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Transparency and Explainable AI (XAI)

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Not a new thing…

- Lots of work on explanations back in the 1980s and 1990s
  - neoMYCIN, etc to explain expert systems
- Ben Shneiderman versus Pattie Maes debate in the 1990s
  - Transparency and trust important
- Also work on autonomous agents and decision-making in the early 2000s
- But really ramped up since 2010s with rise in machine learning and black-box models

Mycin: Is Meningitis a hospital acquired illness?
Doctor: why?
Mycin: [2.0] this will aid in determining the orgamisms that might be causing the infection
It has already established
[2.1] the infection that requires therapy is meningitis
[2.2] organisms were not seen on the stain of this pending csf culture
[2.3] the type of infection is bacterial
[2.4] neurosurgery is not one of the relevant items of patient 100
[2.5] the age of patient 100 is greater than 25
therefore if [2.6] the infection was acquired while the patient was in hospital then there is evidence that the organisms that might be causing the infection are E coli(0.75) staphylococcus-coag-pos(0.3) pseudomonas-aeruginosa(0.3) klebsiella-pneumoniae(0.5)
Doctor: How 2.3
Mycin: The following rules concluded about the likelihood that the type of the infection is bacterial:
[2.7] RULE148 (0.19)
[2.8] RULE500 (0.51)
[2.9] RULE501 (0.95)
[3.0] RULE502 (0.97)
[3.1] RULE526 (0.98)
[3.2] RULE504 (0.97)
[3.3] RULE524 (0.98)

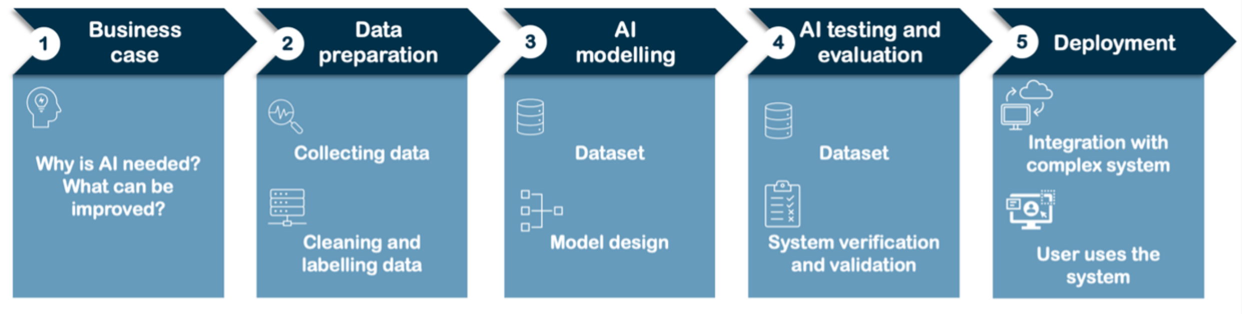
Regulation, standards and guidelines

- Industry-led by tech giants
    - Microsoft’s Guidelines for Human-AI Interactions
    - Google’s Responsible AI practices and People+AI Handbook
    - IBM’s Everyday Ethics for Artificial Intelligence
    - Fujitsu’s AI Ethics Impact Assessment Practice Guide
- EU Assessment List for Trustworthy Artificial Intelligence (ALTAI)
- EU AI Act (in draft)
    - High harm applications need to be assessed and **transparent**
    - Generative AI will have to be **transparent**

Transparency

So what is AI “transparency”?

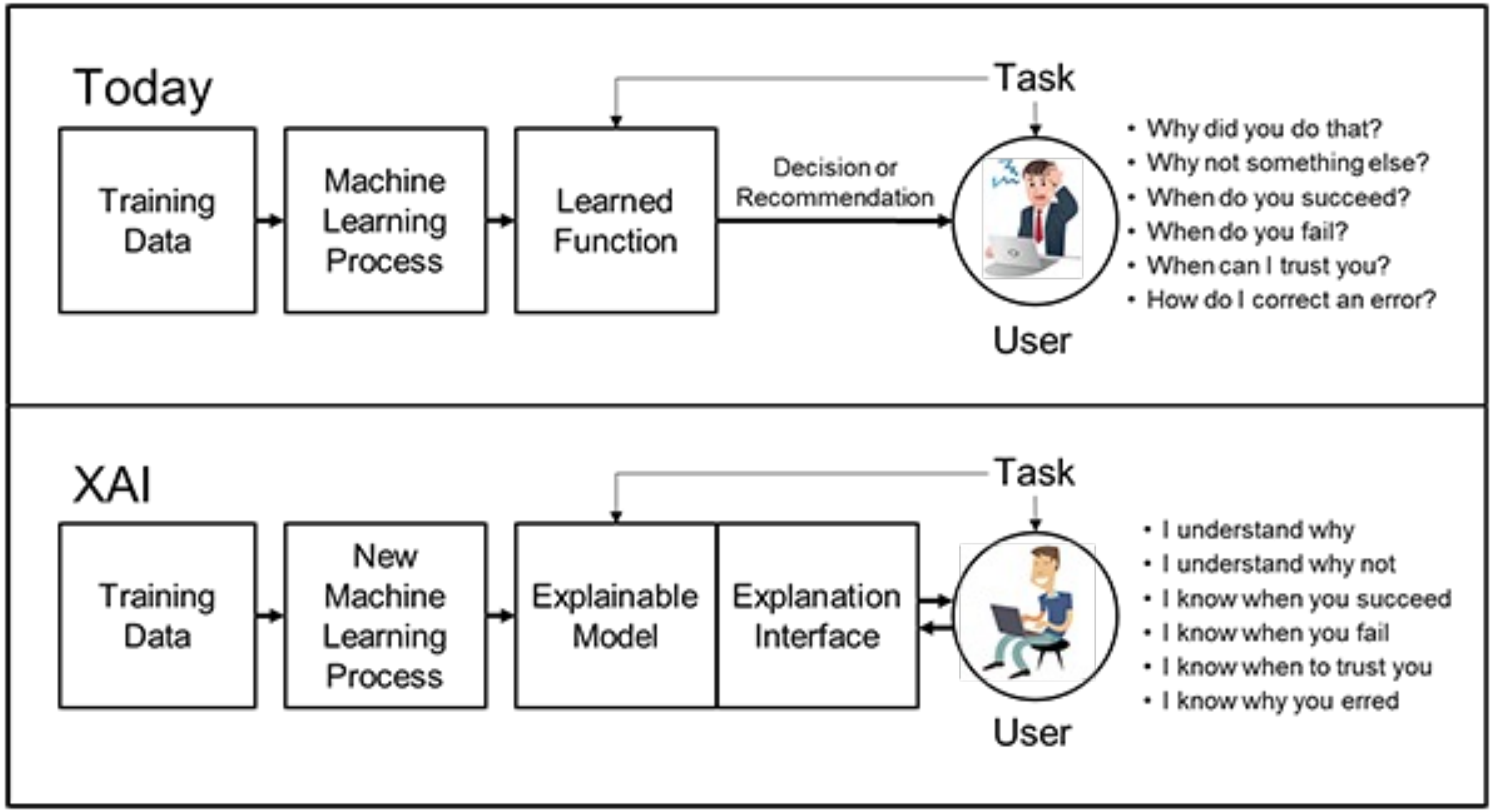
- How the AI model works
- Why a specific prediction was made by the AI …or not



