AI literacy: Empowering People in Human-AI interactions

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ELLITT Symposium, Norrkopping, 15 May 2025

AI literacy?

“Providers and deployers of AI systems shall take measures to ensure, to their best extent, a sufficient level of AI literacy of their staff and other persons dealing with the operation and use of AI systems on their behalf, taking into account their technical knowledge, experience, education and training and the context the AI systems are to be used in, and considering the persons or groups of persons on whom the AI systems are to be used.”

AI literacy?

EU Artificial Intelligence Act

"Providers and deployers of AI systems shall take measures to ensure, to their best extent, a sufficient level of AI literacy of their staff and other persons dealing with the operation and use of AI systems on their behalf, taking into account their technical knowledge, experience, education and training and the context the AI systems are to be used in, and considering the persons or groups of persons on whom the AI systems are to be used."

What is AI Literacy? Competencies and Design Considerations

Authors: Duri Long, Brian Magerko | Authors Info & Claims

CHI '20: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems • Pages 1 - 16
https://doi.org/10.1145/3313831.3376727

AI literacy as a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace.

AI literacy?

Computers and Education: Artificial Intelligence
Volume 2, 2021, 100041

Conceptualizing AI literacy: An exploratory review

Davy Tsz Kit Ng [a], Jac Ka Lok Leung [b], Samuel Kai Wah Chu [a], Maggie Shen Qiao [a]

[a] Faculty of Education, The University of Hong Kong, Pokfulam, Hong Kong
[b] Center for Education Innovation, Hong Kong University of Science and Technology, Hong Kong

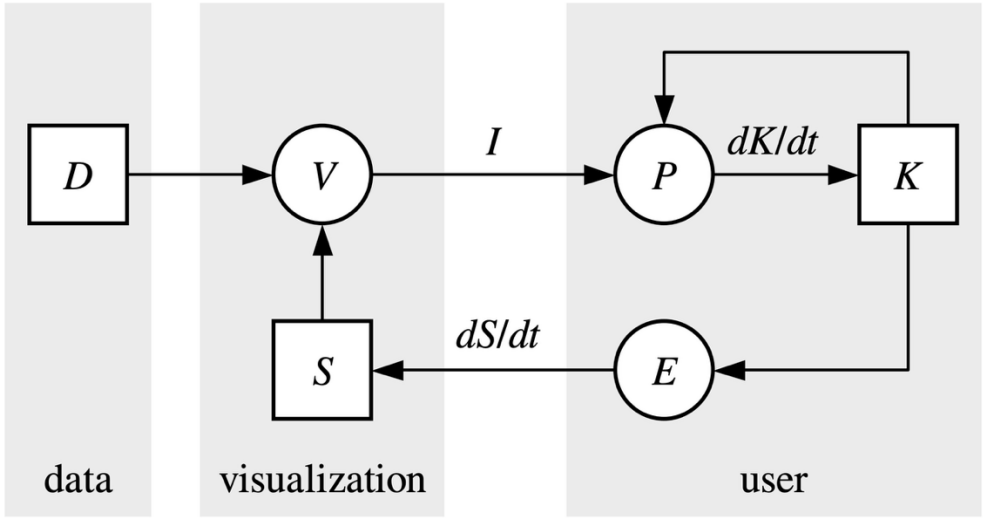
AI literacy	Definitions	N	Sample references
Know & understand AI	Know the basic functions of AI and how to use AI applications.	27	*Even though transparency in algorithms and AI in general has been **acknowledged** to be ethically important, the public lacks understanding of even the basic functions of AI. Efforts to make AI more comprehensible exist (Robinson, 2020).*
Use & Apply AI	Applying AI knowledge, concepts and applications in different scenarios.	30	***Apply** k-means clustering in science contexts.. explore the mapping relationship between facial features and data values and **apply** the concept to brainstorm other objects such as Lego (Wan et al., 2020).*
Evaluate & create AI	Higher-order thinking skills (e.g., evaluate, appraise, predict, design) with AI applications.	19	***Design** & **build** experiences: Technology exploration and **creation** activities supported students in making sense of the underlying AI concepts. (Lee, 2020).*
AI ethics	Human-centered considerations (e.g., fairness, accountability, transparency, ethics, safety).	19	***"AI for social good"** measures an individual's perception of the social environment surrounding the behavior, which is related to subjective norms (Chai et al., 2020).*

empowering **people**

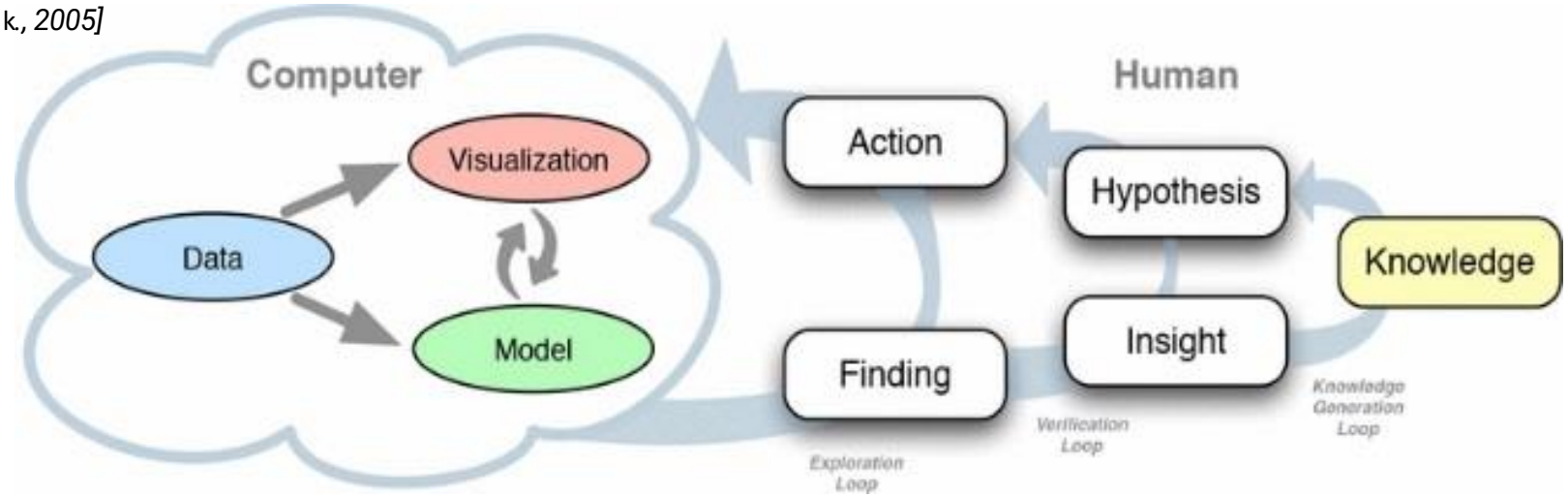
in Human-AI interactions by supporting them in understanding, using, applying, evaluating and creating AI

empowering	people
visualisation	expert audiences
visual analytics	.. data scientists
human-in-the-loop	.. researchers
ai-in-the-loop	.. decision-makers

human-in-the-loop



[van Wijk., 2005]



[SACHA et al., 2014]

Artificial Intelligence Review (2023) 56:3005–3054
https://doi.org/10.1007/s10462-022-10246-w

Human-in-the-loop machine learning: a state of the art

Eduardo Mosqueira-Rey[1] · Elena Hernández-Pereira[1] · David Alonso-Ríos[1] · José Bobes-Bascarán[1] · Ángel Fernández-Leal[1]

Published online: 17 August 2022
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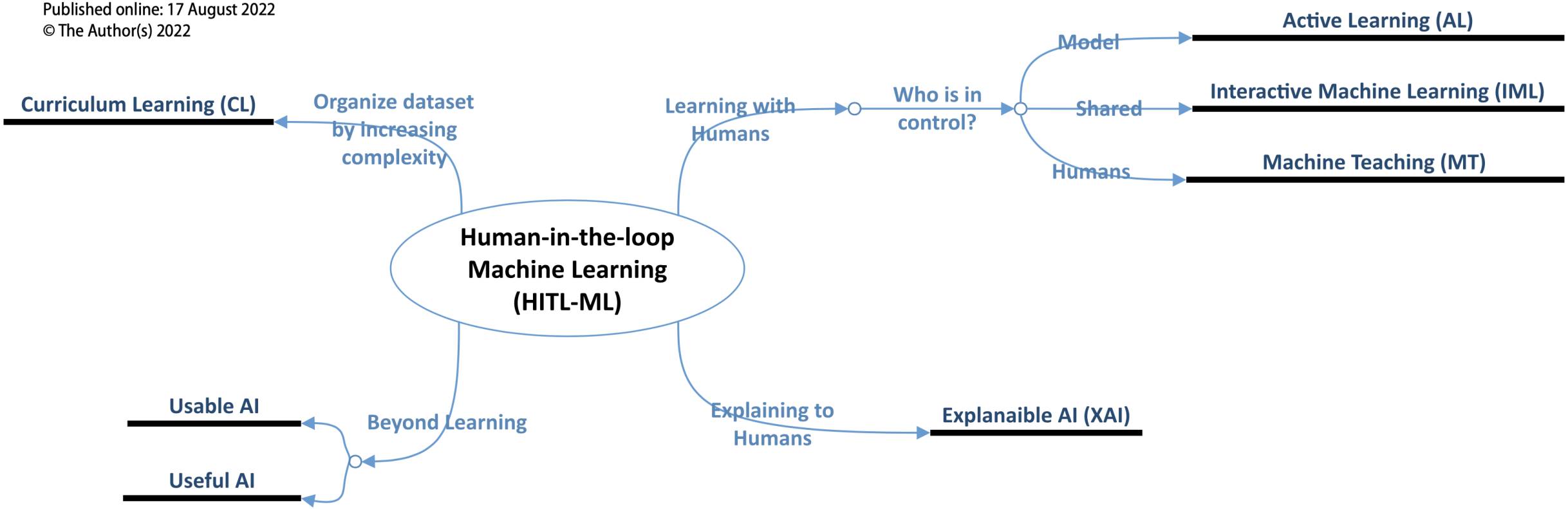
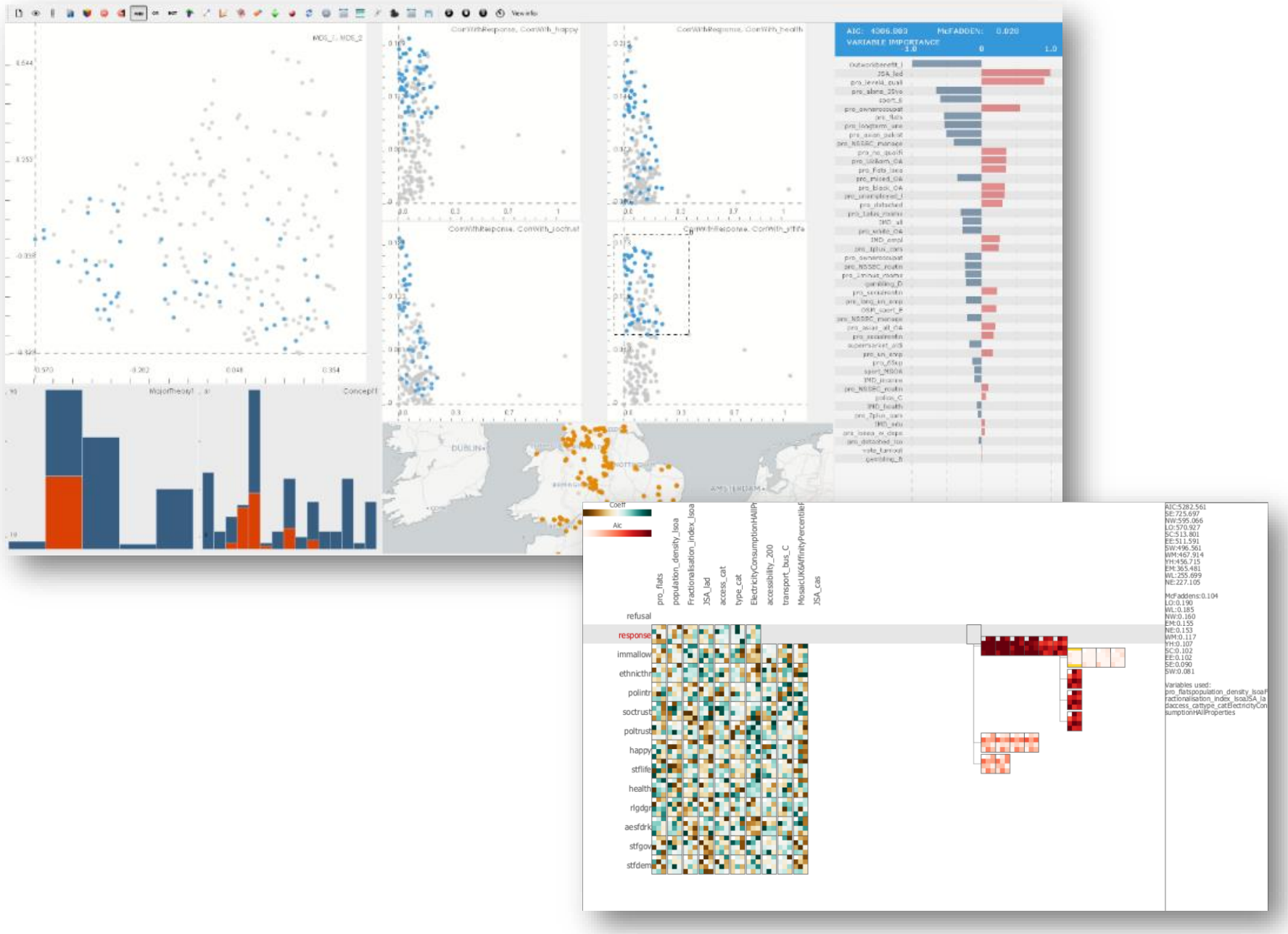


Enhancing a Social Science Model-building Workflow with Interactive Visualisation

