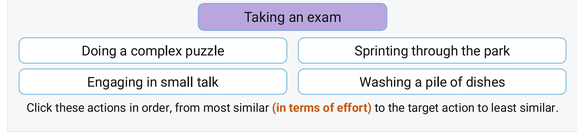
It breaks down in brain disorders

Reduced willingness to exert effort is a feature of depression, schizophrenia and Parkinson's disease [4, 5].

Current measures assume the answer

Questionnaires fix the dimensions in advance. Lab tasks test one kind of effort, such as grip force.

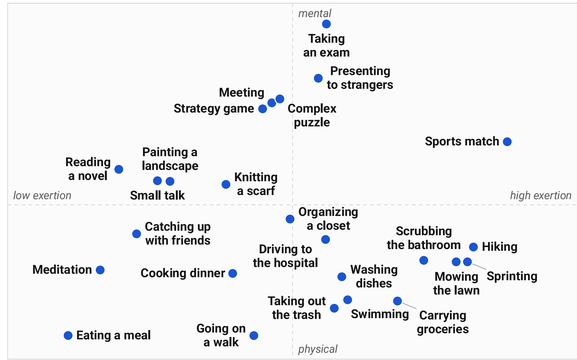
How we asked: rank actions by effort



1. **94 participants** × 150 ranking queries
2. **Each ranking of 4** gives 6 triplets
3. **Queries chosen adaptively,** live [6]
4. **25 everyday activities,** fixed wording

Perceived effort has four axes

Crowd map of 25 everyday activities



Axis 1 overall exertion (51% of variance) × **Axis 2** mental vs. physical (25%)

Four axes, learned from the comparisons and named afterwards

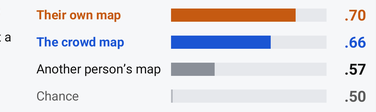
1. **Overall exertion** — 51%
   High: sports match, hiking, sprinting
   Low: meal, meditation, reading
2. **Mental vs. physical** — 25%
   Mental: exam, presentation, puzzle
   Physical: walk, meal, taking out trash
3. **Recreational vs. domestic** — 13%
   Recreational: swimming, hiking, sports
   Domestic: bathroom, dishes, trash
4. **Social vs. solitary** — 11%
   Social, stressful: hospital drive, meeting
   Solitary, calm: painting, knitting

Personal maps

Preliminary

How well does each map predict a person's held-out answers?

Noisy, but they carry something the crowd map does not.



held-out comparisons · N = 66

Comparisons need no rating scale and LORE needs no assumed dimensions, so the structure of effort comes from the data.

References

[1] Stewart, Brown & Chater, "Absolute identification by relative judgment," Psychological Review, 2005.
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[3] Lagunas et al., "A similarity measure for material appearance," ACM Transactions on Graphics, 2019.
[4] Treadway et al., "Effort-based decision-making in major depressive disorder," Journal of Abnormal Psychology, 2012.
[5] Husain & Roiser, "Neuroscience of apathy and anhedonia: a transdiagnostic approach," Nature Reviews Neuroscience, 2018.
[6] Canal, Fenu & Rozell, "Active ordinal querying for tuplewise similarity learning," AAAI, 2020.

Acknowledgements

We thank Michael Treadway and Marta Migo for their collaboration on the effort-perception study. This work was supported by the National Science Foundation under Grant No. CCF-2107455. Additionally, supported in part by the NIH BRAIN Initiative through NIMH grant R61MH138966, the National Center for Advancing Translational Sciences of the National Institutes of Health under Award Number UL1TR002378 and KL2TR002381, and the Julian T. Hightower Chair at Georgia Tech. Vivek Anand was supported by the National Institutes of Health under the Data Science in Computational Neural Engineering Training Grant T32EB025816 and the National Defense Science and Engineering Graduate (NDSEG) Fellowship Program.