- Currently somewhat overlooked:
  - Why was the model developed in the first place
  - What training data was used to develop the model
  - How was the model evaluated
  - How good is it
  - What biases or blind spots does it have
  - What decisions about the AI were made during its development

Explainable AI (XAI)

Explainable AI (XAI) vision (2016)



Calibrated / appropriate trust

Motivation for XAI

Model understanding is absolutely critical in several domains, particularly those involving *high potential for harm,* to support **debugging**, **bias detection** and **recourse**

Lots of work to make ML 'explainable' [Molnar 2022]

- Global explanations:
  - Exposing the model
- Local explanations:
  - Exposing (combination of) features that contribute to a decision

Local explanations

LIME: Local Interpretable Model-Agnostic Explanations

- Explains important feature that led to a decision
- Uses a post-hoc explanation on a simplified model
- Another popular method which outputs feature importances: SHAP

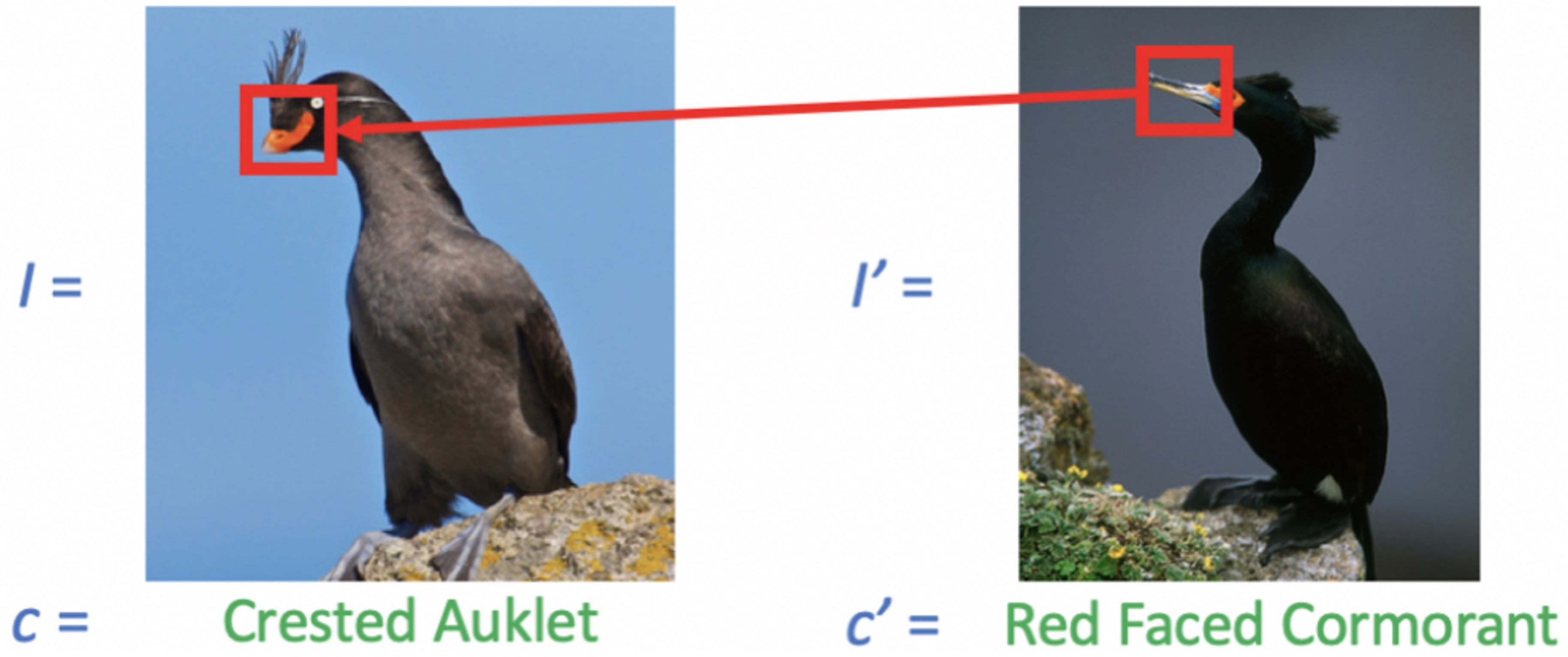
[Ribeiro et al. KDD 2016]

Prototypes/Example

- Use examples (synthetic or natural) to explain individual predictions
  - Identify instances in the training set that are responsible for the prediction of a given test instance
  - Identify examples (synthetic or natural) that strongly activate a function (neuron) of interest

Counterfactual Explanations

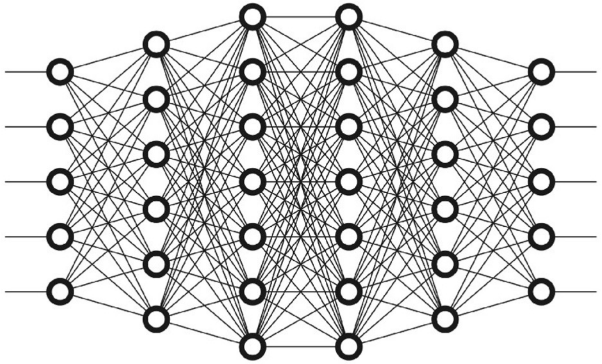
What features need to be changed and by how much to flip a model's prediction?