Turkay, C., Slingsby, A., Lahtinen, K., Butt, S., & Dykes, J., ESANN 2016 (& Neurocomputing 2017)



European Social Survey

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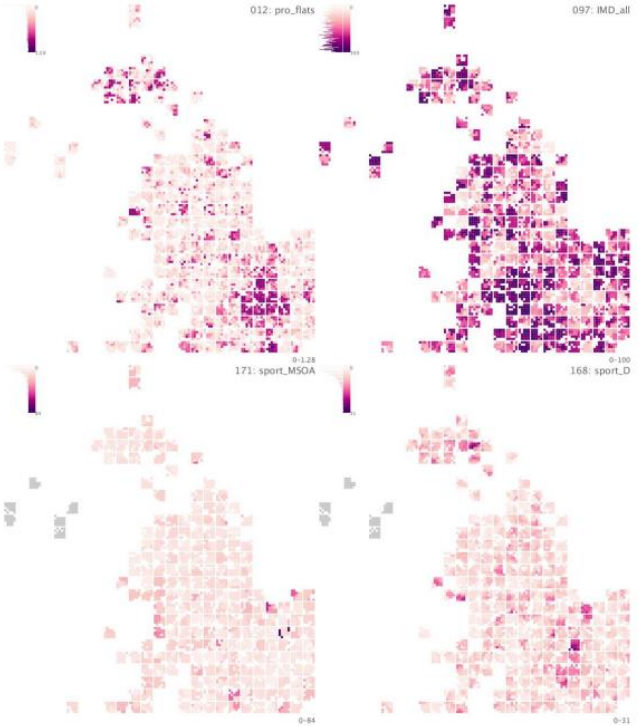
giCentre
www.gicentre.net

*"We (social scientists) **need** (data-based) models that we can **understand** and **explain** so that we can defend them to our peers in **full confidence.**"*

A quote from collaborators at our AddResponse project on data-based models



From: Lahtinen, K. et al. (2015). Informing Non-Response Bias Model Creation in Social Surveys with Visualisation. Poster VIS 2015

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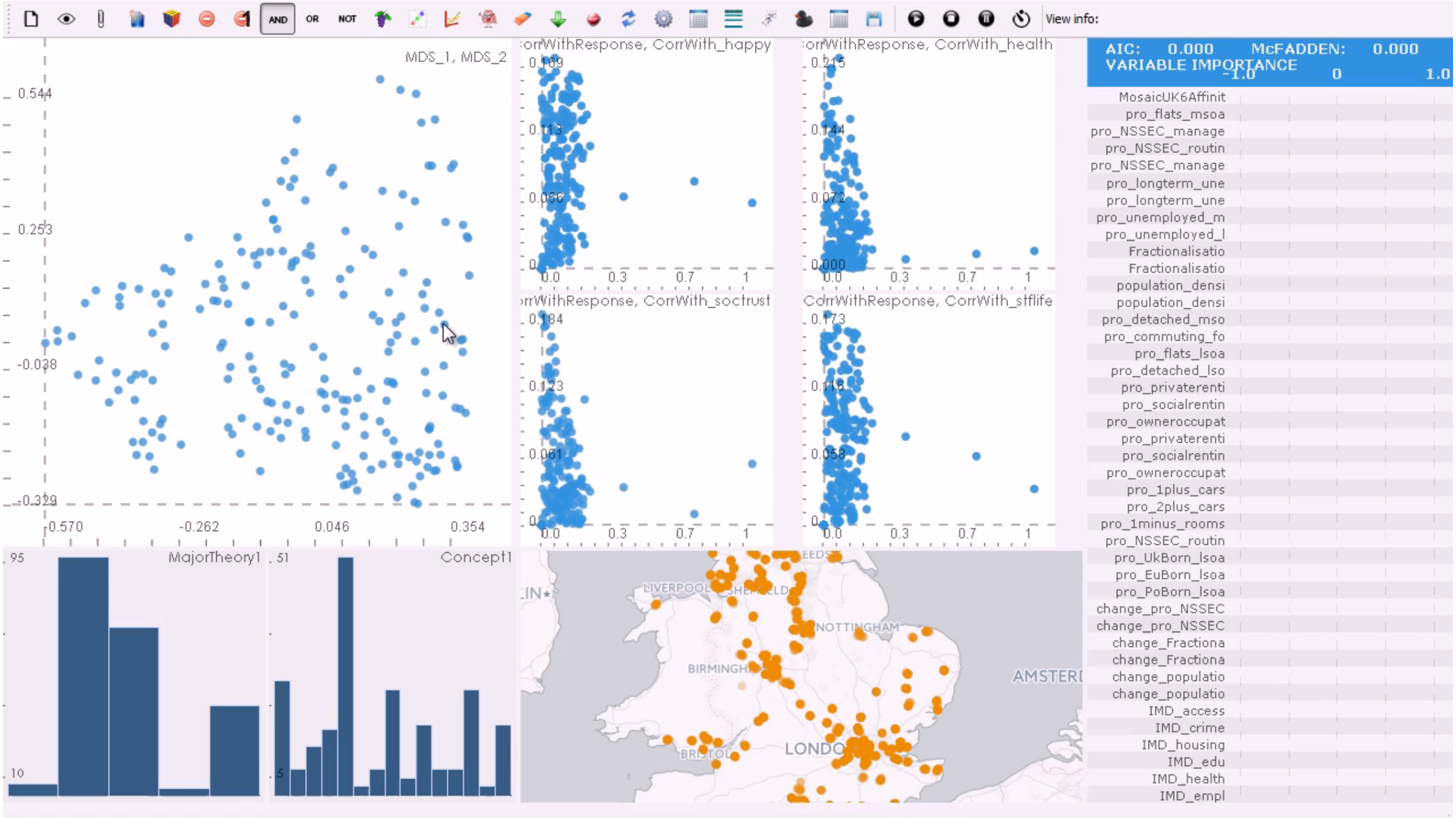
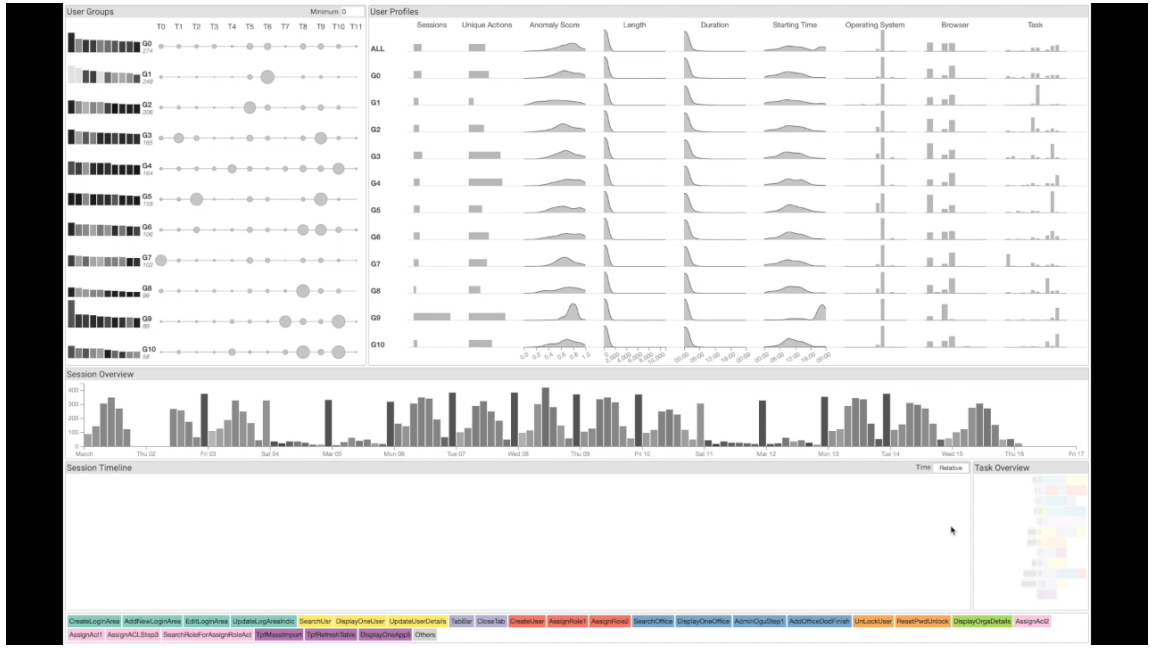

AND
OR
NOT
View info:
MDS_1, MDS_2
0.544
0.253
-0.038
-0.329
-0.570
-0.262
0.046
0.354
corrWithResponse, CorrWith_happy
0.169
0.113
0.056
0.0
0.3
0.7
1
corrWithResponse, CorrWith_health
0.215
0.144
0.072
0.000
corrWithResponse, CorrWith_soctrust
0.184
0.123
0.061
CorrWithResponse, CorrWith_stflife
0.173
0.116
0.058
AIC: 0.000
McFADDEN: 0.000
VARIABLE IMPORTANCE
-1.0
0
1.0
MosaicUK6Affinit
pro_flats_msoa
pro_NSSEC_manage
pro_NSSEC_routin
pro_NSSEC_manage
pro_longterm_une
pro_longterm_une
pro_unemployed_m
pro_unemployed_l
Fractionalisatio
Fractionalisatio
population_densi
population_densi
pro_detached_mso
pro_commuting_fo
pro_flats_lsoa
pro_detached_lso
pro_privaterenti
pro_socialrentin
pro_owneroccupat
pro_privaterenti
pro_socialrentin
pro_owneroccupat
pro_1plus_cars
pro_2plus_cars
pro_1minus_rooms
pro_NSSEC_routin
pro_UkBorn_lsoa
pro_EuBorn_lsoa
pro_PoBorn_lsoa
change_pro_NSSEC
change_pro_NSSEC
change_Fractiona
change_Fractiona
change_populatio
change_populatio
IMD_access
IMD_crime
IMD_housing
IMD_edu
IMD_health
IMD_empl
95
10
MajorTheory1
51
5
Concept1
LIVERPOOL
NOTTINGHAM
BIRMINGH
BRISTOL
LONDO
AMSTERD

CASE STUDY –

Interactive User Behaviour Analytics in Cyber Systems

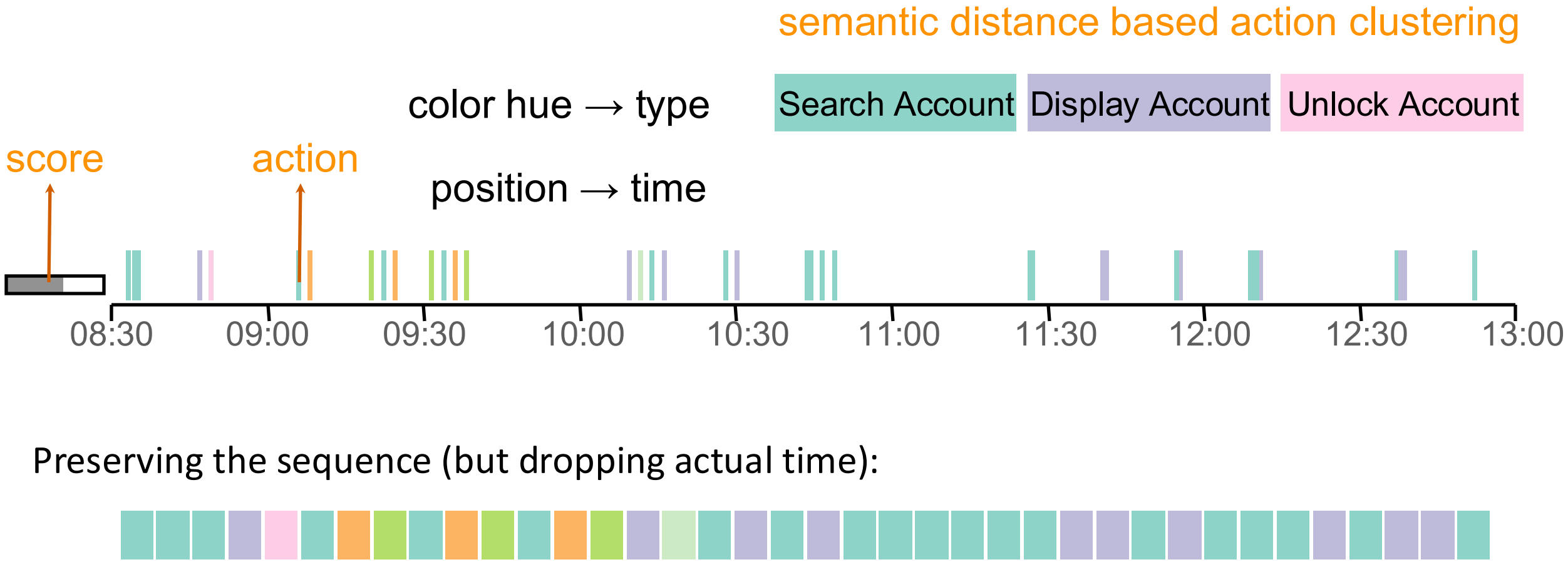
VASABI: Hierarchical User Profiles for Interactive Visual User Behaviour Analytics

Nguyen PH, Henkin R, Chen S, Andrienko N, Andrienko G, Thonnard O, Turkay C.
IEEE TVCG, 2019



Understanding User Behaviour through Action Sequences: from the Usual to the Unusual

Nguyen, P.H., Turkay, C., Andrienko, G., Andrienko, N., Thonnard, O. and Zouaoui, J. , IEEE TVCG, 2018

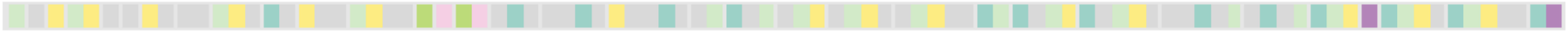


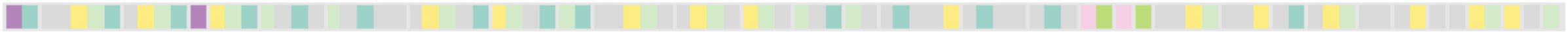
Preserving the sequence (but dropping actual time):

Most important decision to make is:

How expected is

… given that the user has done all of …





… before?

the algorithm says …

0.7

Many facets / questions to think about …

- Is the set of **actions in** this **session** are indicative of problematic behaviour?
- What **kinds of tasks** might the user be conducting?
- Is this a “usual” session when the **history of all the sessions** from this user is considered?
- Is this a “usual” session when the history of all the sessions from **similar users** are considered?
- Does the session fit within the **roles of the user**?
- What **tasks** are **common** for that particular **role**?
- ….

Many facets / questions to think about …

- Is the set of **actions in** this **session** are indicative of problematic behaviour?
- What **kinds of tasks** might the user be conducting?
- Is this a “usual” session when the **history of all the sessions** from this user is considered?
- Is this a “usual” session when the history of all the sessions from **similar users** are considered?
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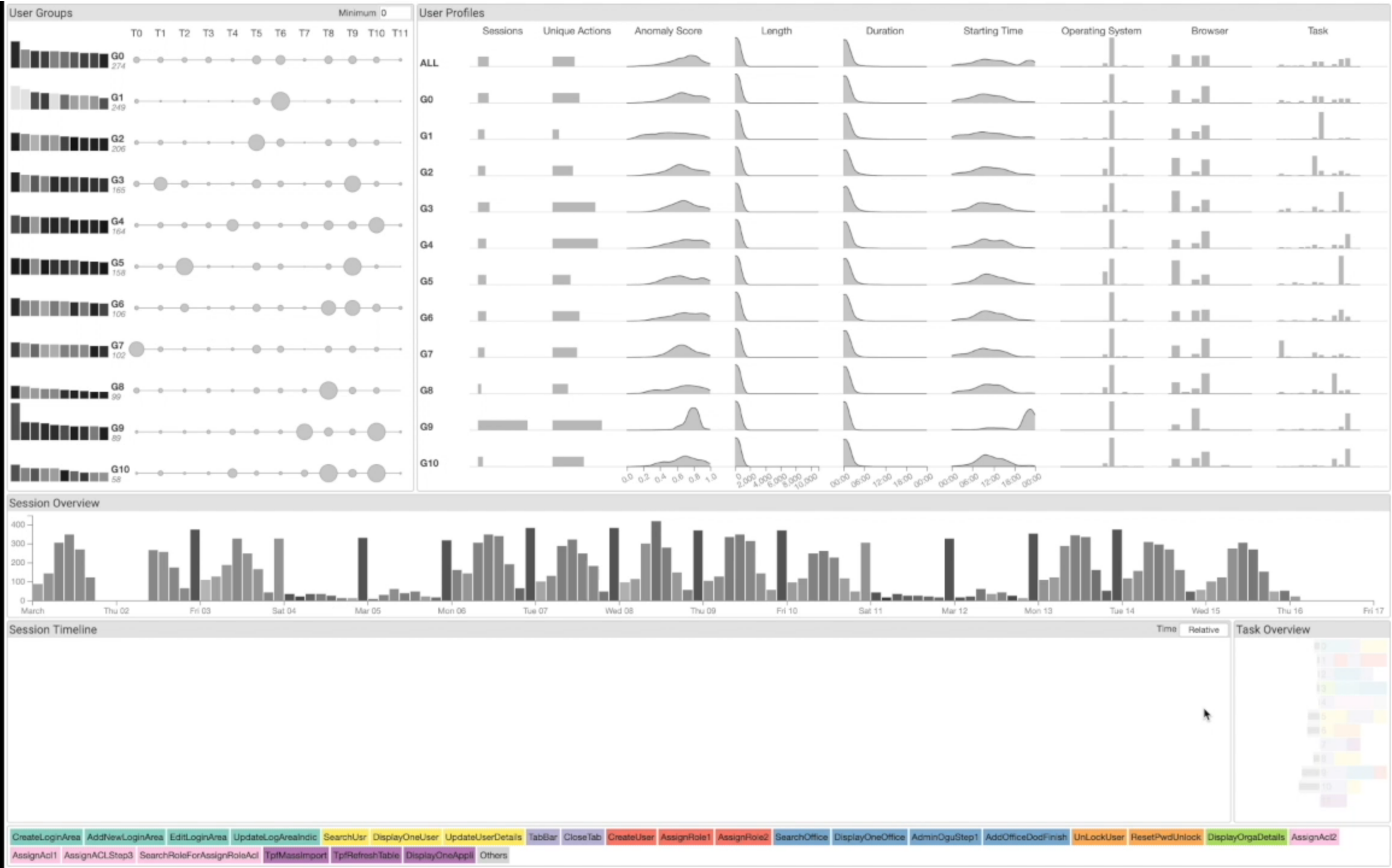
….


User Groups
Minimum 0
T0 T1 T2 T3 T4 T5 T6 T7 T8 T9 T10 T11
G0 274
G1 249
G2 206
G3 165
G4 164
G5 158
G6 106
G7 102
G8 99
G9 89
G10 58
User Profiles
Sessions
Unique Actions
Anomaly Score
Length
Duration
Starting Time
Operating System
Browser
Task
ALL
G0
G1
G2
G3
G4
G5
G6
G7
G8
G9
G10
0.0 0.2 0.4 0.6 0.8 1.0
0 2,000 4,000 6,000 8,000 10,000
00:00 06:00 12:00 18:00 00:00
Session Overview
400
300
200
100
0
March
Thu 02
Fri 03
Sat 04
Mar 05
Mon 06
Tue 07
Wed 08
Thu 09
Fri 10
Sat 11
Mar 12
Mon 13
Tue 14
Wed 15
Thu 16
Fri 17
Session Timeline
Time
Relative
Task Overview
CreateLoginArea
AddNewLoginArea
EditLoginArea
UpdateLogAreaIndic
SearchUsr
DisplayOneUser
UpdateUserDetails
TabBar
CloseTab
CreateUser
AssignRole1
AssignRole2
SearchOffice
DisplayOneOffice
AdminOguStep1
AddOfficeDodFinish
UnLockUser
ResetPwdUnlock
DisplayOrgaDetails
AssignAcl2
AssignAcl1
AssignACLStep3
SearchRoleForAssignRoleAcl
TpfMassImport
TpfRefreshTable
DisplayOneAppli
Others

How does VIS empower people here?

- **Ability to bring in contextual knowledge**
  - Selecting relevant data features, e.g., those that relate to a particular social theory
  - Discarding data features / regions that are known to be problematic
- **Facilitating interpretation**
  - Explaining observations in dialogue with theory/knowledge, e.g., why do we see the model/pattern we are seeing
  - Generating knowledge based on the observations
- **Supporting translation to real-world actions**
  - Making decisions and taking actions based on the observations

AI*-in-the-loop – a new paradigm?

(Note: AI understood as Foundational Generative AI (e.g. LLMs))

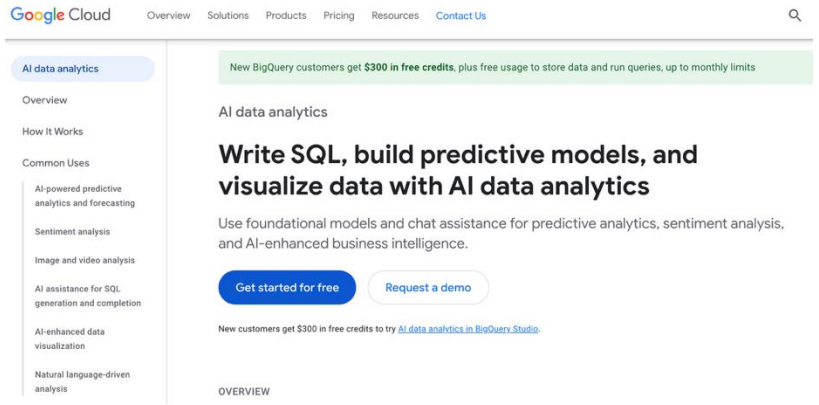
LLM4DS: Evaluating Large Language Models for Data Science Code Generation

Nathalia Nascimento, *EASER, Eng. Division, Pennsylvania State University, Great Valley, USA, nqm5742@psu.edu*

Everton Guimaraes, *EASER, Eng. Division, Pennsylvania State University, Great Valley, USA, ezt157@psu.edu*

Sai Sanjna Chintakunta, *EASER, Eng. Division, Pennsylvania State University, Great Valley, USA, sqc6557@psu.edu*

Santhosh Anitha Boominathan, *EASER, Eng. Division, Pennsylvania State University, Great Valley, USA, sfa5971@psu.edu*

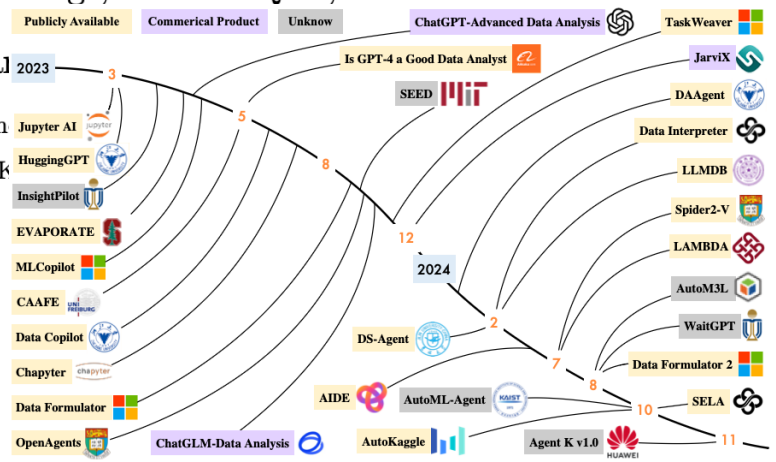


A Survey on Large Language Model-based Agents for Statistics and Data Science

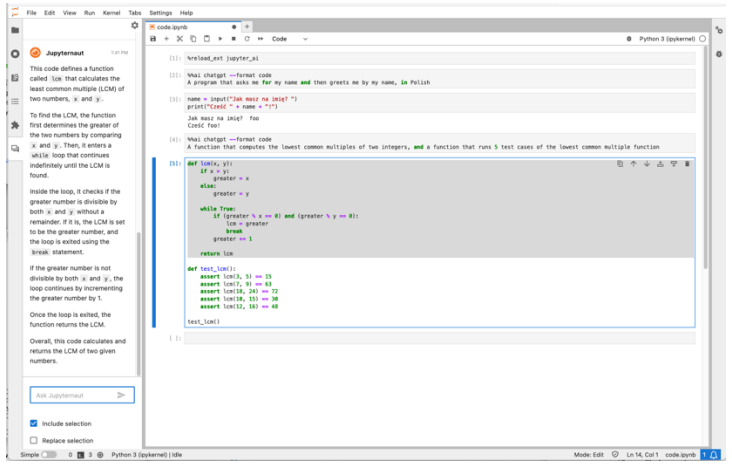
Maojun Sun[a], Ruijian Han[a], Binyan Jiang[a], Houduo Qi[a,b], Defeng Sun[b], Yancheng Yuan[a*] al

[a]Department of Data Science and Artificial Intelligence, Th

[b]Department of Applied Mathematics, The Hong K



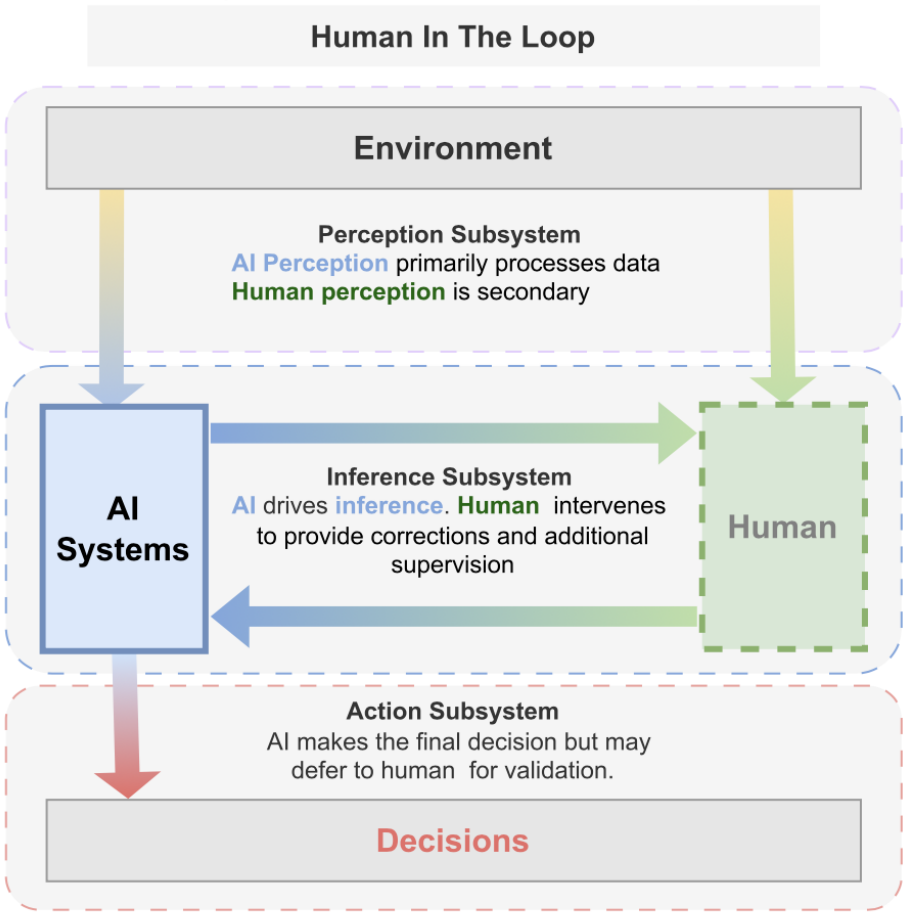
https://github.com/jupyterlab/jupyter-ai