[Mothilal et al 2020]

Saliency Maps

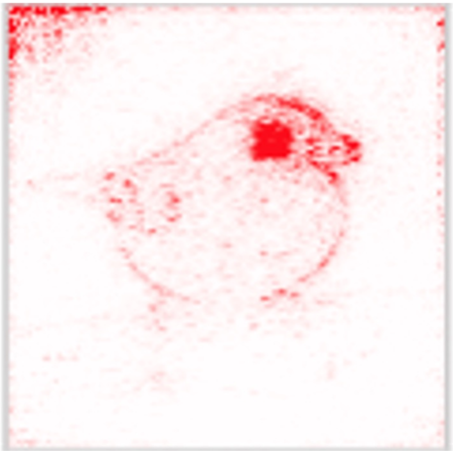
Input



Prediction

Junco Bird

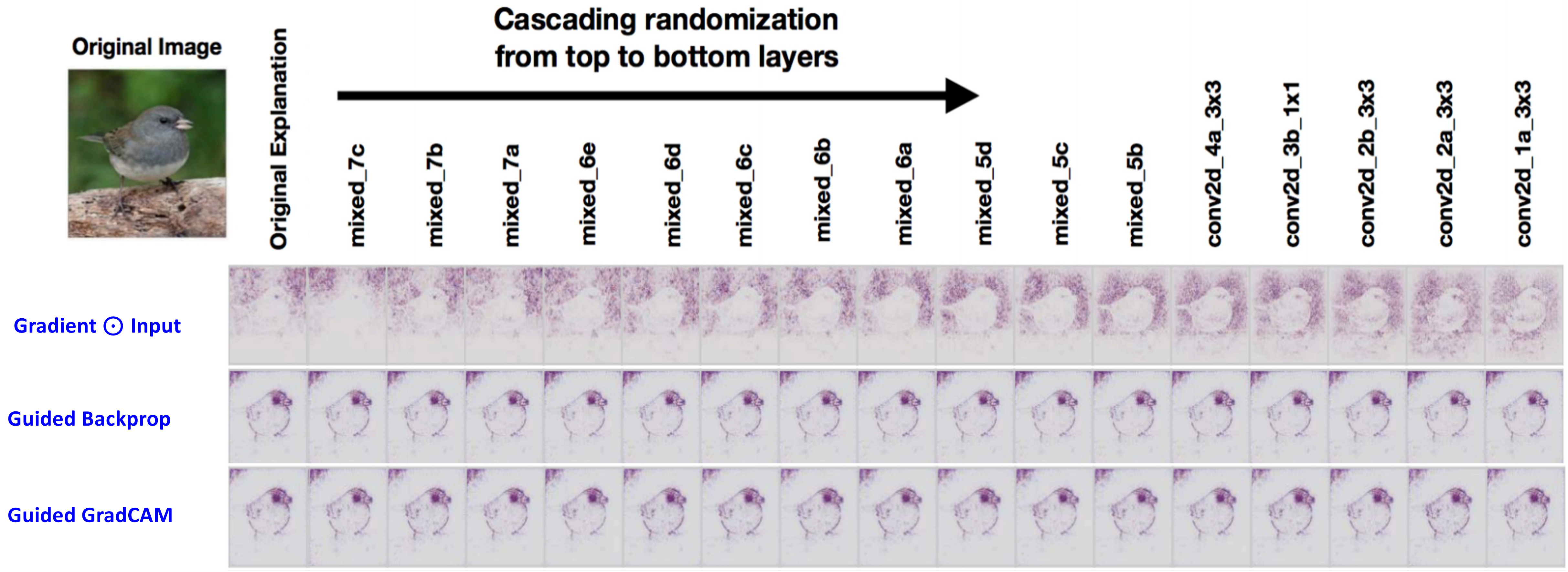
What parts of the input are most relevant for the model's prediction: 'Junco Bird'?



Saliency Map

But beware: “explanation” might be misleading

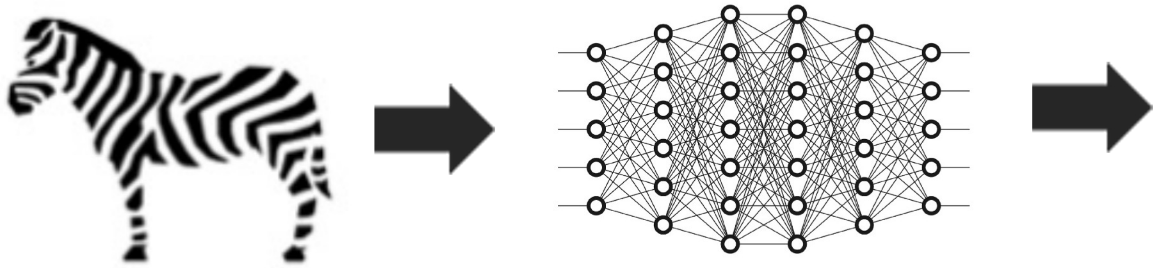
Model parameter randomization test



Adebayo, Julius, et al. "Sanity checks for saliency maps." NeurIPS, 2018.

Global explanations

Representation Based Explanations

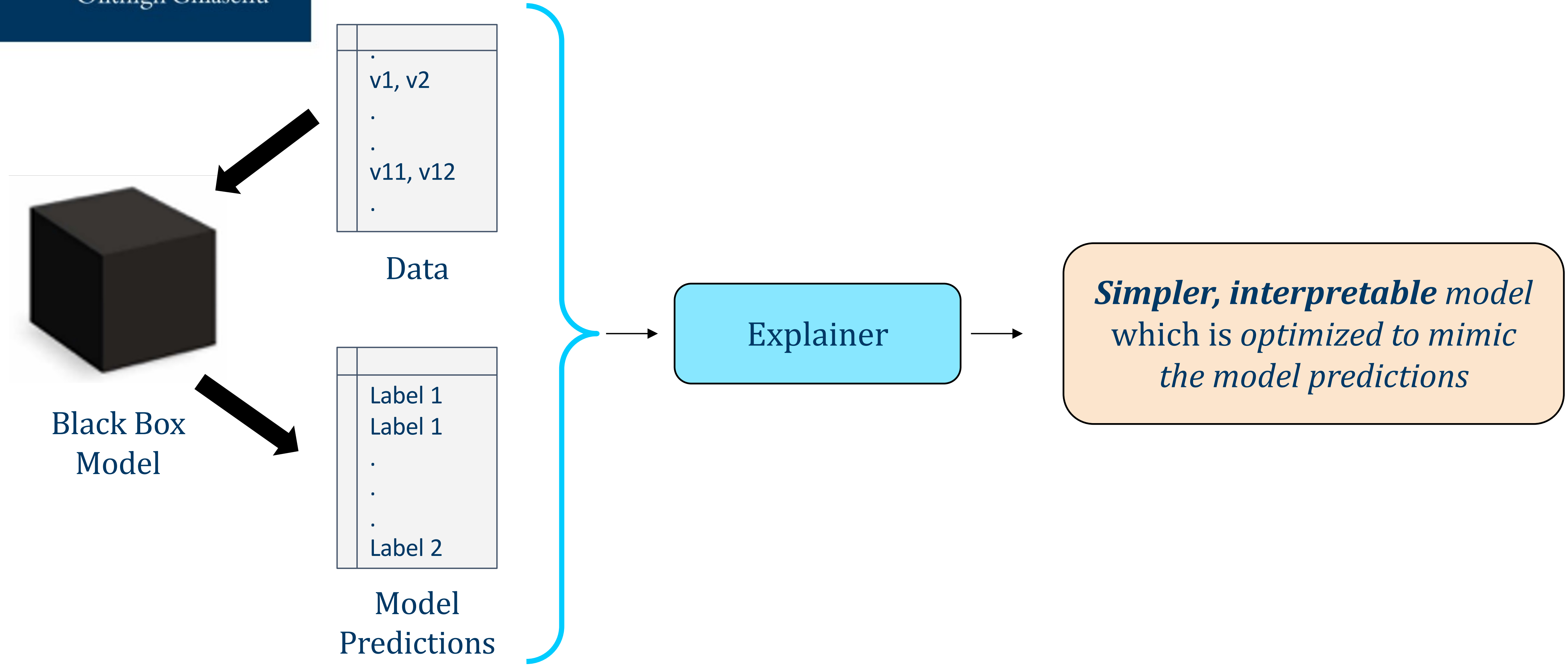


Zebra
(0.97)

How important is the notion of “stripes” for this prediction?

[Kim et. al., 2018]

Model Distillation



Human-Centric Explanations

Explainability versus Interpretability

- Explainability = **system-centric** ability of an AI system to explain itself

- Interpretability = **human-centric** ability of a user to build an appropriate *mental model* that guides interaction with the AI system
  - Understanding of how the system works
  - Being able to use the system successfully
  - Being able to ’trouble-shoot’ system and fix ‘mistakes’

Mental Models

- A mental model is a kind of internal representation in someone's thought process for how something works in the real world

- Users build mental models to guide how they interact, behave or fix things when they go wrong through
  - Extending and adapting existing mental models
  - Exploring and using a system
  - Being taught or having things explained

See:
- Norman 1983
- Johnson-Laird 1983

Lots of work to make explanations 'useable'

- What should be explained?
  - Global/local explanations, intelligibility types, etc.

- How should we explain?
  - Natural language dialogue, textual explanations, visualisations, etc.

Intelligibility types [Lim and Dey CHI 2009]

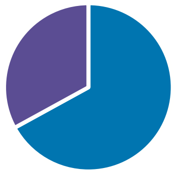
- What did the system do?
- Why did the system do W?
- Why did the system not do X?
- What would the system do if Y happens?
- How can I get the system to do Z, given the current context?

Explanation content versus explanation presentation/style

- What information is transmitted in an explanation versus its form and presentation
- E.g. decision confidence

0.67341

67% Accept / 33% Reject



I think it’s a little bit more likely that this application should be accepted.

Different stakeholders = different explanations?

- End users / lay users (e.g. loan applicants)
- Decision makers / domain experts (e.g. doctors, judges)
- Regulatory agencies (e.g. FDA, European commission)
- Researchers, developers and engineers