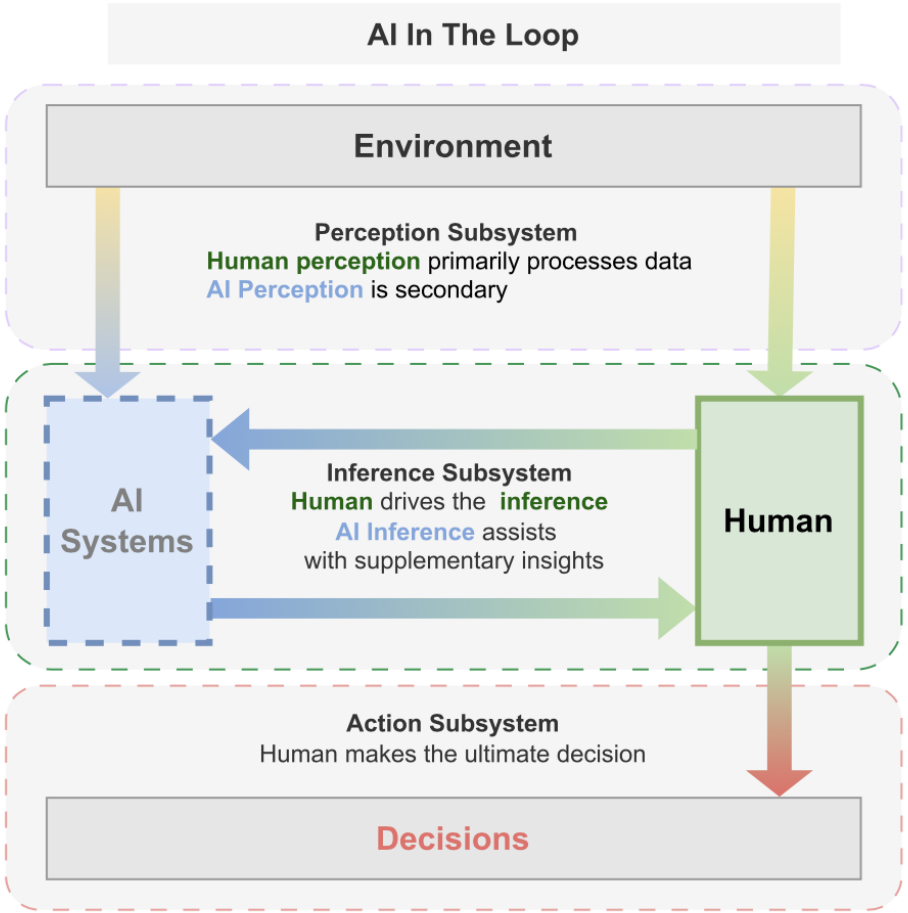


Human-in-the-loop or AI-in-the-loop? Automate or Collaborate?

Sriraam Natarajan[1], **Saurabh Mathur**[1*], **Sahil Sidheekh**[1*], **Wolfgang Stammer**[2,3], **Kristian Kersting**[2,3]

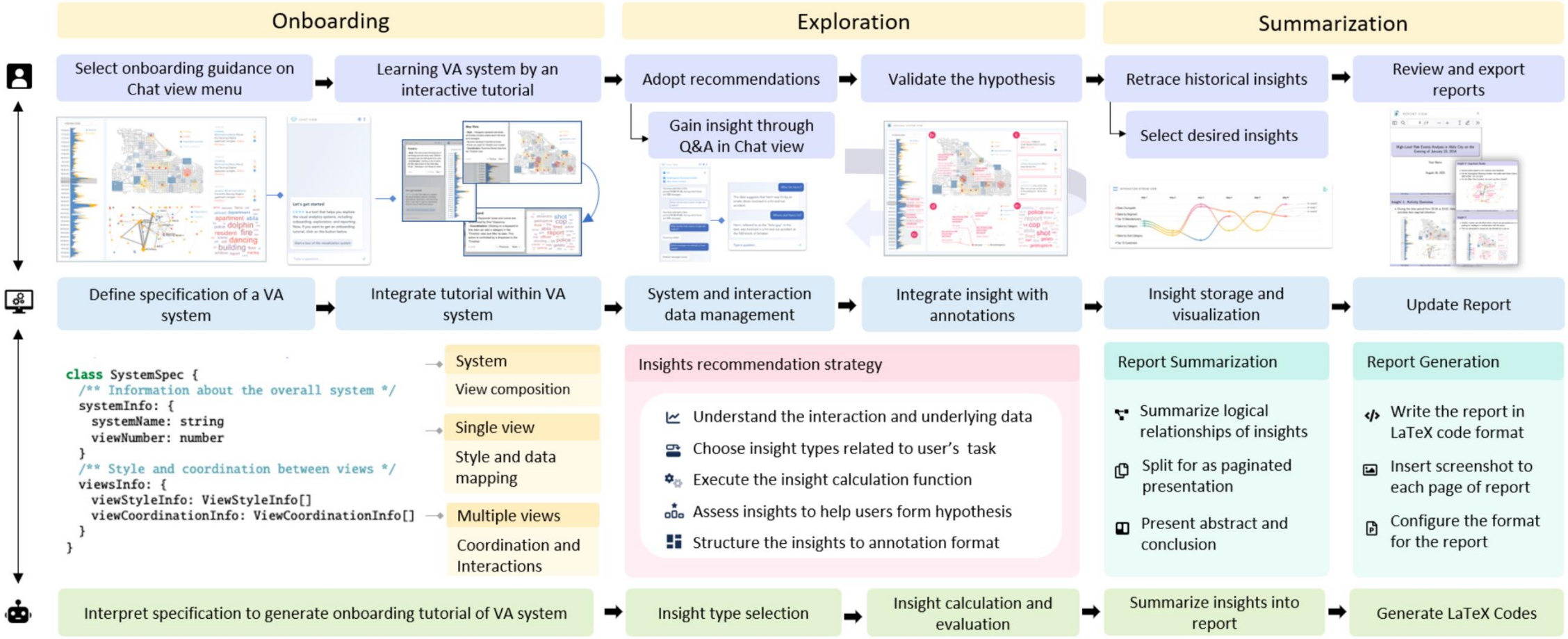
[1] University of Texas at Dallas,
[2] Technical University of Darmstadt,
[3] Hessian Center for Artificial Intelligence (hessian.ai), Darmstadt, Germany





Natarajan, S., Mathur, S., Sidheekh, S., Stammer, W. and Kersting, K., 2025, April. Human-in-the-loop or AI-in-the-loop? Automate or Collaborate?. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 39, No. 27, pp. 28594-28600).

LEVA: Using Large Language Models to Enhance Visual Analytics

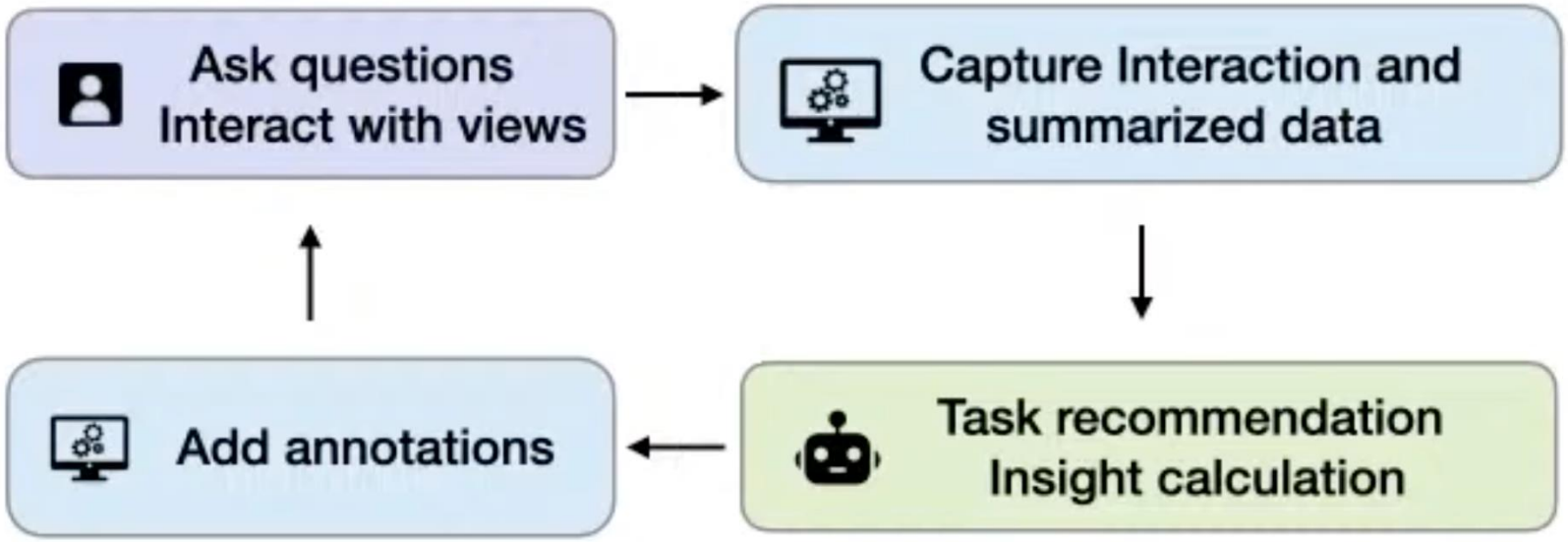


Y. Zhao *et al.*, "LEVA: Using Large Language Models to Enhance Visual Analytics," in *IEEE Transactions on Visualization and Computer Graphics*, vol. 31, no. 3, pp. 1830-1847, 2025

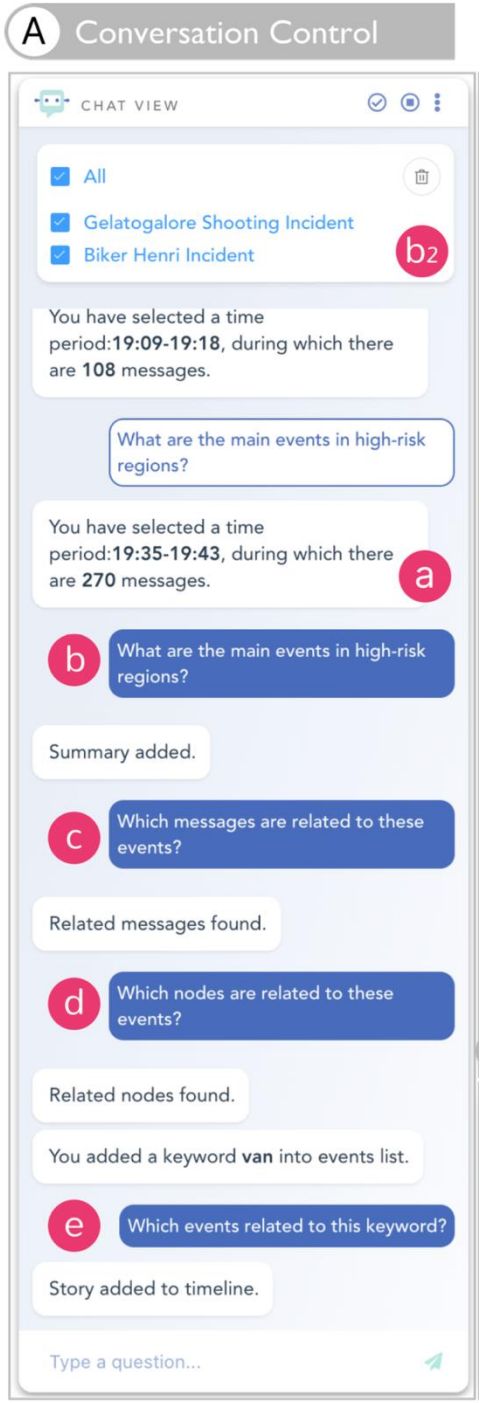
LEVA: Using Large Language Models to Enhance Visual Analytics

L·E·V·A

Yuheng Zhao, Yixing Zhang, Yu Zhang, Xinyi Zhao, Junjie Wang,
Zekai Shao, Cagatay Turkay, Siming Chen



Insight type	Description
Outstanding No.1	The leading value is significantly higher than all the remaining values.
Outstanding Top 2	The leading two values are significantly higher than all the remaining values.
Outstanding Last	The value is remarkably lower than all the remaining values.
Attribution	The leading value dominates (accounting for $\geq 50\%$) the group.
Change Point	A specific point in time where there is a significant change or shift in the underlying data-generating process.
Outlier	An observation or data point that significantly deviates from the rest of the data.
Seasonality	A regular and predictable pattern of fluctuations or variations that occur at specific intervals of time.
Trend	A time series has an obvious trend (increase or decrease) with a certain turbulence level (steadily/ with turbulence).
Correlation	The statistical relationships between random variables, multidimensional data or time series.
Difference	The similarity or difference between two or more datasets
Aggregation	The descriptive statistical indicators (e.g., average, sum, count, etc.) based on the data attributes.
Value	The the exact value of data attribute(s) under specific criteria.
Text summary	The core ideas of a text dataset. The summary might have spatial or temporal features.
Important nodes or links	The important nodes or links in a graph under specific criteria.
Important text or keywords	The important original texts or keywords under specific criteria.



Prompt template for insight type selection:

When the user makes an action, the system changes. You should analyze data types of connected views based on the coordination information between views.

{ current selection }

{ view style info }

{ views coordination info }

According to the data info in each view and the analytical task, you should select all suitable analytical functions related to the user's task. You also need to give a relevance score to assess how closely related the insight is to the task.