Human-centric explainable AI (HCXAI) design

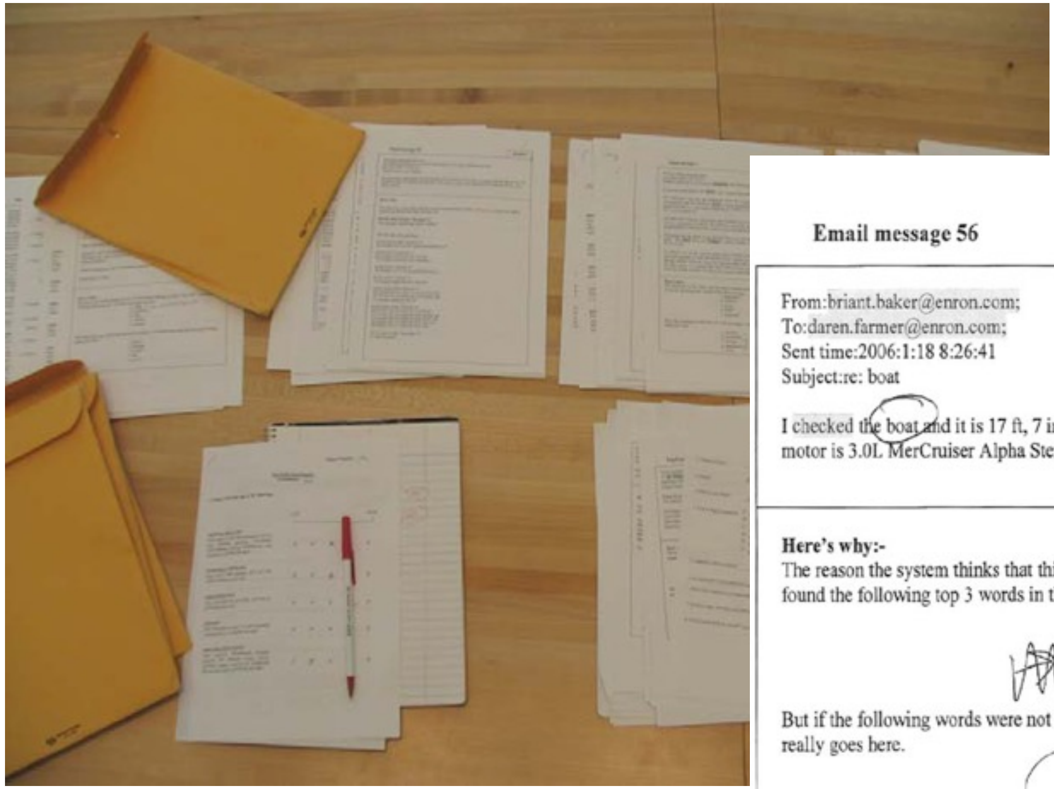
- Need to know who the user is

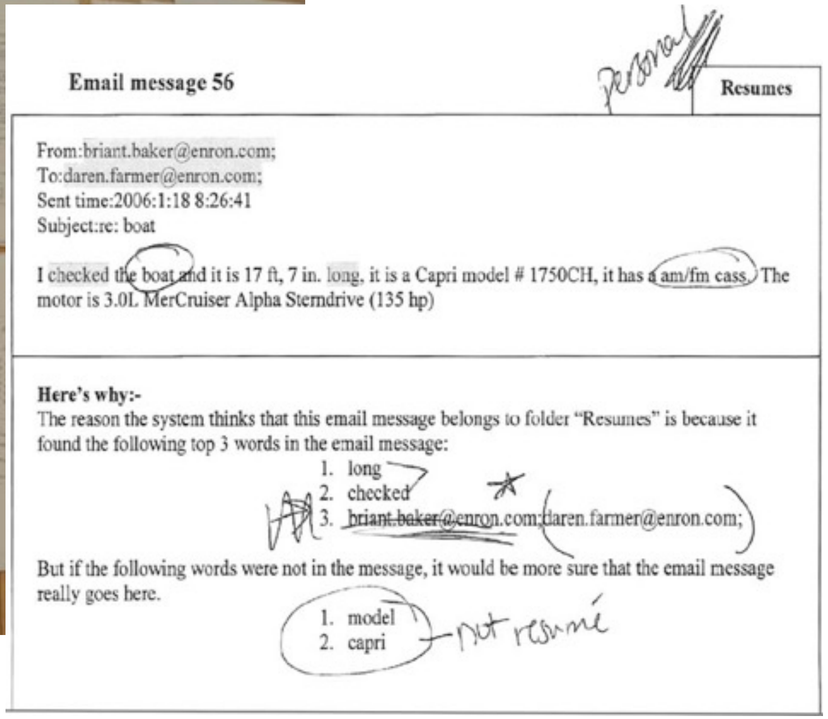
- Global or local explanations or both?

- Global explanations
  - How the model works
  - The accuracy of the model
  - Important features
- Local explanations
  - Important features for this decision
  - Decision confidence

Explanation “styles” [Stumpf et al. IJHCS 2009]

- What explanation styles do end-users prefer?





Personal

Email message 56 | **Resumes**

From:briant.baker@enron.com;
To:daren.farmer@enron.com;
Sent time:2006:1:18 8:26:41
Subject:re: boat

I checked the boat and it is 17 ft, 7 in. long, it is a Capri model # 1750CH, it has a am/fm cass. The motor is 3.0L MerCruiser Alpha Sterndrive (135 hp)

Here’s why:-
The reason the system thinks that this email message belongs to folder “Resumes” is because it found the following top 3 words in the email message:

1. long
2. checked
3. ~~briant.baker@enron.com~~;daren.farmer@enron.com;

But if the following words were not in the message, it would be more sure that the email message really goes here.

1. model
2. capri

not resumé

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Explanation styles

Keyword

Personal

From: buylow@houston.rr.com
To: j..farmer@enron.com
Subject: life in general

Good god -- where do you find time for all of that? You should w...

By the way, what is your new address? I may want to come by ... your work sounds better than anything on TV.

You will make a good trader. Good relationships and flexible pri... a few zillion other intangibles you will run into. It beats the hell o... other things.

I'll let you be for now, but do keep those stories coming we love...

The reason the system thinks that this email message belongs to folder "Personal" is because it found the following top 5 words in the email message:

1. ill
2. love
3. better
4. things
5. god

But if the following words were not in the message, it would be more sure the email message really goes here.

1. keep
2. find
3. trader
4. book
5. general

Rule

Resume

From: toni.graham@enron.com
To: daren.farmer@enron.com
Subject: re: job posting

Daren, is this position budgeted and who does it report to?
Thanks,
Toni Graham

The reason the system thinks that this email message belongs to folder "Resume" is because the highest priority rule that fits this email message was:

- **Put the email in folder "Resume" if:
It's from toni.graham@enron.com.**

The other rules in the system are:

...

- Put the email in folder "Personal" if:
The message does not contain the word "Enron" and
The message does not contain the word "process" and
The message does not contain the word "term" and
The message does not contain the word "link".
- Put the email in folder "Enron News" if:
No other rule applies.

Similarity

Resume

Message #2
From: 40enron@enron.com
To: All ENW employees
Subject:enron net works t&e policy
From: Greg Piper and Mark Pickering

Please print and become familiar with the updated ENW T&E P... business-first travel, with supervisor approval, for international fli... Mexico). Supervisors will be responsible for making the decision...

If you have any questions about the policy or an expense not co... Costello.

Wow! The message is really similar to the message #3 in "**Resume**" because #2 and #3 have important words in common.

Message #3
From: toni.graham@enron.com
To: lisa.csikos@enron.com, rita.wynne@enron.com, daren.farmer@enron.com
CC: renda.herod@enron.com
Subject: confirming requisitions

Confirming the open requisitions for your group. If your records indicate otherwise, please let me know.

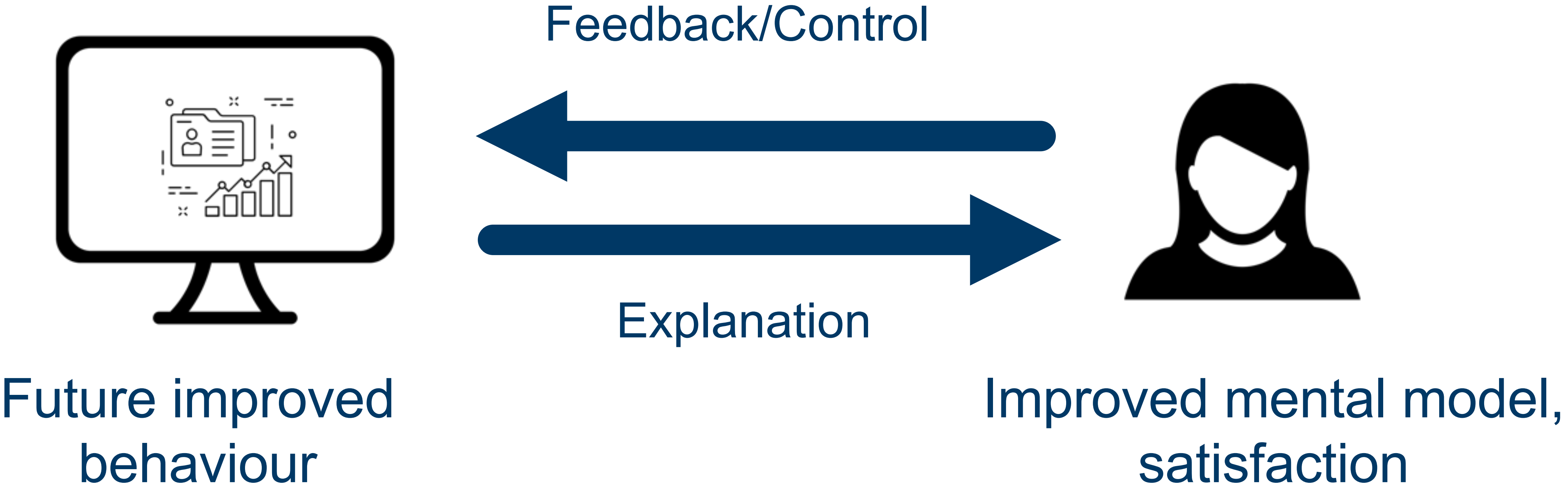
Lisa Csikos 104355, 104001
Rita Wynne 104354
Daren Farmer 104210
Mike Eiben 104323
Pat Clynes 104285

The posting dates have all been **updated** to reflect a current posting date

Results

- Explanation styles:
  - Rule-based best understood
  - Keyword-based also good but negative weights problematic (absence of features)
  - Serious understandability problems with Similarity-based
  - No clear overall preference, very individual

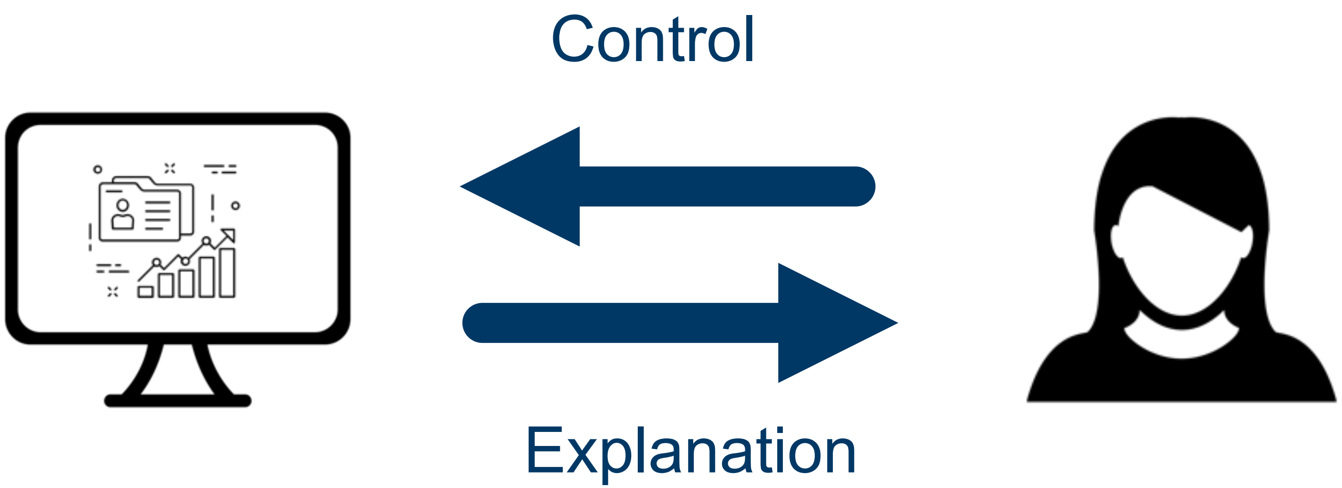
Explanatory debugging for interactive machine learning