{ analytical task }

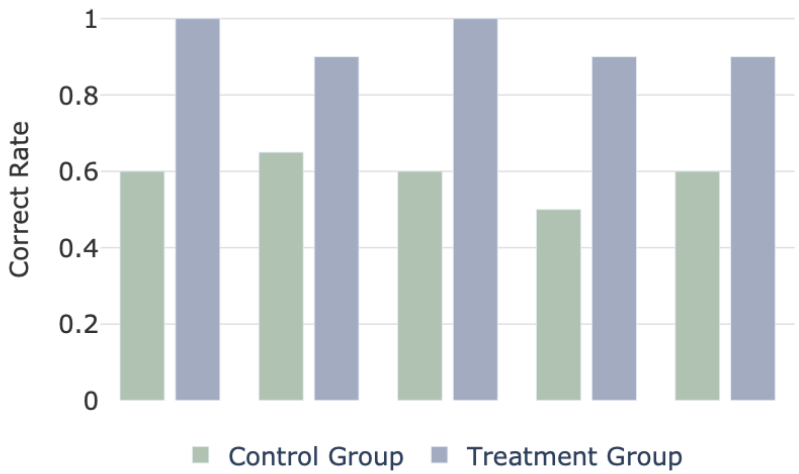
{ insight function APIs }

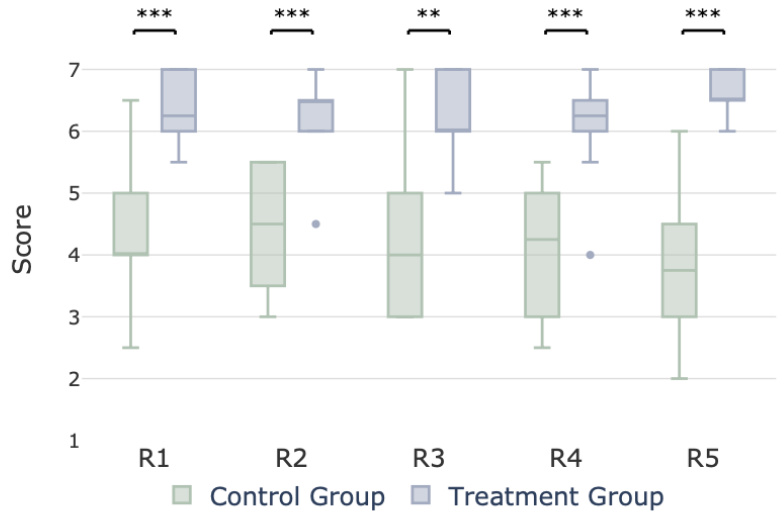
Please give your answer in the following format:

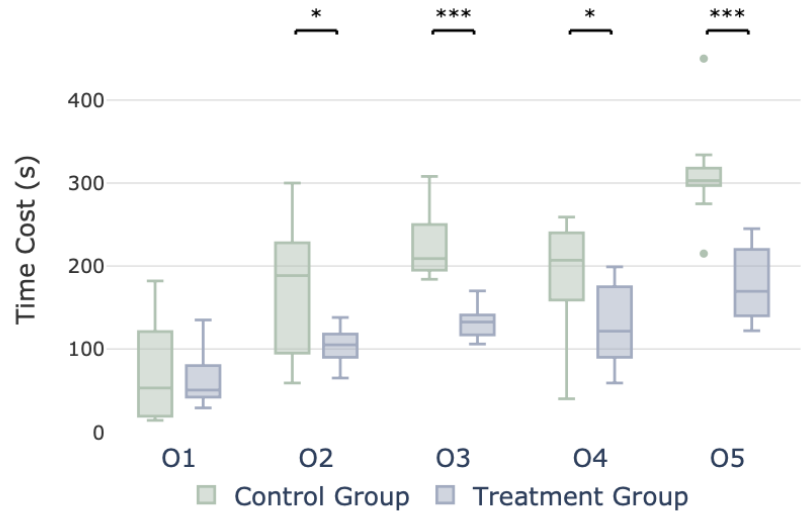
{ format requirements }

According to the data info in each view and the analytical task, you should select all suitable analytical functions related to the user's task. If a view contains more than one measure, all measures need to be considered to find appropriate functions. Cross-view insights, such as correlation, are allowed. You also need to give a relevance score to assess how closely related the insight type is to the task.

```
{"user task": "Analyze the sales of the superstore from
      different perspectives."}
"functions": [
  {
    "name": "get_change_point",
    "description": "Get the change point in a time
        series dataset"
  },{
    "name": "get_seasonality",
    "description": "Get the seasonality in a time
        series dataset"
  },{
    "name": "get_trend",
    "description": "Get the trend in a time series
        dataset"
  },{
    "name": "get_outlier",
    "description": "Get outliers in a dataset",
  },{
```







Type	Specific questions
R1: Perceptual visual encoding	**O1:**What do the visual encoding and corresponding data mean for the timeline view? **S1:** Do you know what each data variaiables means? **S2:** Do you understand the meaning of the visual elements?
R2: Interaction and Coordination	**O2:** How the timeline view coordinated with other views? **S3:** Are you clear on how to interact in each view? **S4:** Are you clear on how the views are related?
R3: Data Pattern Discovery	**O3:** What high-risk level events occurred in the peak period? **S5:** Is it easy to get data findings (such as events, key nodes) in these views?
R4: Hypothesis Formulation and Validation	**O4:** What are the key player and location of the summarized event? **S6:** Are you clear about the next step analysis for validation? **S7:** Do you have easy access to rich hypotheses?
R5: Summarization of Exploration Results	**O5:** Discover related events of the keyplayer and summarize them into a report. **S8:** Is it easy to write an analysis report on the interaction results? **S9:** Are you satisfied with the quality of the report you wrote?

How AI empowers people?

As an interaction mechanism, i.e., natural language interface to functionality, lowering barriers

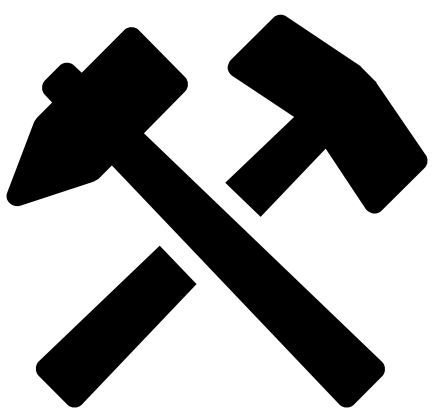
As a guidance mechanism

- Suggestions/recommendations: data sections to inspect for fuller data/pattern coverage

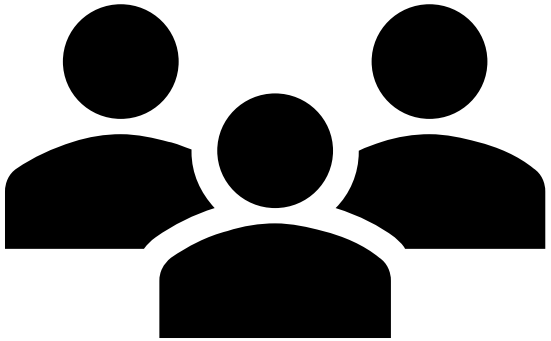
By communicating disclaimers/assumptions/additional context, e.g., model/data assumptions – improving the quality and rigour of the process and insights drawn

empowering	people
visualisation	expert audiences
human-in-the-loop	.. data scientists
ai-in-the-loop	.. researchers
…	.. decision-makers
	everyone else?

Human-AI Interaction



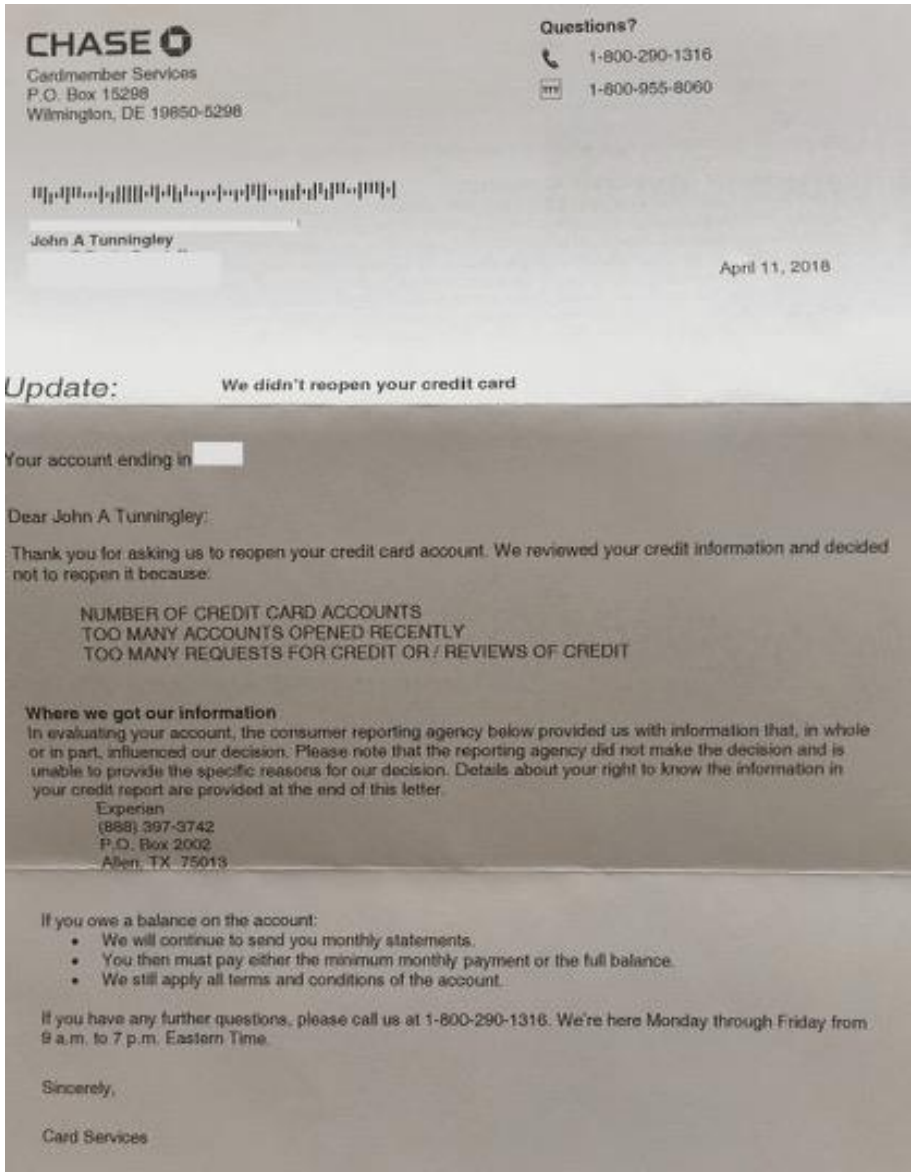
Developers



(Expert) users

Decision-Subject

Human Agency



CHASE

Cardmember Services
P.O. Box 15298
Wilmington, DE 19850-5298

Questions?
1-800-290-1316
1-800-955-8060

John A Tunningley

April 11, 2018

Update: We didn't reopen your credit card

Your account ending in

Dear John A Tunningley:

Thank you for asking us to reopen your credit card account. We reviewed your credit information and decided not to reopen it because:

NUMBER OF CREDIT CARD ACCOUNTS
TOO MANY ACCOUNTS OPENED RECENTLY
TOO MANY REQUESTS FOR CREDIT OR / REVIEWS OF CREDIT

Where we got our information
In evaluating your account, the consumer reporting agency below provided us with information that, in whole or in part, influenced our decision. Please note that the reporting agency did not make the decision and is unable to provide the specific reasons for our decision. Details about your right to know the information in your credit report are provided at the end of this letter.

Experian
(888) 397-3742
P.O. Box 2002
Allen, TX 75013

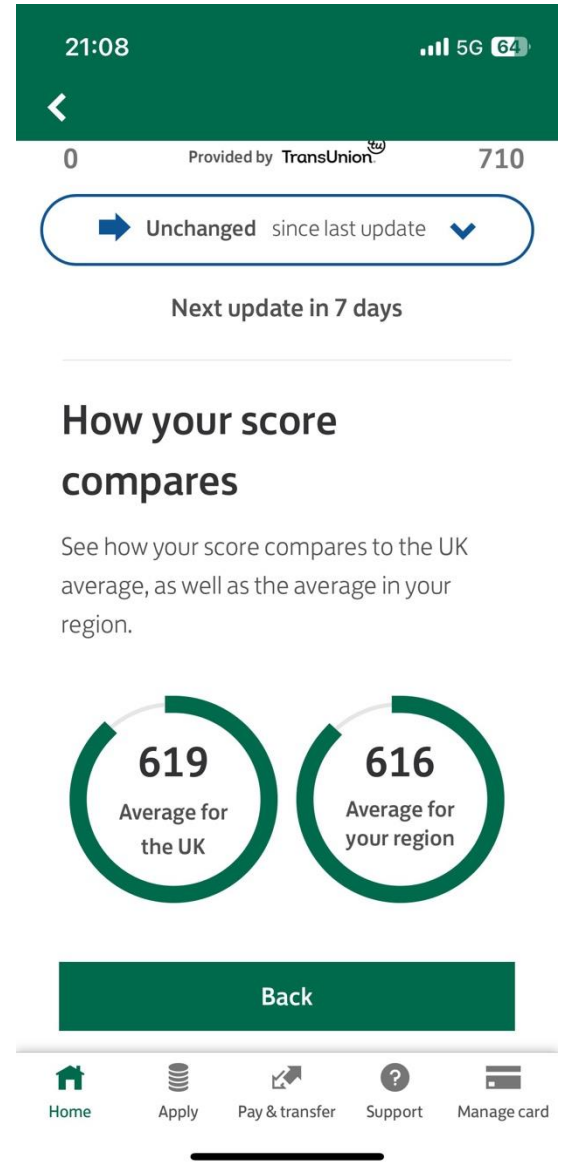
If you owe a balance on the account:

- We will continue to send you monthly statements.
- You then must pay either the minimum monthly payment or the full balance.
- We still apply all terms and conditions of the account.

If you have any further questions, please call us at 1-800-290-1316. We're here Monday through Friday from 9 a.m. to 7 p.m. Eastern Time.

Sincerely,

Card Services



Moving from Explainability to Actionability

Move beyond understanding AI decisions to empowering action.

Can explanations empower users to identify and challenge mistakes when algorithms go wrong?

Explainability → Actionability (Contestation as an action)

An Actionability Assessment Tool for Explainable AI

Ronal Singh, Tim Miller, Liz Sonenberg, Eduardo Velloso, Frank Vetere, Piers Howe, Paul Dourish

"An explanation of a decision is actionable if people can use the information to identify actions to take to change the decision"

Financial Conduct Authority

Research Note

24 February 2025

Credit where credit is due: how can AI's role in credit decisions be explained?

Cameron Belton, Daniel Bogiatzis-Gibbons, Isaac Keeley, Jackie Spang, Cagatay Turkay, Yulu Pi

What?: to explore how different methods ('genres') of explaining AI-assisted decisions about creditworthiness can empower users to better **understand whether an AI-assisted decision is appropriate for them** and to what extent they **enable people to contest the decision**

1 Sampling & Task Setting

A sample of
N = 8708 UK adults

*.. asked to imagine themselves as someone receiving an **AI-assisted decision** to a credit card application*

*Each participant is assigned to one of the explanation **genre** groups*

2 Explanation genre groups

Explanations involve …

data | **data features** | **logical rules**

Four explanations **genres**

G1:

G2:

G3: +

G4: + +

3 Ability to Assess AI Decisions

*Each participant considers five hypothetical credit application **scenarios** all explained with their assigned **genre** ..*

Two correct decisions

- Correct Acceptance
- Correct Rejection

Three incorrect decisions with distinct **error types**

- Wrong Rejection: input data error
- Wrong Rejection: over-reliance on one feature
- Wrong Rejection: failure to consider relevant information

.. and asked, do you ..

ACCEPT

or

CHALLENGE

.. the **AI-assisted decision** and then asked **WHY?**

4 Comprehension Test

After doing the task once, they are then asked to complete a comprehension test on:

- Role of algorithm in credit decision-making
- Feature Effect
- Feature Importance

5 Attitude Survey

After doing the task four more times, they are then asked to complete a survey on:

- Importance of Information
- Helpfulness of Information
- Sufficiency of Information
- Confidence in Disagreement

Profile Summa

Your profile (about you):

- Debt collection accounts opened in last 24 months: 0
- Late payments or overdue accounts in last 24 months: 1
- Percentage of credit that you've already paid off: 2%
- Percentage of available credit limit that you're using: 80%
- Annual income: £280,000
- Current total credit card limit: £2,000

Message received from the credit provider:

Thank you for your application for our Regular Credit Card. We would like to inform you that the result of your application is: **Rejected**

We have a tool that uses algorithms to assess credit card applications. The tool doesn't make decisions on its own and the application would not be rejected by the tool alone, but it helps our credit card officers find applications that might have a higher risk of not being repaid.

How the algorithm helped us make this decision:

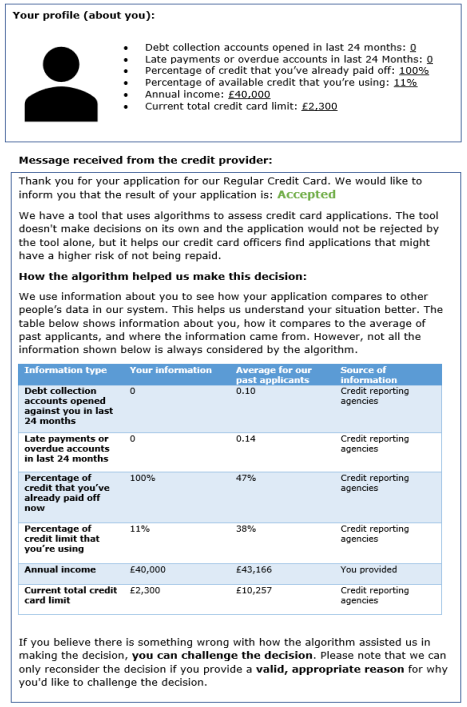
We use information about you to see how your application compares to other people's data in our system. This helps us understand your situation better. The table below shows information about you, how it compares to the average of past applicants, and where the information came from. However, not all the information shown below is always considered by the algorithm.

Information type	Your information	Average for our past applicants	Source of information
Debt collection accounts opened against you in last 24 months	0	0.10	Credit reporting agencies
Late payments or overdue accounts in last 24 months	1	0.14	Credit reporting agencies
Percentage of credit that you've already paid off now	2%	47%	Credit reporting agencies
Percentage of credit limit that you're using	80%	38%	Credit reporting agencies
Annual income	£280,000	£43,166	You provided
Current total credit card limit	£2,000	£10,257	Credit reporting agencies

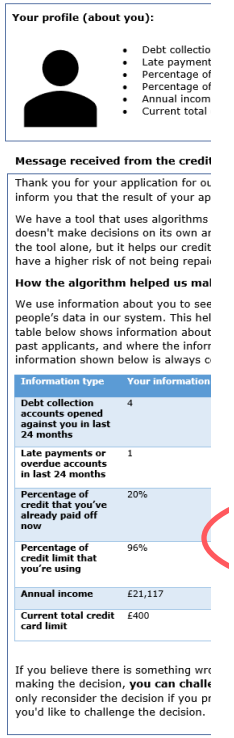
If you believe there is something wrong with how the algorithm assisted us in

Reason:
failure to consider relevant feature

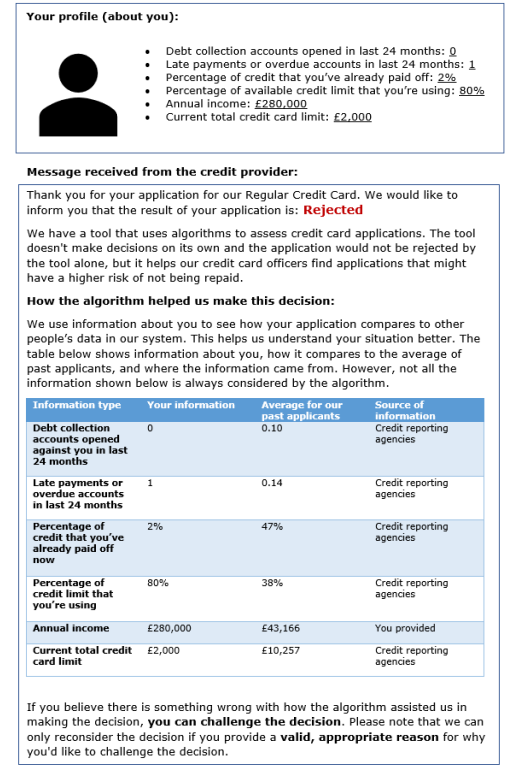
Profile 1: Correct acceptance



Profile 2: Cor



Profile 5: Incorrect rejection



***Please note:** All profile examples from contro*

Genre-1:

Data-centric explanation

Information type	Your information	Average for our past applicants	Source of information
Debt collection accounts opened against you in last 24 months	1	0.10	Credit reporting agencies
Late payments or overdue accounts in last 24 months	0	0.14	Credit reporting agencies
Percentage of credit that you've already paid off now	100%	47%	Credit reporting agencies
Percentage of credit limit that you're using	11%	38%	Credit reporting agencies
Annual income	£180,000	£43,166	You provided
Current total credit card limit	£6,000	£10,257	Credit reporting agencies

Genre-2:

Features-based explanation

Information type	Your application	Importance of information	Effect of information
Debt collection accounts opened against you in last 24 months	1	Most important	Decreased your likelihood of approval

Genre-3:

Data-centric + Features-based explanation

Information type	Your application	Average for past applicants	Importance of information	Effect of information	Source of information
Debt collection accounts opened against you in last 24 months	1	0.10	Most important	Decreased your likelihood of approval	Credit reporting agencies

Genre-4:

Data + Features + Decision Logic explanation

Information type	Your application	Average for past applicants	Importance of information	Effect of information	Source of information
Debt collection accounts opened against you in last 24 months	1	0.10	Most important	Decreased your likelihood of approval	Credit reporting agencies

The following decision rule was applied:

If debt collection accounts opened against you in last 24 months is greater than 0.5 then Reject the application

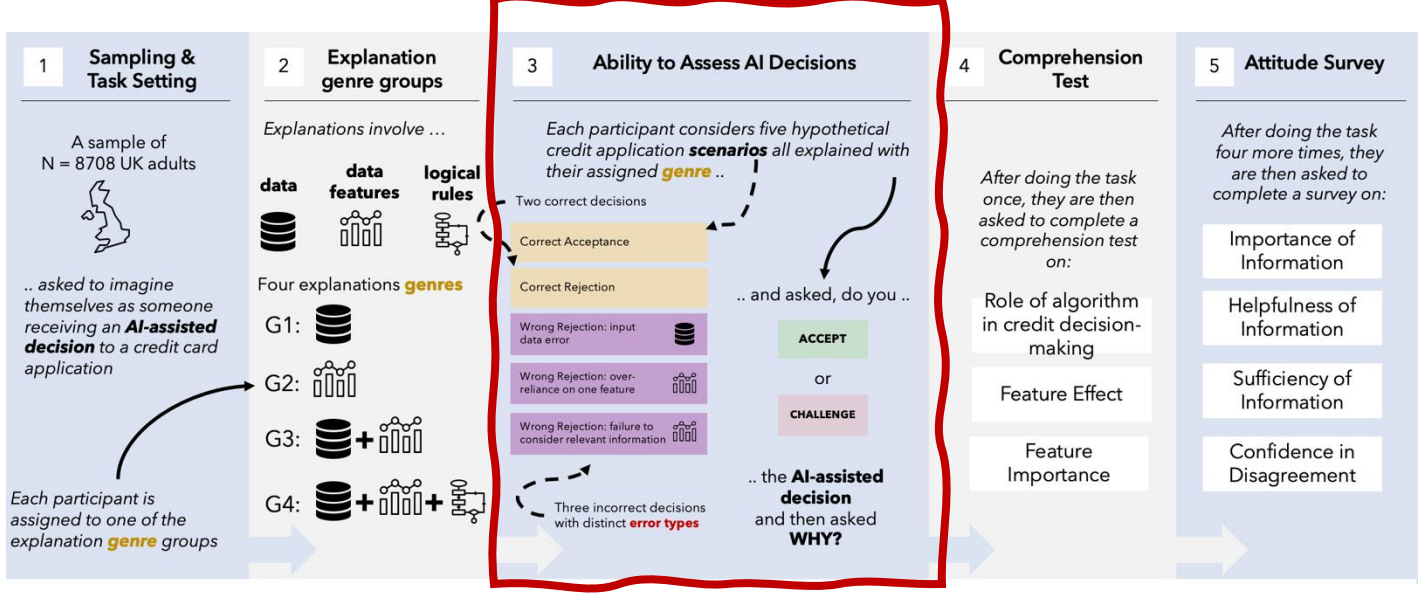
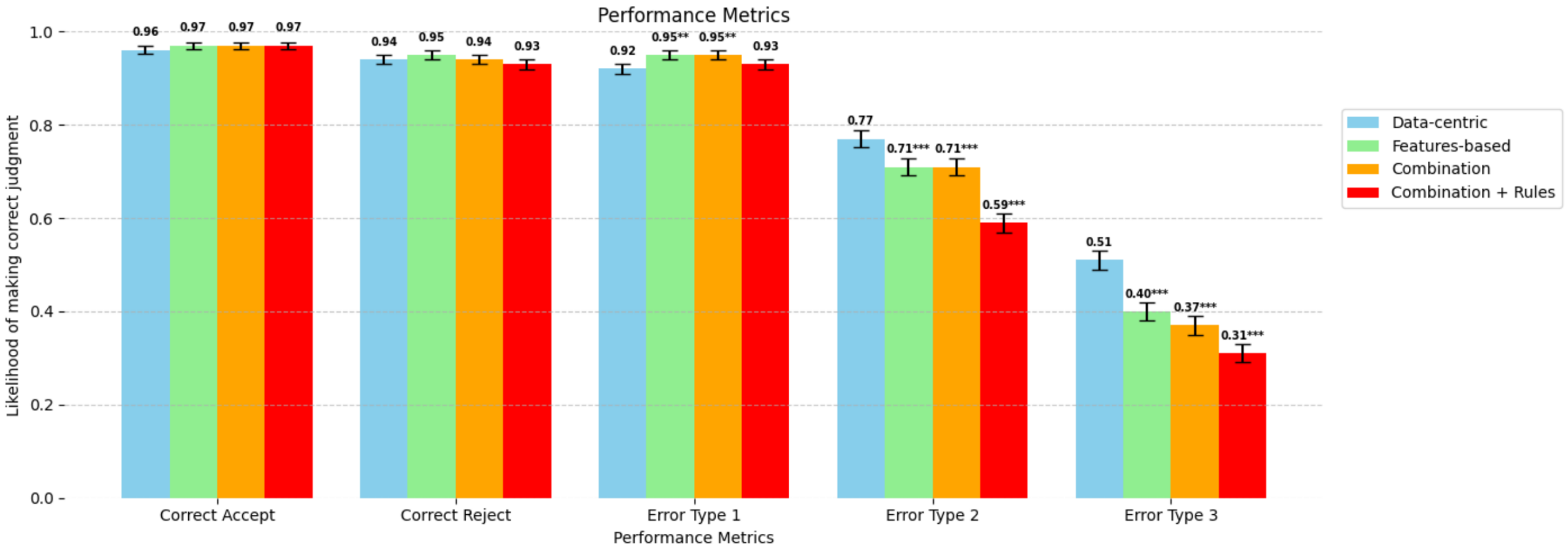