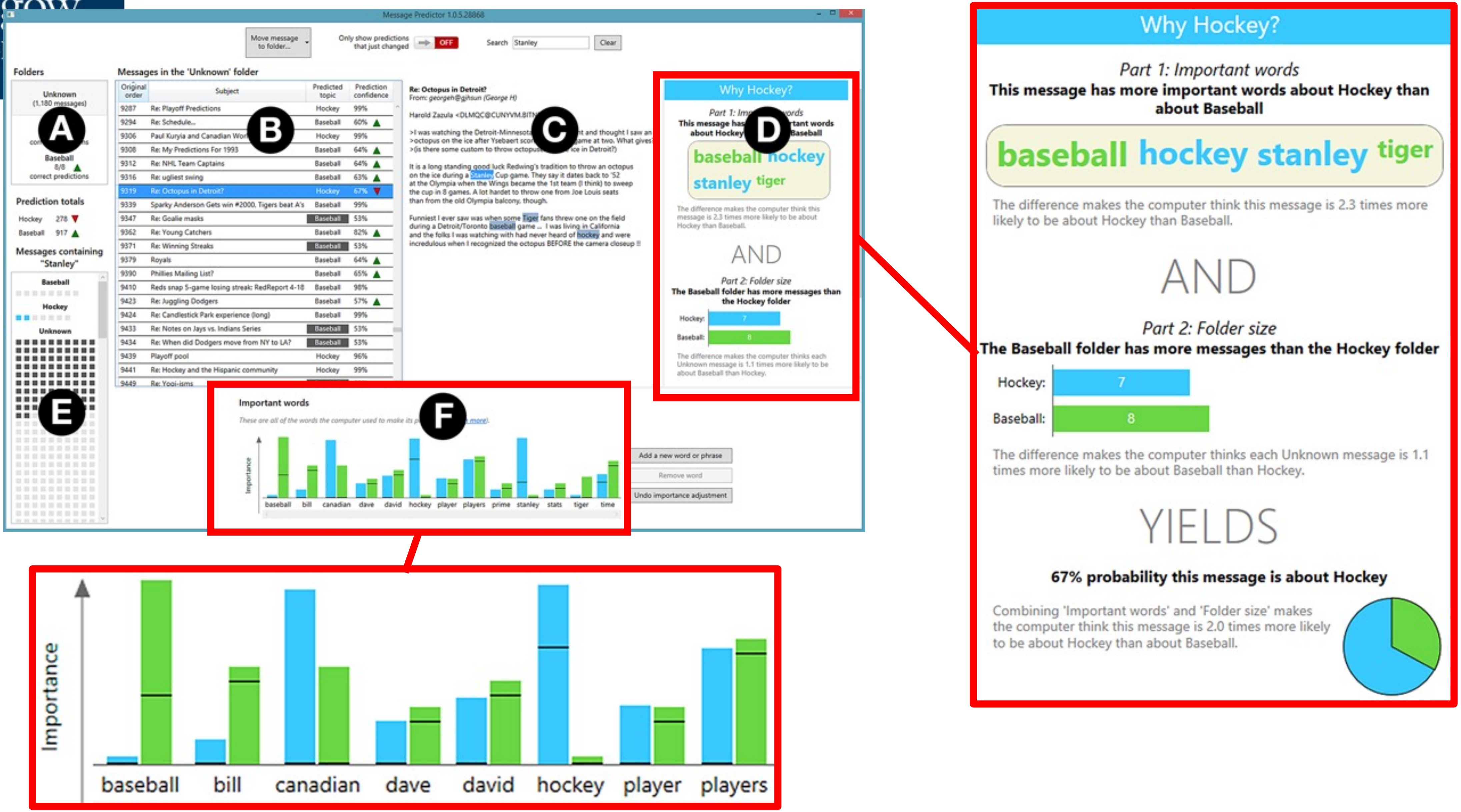


See:
- Stumpf et al. IJHCS 2009
- Kulesza et al. TiiS 2011
- Kulesza et al. CHI 2012
- Das et al. AI 2013
- Kulesza et al. IUI 2015

Explanatory debugging principles

- Explanation
  - Iterative
  - Sound
  - Complete
  - Don’t overwhelm
- Control
  - Actionable
  - Incremental
  - Reversible
  - Honour feedback





Message Predictor 1.0.5.28868
Move message to folder...
Only show predictions that just changed
OFF
Search
Stanley
Clear
Folders
Messages in the 'Unknown' folder
Unknown (1,180 messages)
Baseball 8/8 correct predictions
Prediction totals
Hockey 278
Baseball 917
Messages containing "Stanley"
Baseball
Hockey
Unknown
Original order
Subject
Predicted topic
Prediction confidence
Re: Octopus in Detroit?
Important words
A
B
C
D
E
F
Add a new word or phrase
Remove word
Undo importance adjustment
Why Hockey?
Part 1: Important words
This message has more important words about Hockey than about Baseball
baseball hockey stanley tiger
The difference makes the computer think this message is 2.3 times more likely to be about Hockey than Baseball.
AND
Part 2: Folder size
The Baseball folder has more messages than the Hockey folder
Hockey:
7
Baseball:
8
The difference makes the computer thinks each Unknown message is 1.1 times more likely to be about Baseball than Hockey.
YIELDS
67% probability this message is about Hockey
Combining 'Important words' and 'Folder size' makes the computer think this message is 2.0 times more likely to be about Hockey than about Baseball.
Importance
baseball
bill
canadian
dave
david
hockey
player
players

Results

- More accurate system with less effort
  - 85% for our system versus 77% without explanations at end of study
  - Made adjustments to 47 messages while without explanations had to label 182 messages

- With better understanding
  - 15.8 mental model score versus 10.4
  - The more you understand, the better you can make the system

- Does not overwhelm
  - No difference in workload measures

HCXAI Challenges

- No explanations desired for certain tasks and contexts [Bunt et al. IUI 2012]
- Different people need different explanations [Gunning et al. Science Robotics 2019]; lay users neglected at the moment
- Explanations calibrate trust and reliance [Bussone et al. ICMI 2015, Holliday et al. IUI 2016, Nourani et al. HCOMP 2019]; “placebic” explanations [Eiband et al. CHI 2019]
- Explanations might come from outside of the ML [Ehsan et al. CHI 2021]
- Explanations, and then what? [Wang et al. 2022]