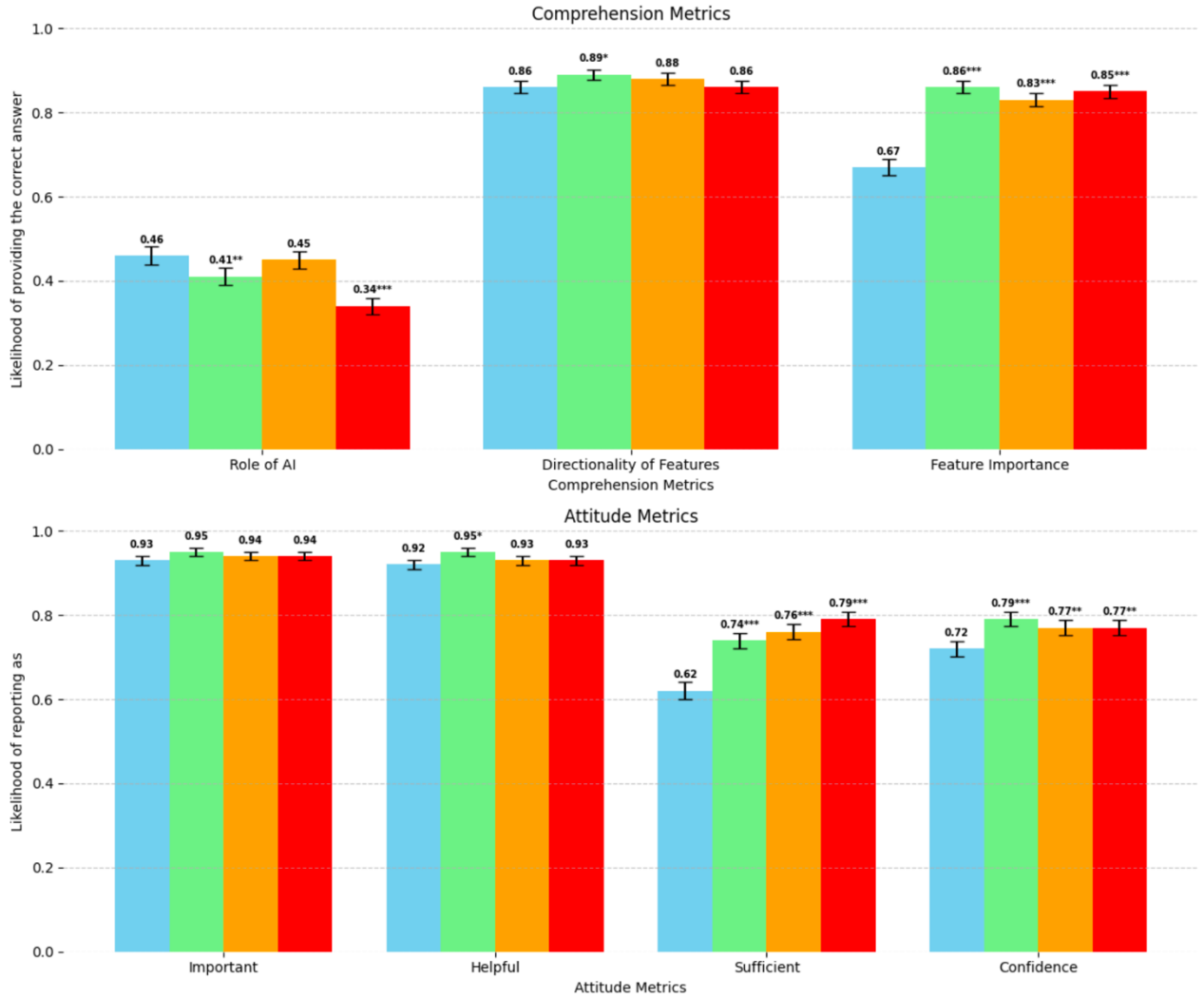
Table 6: Error Types and Corresponding Correct Reasons for Contestation

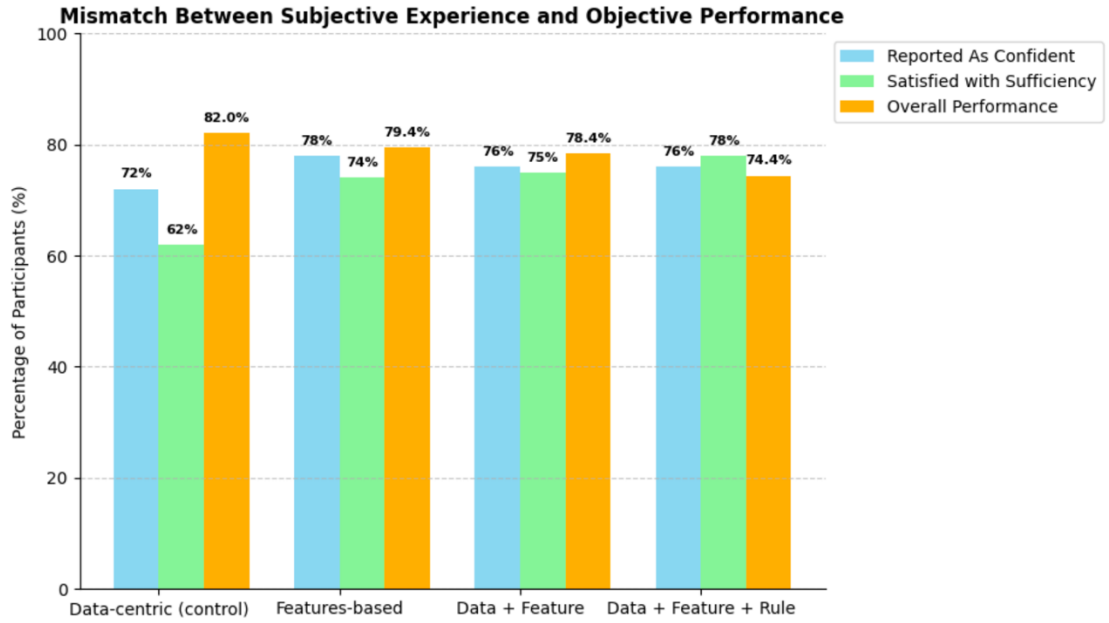
Error Type	Correct Contestation Reason
Incorrect Data Input (Scenario 3)	"I would like to challenge the decision because my information has been entered into the algorithm incorrectly"
Overreliance on One Feature (Scenario 4)	"I would like to challenge the decision because the algorithm is over-relying on one piece of information and not considering other important pieces of information"
Failure to Consider Relevant Features (Scenario 5)	"I would like to challenge the decision because the algorithm is not considering a piece of information that is important for the decision"

Explanation Details and Error Types Influence the Capacity to Identify AI Errors



Increased Confidence and Perceived Information Sufficiency Despite Decreased Performance





Ability to contest effectively

(i.e., correctly judge an incorrect decision *and* identify the relevant error)

… not great..

Error type: *Incorrect prediction due to data input error* ***(Profile 3)***

Treatment	% identifying correct error having said that decision was incorrect*
Data-centric	69%
Features-based	81% **(+12pp)**
Combination data-centric/features-based	78% **(+9pp)**
Combination data/features + rules	79% **(+10pp)**

Error type: *Misclassification due to overreliance on one feature* ***(Profile 4)***

Treatment	% identifying correct error having said that decision was incorrect*
Data-centric	18%
Features-based	12% **(-6pp)**
Combination data-centric/features-based	15% **(-3pp)**
Combination data/features + rules	15% **(-3pp)**

Error type: *Misclassification due to failure to consider relevant features* ***(Profile 5)***

Treatment	% identifying correct error having said that decision was incorrect*
Data-centric	62%
Features-based	41% **(-21pp)**
Combination data-centric/features-based	45% **(-17pp)**
Combination data/features + rules	44% **(-18pp)**

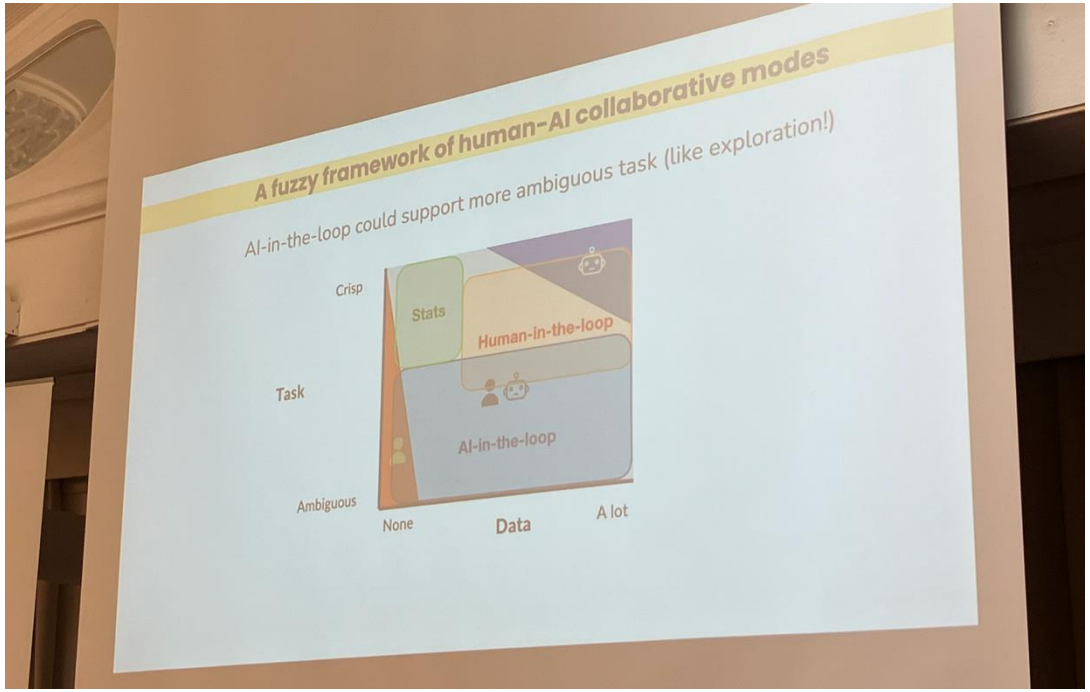
Please note: *Refers to proportion of participants from pool that correctly identified the incorrect AI-decision for these profiles*

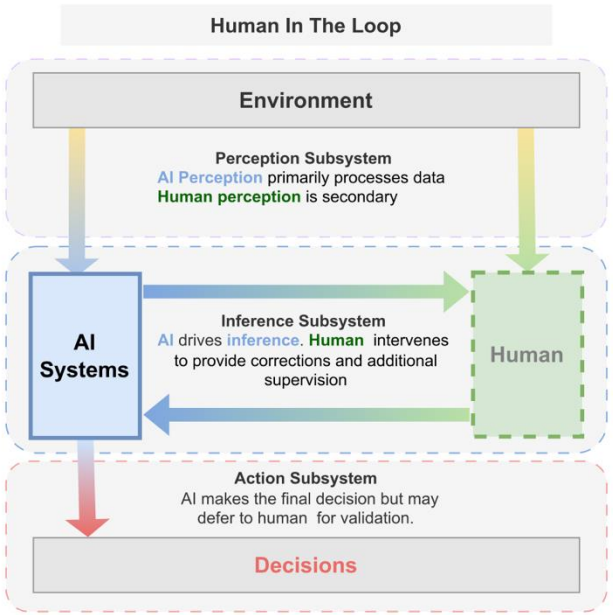
empowering	people
visualisation	expert audiences
human-in-the-loop	.. data scientists
ai-in-the-loop	.. researchers
…	.. decision-makers
explainable AI	**everyone else**
????	
???	

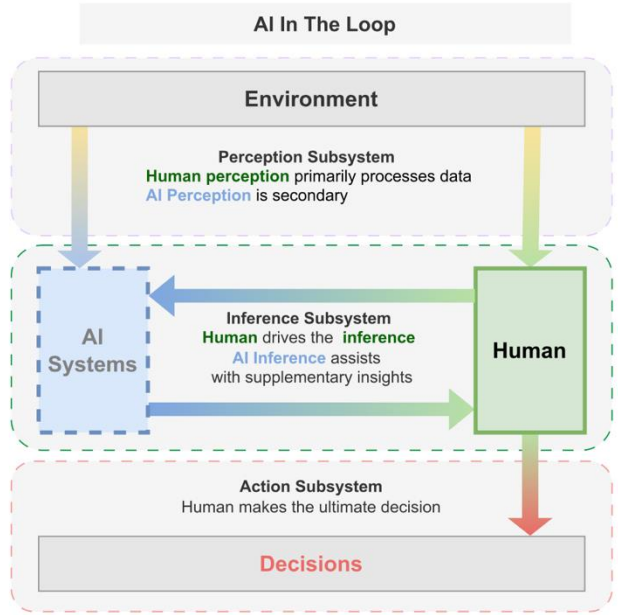
C1: the “humans” in the human-in-the-loop?

- Are we (as VIS community) obsessed with “expert humans”?
- How to be more inclusive?
- AI offer new opportunities but is AI human-literate?

C2: Balancing what people & AI are best at







Natarajan, S., Mathur, S., Sidheekh, S., Stammer, W. and Kersting, K., 2025, April. Human-in-the-loop or AI-in-the-loop? Automate or Collaborate?. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 39, No. 27, pp. 28594-28600).

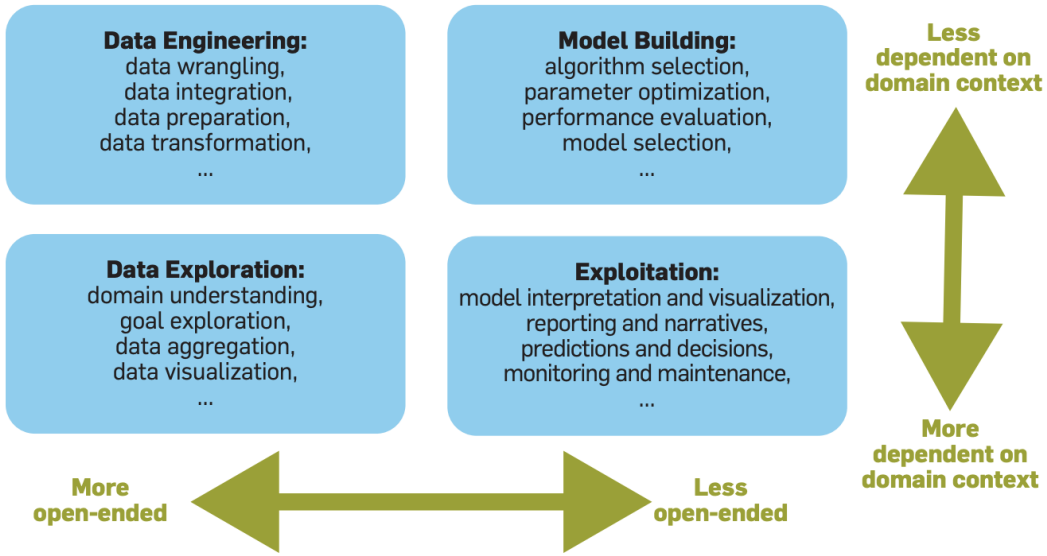
C2: Balancing what people & AI are best at

DOI:10.1145/3495256

Given the complexity of data science projects and related demand for human expertise, automation has the potential to transform the data science process.

BY TIJL DE BIE, LUC DE RAEDT, JOSÉ HERNÁNDEZ-ORALLO, HOLGER H. HOOS, PADHRAIC SMYTH, AND CHRISTOPHER K.I. WILLIAMS

Automating Data Science



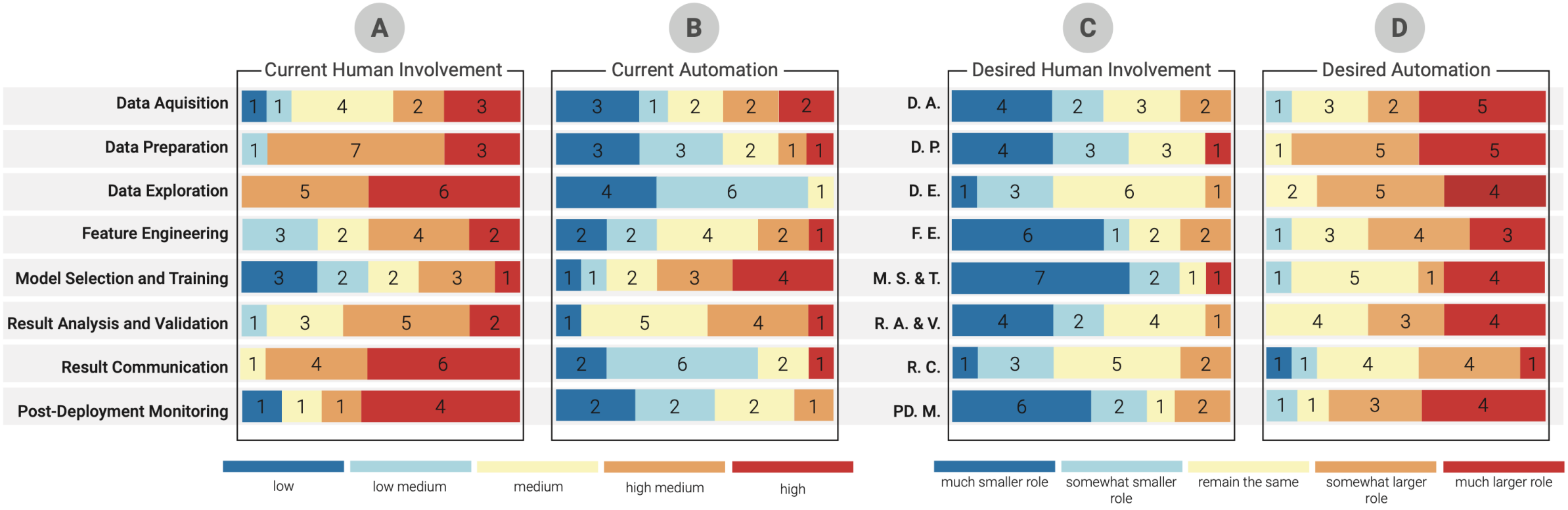
… useful and significant advances in the **automation of data science** in the three **most accessible quadrants** in Figure 1: **data engineering model building** and **exploitation**

…the most challenging quadrant of **data exploration, and for tasks in the other quadrants where representation of domain knowledge and goals is needed**, we anticipate that progress will require more effort. … we see great potential for the assistance form of automation, through systems that complement human experts, tracking and analyzing workflows, spotting errors, detecting and exposing bias, and providing high-level advice…

C2: Balancing what people & AI are best at

Visualization and Automation in Data Science: Exploring the Paradox of Humans-in-the-Loop

Jen Rogers, Marie Anastacio, Jürgen Bernard, Mehdi Chakhchoukh, Rebecca Faust, Andreas Kerren, Steffen Koch, Lars Kotthoff, Cagatay Turkay, Emily Wall



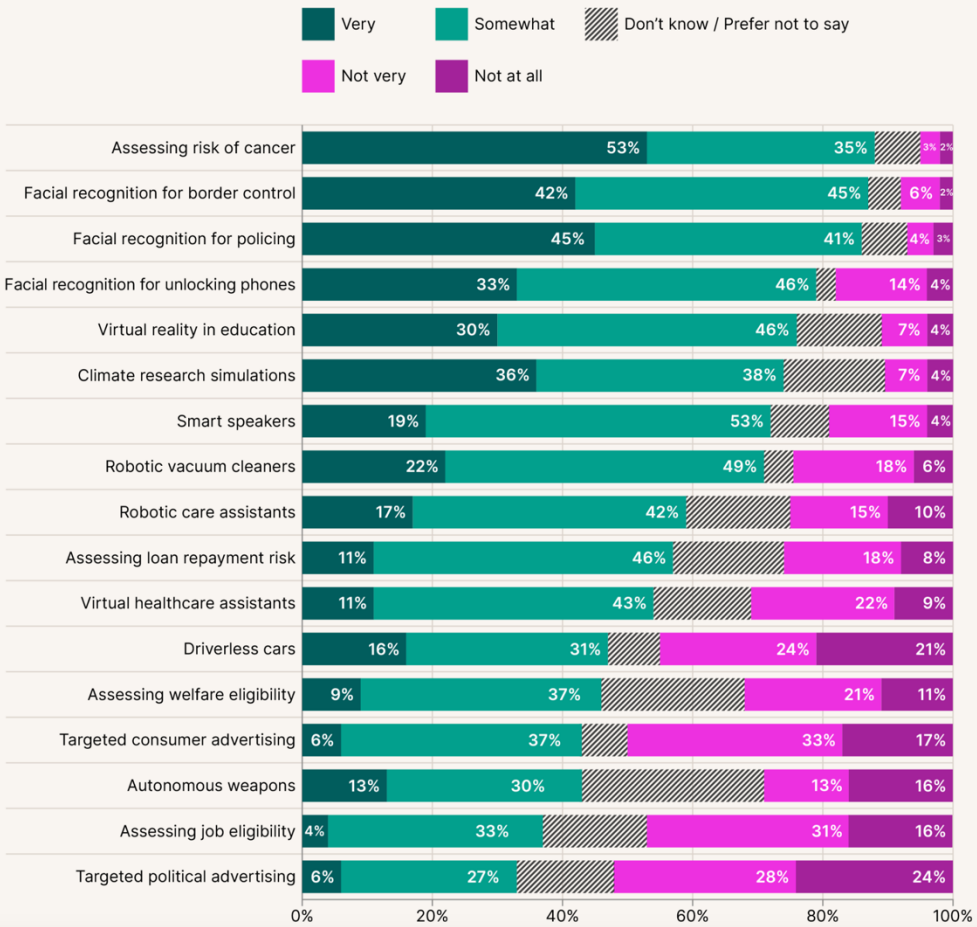
The Alan Turing Institute

Home + Research + Research projects

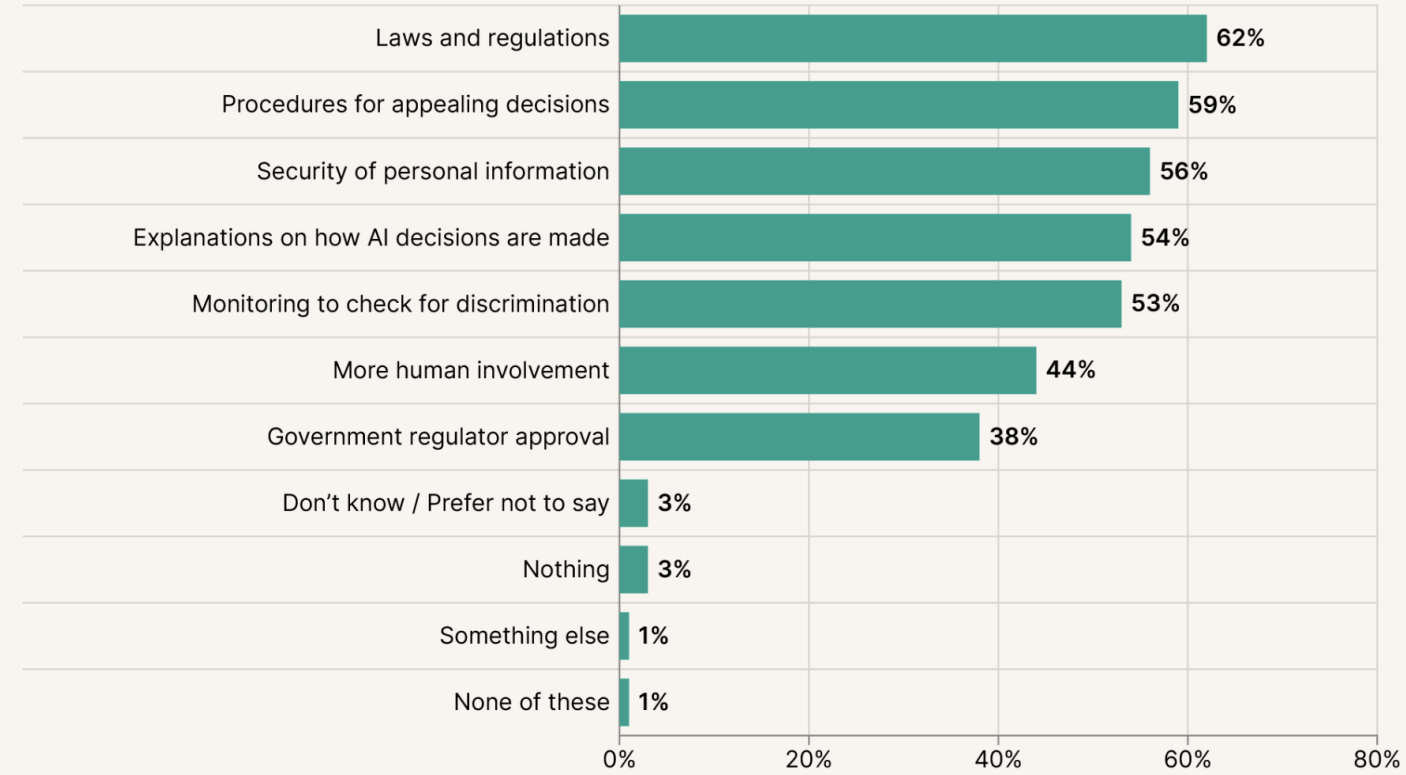
Understanding Public Attitudes to AI

Understanding public awareness, experience and attitudes towards different uses of artificial intelligence

'To what extent do you think that the use of this technology will be beneficial?'



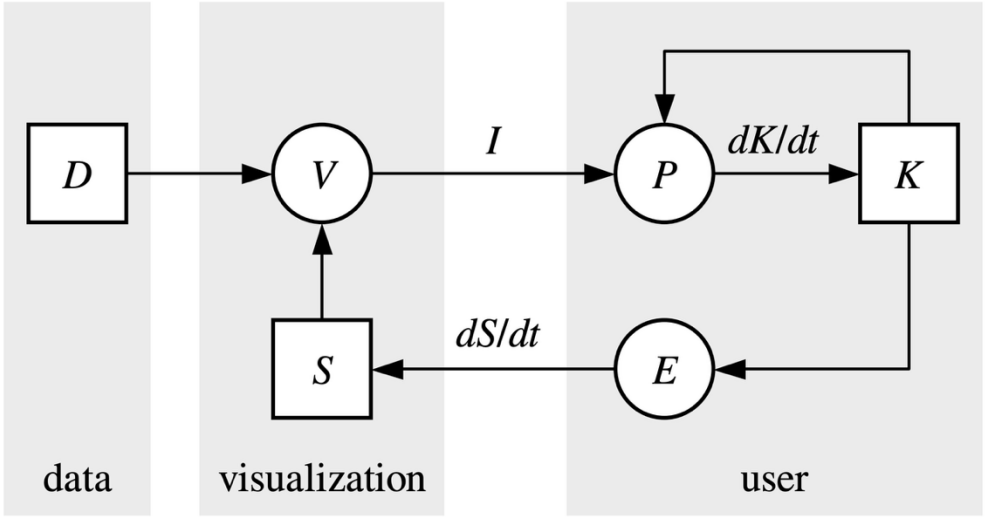
'Which of the following, if any, would make you more comfortable with AI technologies being used?'



C2: Balancing what people & AI are best at

Reflecting on what's difficult, complex, valuable in human-AI interaction?

How to distribute the tasks?



[van Wijk., *2005*]

Moravec's paradox

"It is comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility."

C3: limited means of expression for “human input”

- Are we providing sophisticated enough means for people to express themselves? e.g., contestation, relabelling?
- What is the “bandwidth” of interaction in interactive data analysis?

C3: Existing algorithms (AI) are not setup for humans-in-the-loop

- e.g., You can contest a decision but what does that mean for the next person?
- Can models learn meaningfully from human input? Are new AI models too intractable by design?

A few final reflections..

Critical, informed and rigorous engagements with data, models and AI artefacts for everyone

Is the loop really a loop? Tighter/deeper involvement of the human and new algorithms to "***close the loop***"

everyday human-AI interactions

Thanks ..

Yulu Pi, CIM, Warwick

Daniel Bogiatzis-Gibbons, Jackie Spang, Cameron Belton, Isaac Keeley from the UK's Financial Conduct Authorithy

Siming Chen and Yuheng Zhao from Fudan

DiSIEM project (EU Horizon 2020 - 700692)

Helwig Hauser, University of Bergen

Selim Balcisoy, Erdem Kaya from Sabanci University

giCentre and AddResponse team @ City, University of London

Dagstuhl Seminar 23372 "Human-Centered Approaches for Provenance in Automated Data Science"

AI literacy: Empowering People in Human-AI interactions

Cagatay Turkay
Professor,
Centre for Interdisciplinary Methodologies
University of Warwick

ELLITT Symposium, Norrkopping, 15 May 2025