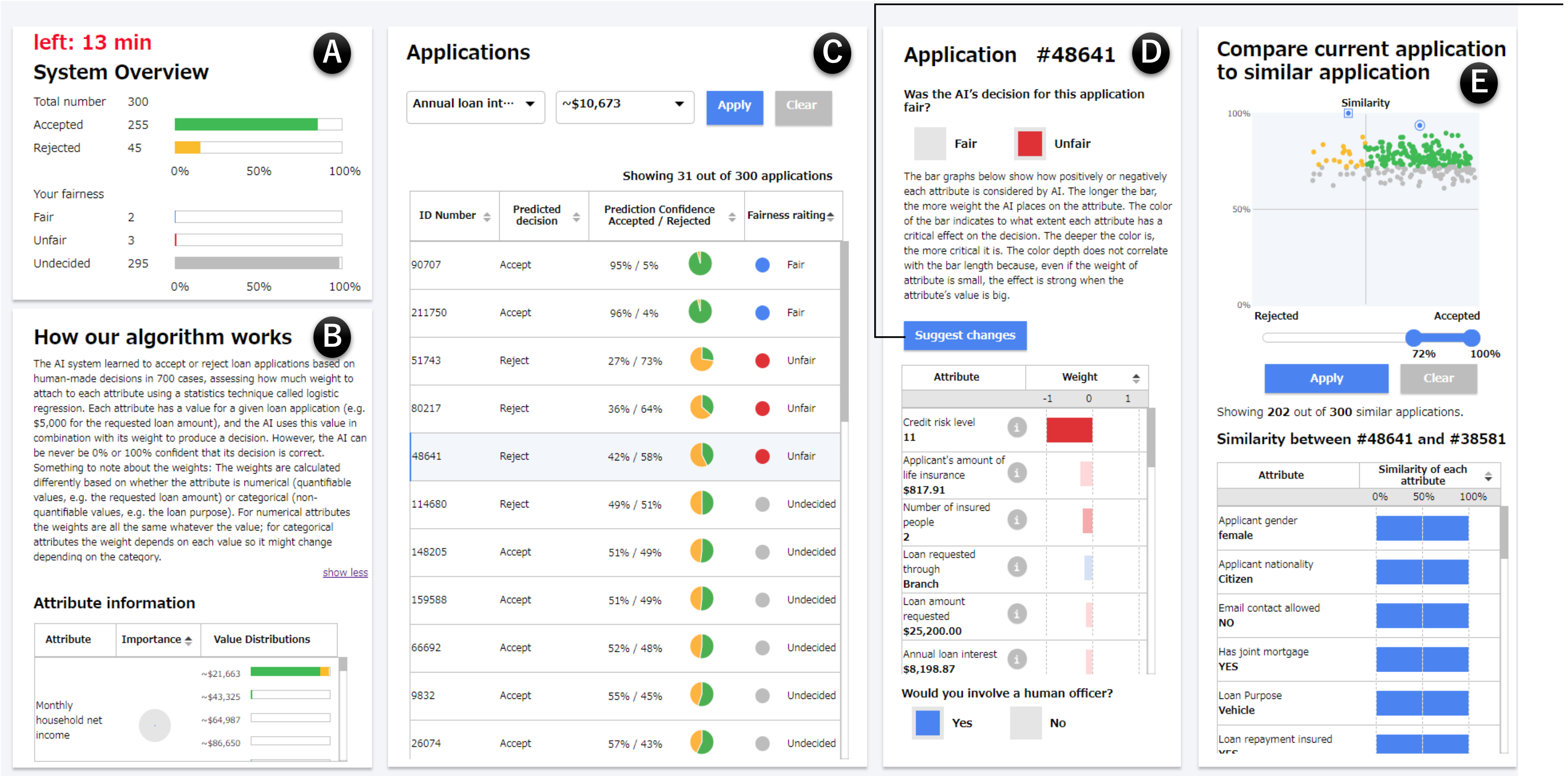
Transparency for Fairness

Bias and fairness in AI

- Biased humans produce biased data which gets trained into model or AI can also go ‘rogue’ and produce a biased model
- Tools to find and mitigate bias are emerging
  - 20+ different fairness metrics
  - IBM AI Fairness 360
  - FairML
  - Google’s What-if
- Fairness is a human value and can’t be necessarily reduced to metrics
  - Need transparency to understand if something is fair (or not)
  - Human-in-the-loop fairness tools such as FairVis, FairSight, etc

Towards Involving End-users in Interactive Human-in-the-loop AI Fairness [TiiS 2022]

- Leverages work from Explanatory Debugging -> find and fix fairness ‘bugs’ that do not meet users’ expectations
- Loan application domain, anonymized dataset from a partner bank
- 388 participants recruited through Prolific, no technical or domain expertise needed
- Logistic regression, 61.8% accuracy, failed DI metric (0.718) on Nationality attribute
- Using the average weight value for each attribute suggested by the participants on an application, recalculated model


left: 13 min
System Overview
A
Total number 300
Accepted 255
Rejected 45
0% 50% 100%
Your fairness
Fair 2
Unfair 3
Undecided 295
How our algorithm works
B
The AI system learned to accept or reject loan applications based on human-made decisions in 700 cases, assessing how much weight to attach to each attribute using a statistics technique called logistic regression. Each attribute has a value for a given loan application (e.g. $5,000 for the requested loan amount), and the AI uses this value in combination with its weight to produce a decision. However, the AI can be never be 0% or 100% confident that its decision is correct. Something to note about the weights: The weights are calculated differently based on whether the attribute is numerical (quantifiable values, e.g. the requested loan amount) or categorical (non-quantifiable values, e.g. the loan purpose). For numerical attributes the weights are all the same whatever the value; for categorical attributes the weight depends on each value so it might change depending on the category.
show less
Attribute information
Attribute
Importance
Value Distributions
Monthly household net income
~$21,663
~$43,325
~$64,987
~$86,650
Applications
C
Annual loan int···
~$10,673
Apply
Clear
Showing 31 out of 300 applications
ID Number
Predicted decision
Prediction Confidence Accepted / Rejected
Fairness raiting
90707 Accept 95% / 5% Fair
211750 Accept 96% / 4% Fair
51743 Reject 27% / 73% Unfair
80217 Reject 36% / 64% Unfair
48641 Reject 42% / 58% Unfair
114680 Reject 49% / 51% Undecided
148205 Accept 51% / 49% Undecided
159588 Accept 51% / 49% Undecided
66692 Accept 52% / 48% Undecided
9832 Accept 55% / 45% Undecided
26074 Accept 57% / 43% Undecided
Application #48641
D
Was the AI's decision for this application fair?
Fair
Unfair
The bar graphs below show how positively or negatively each attribute is considered by AI. The longer the bar, the more weight the AI places on the attribute. The color of the bar indicates to what extent each attribute has a critical effect on the decision. The deeper the color is, the more critical it is. The color depth does not correlate with the bar length because, even if the weight of attribute is small, the effect is strong when the attribute's value is big.
Suggest changes
Attribute
Weight
-1 0 1
Credit risk level 11
Applicant's amount of life insurance $817.91
Number of insured people 2
Loan requested through Branch
Loan amount requested $25,200.00
Annual loan interest $8,198.87
Would you involve a human officer?
Yes
No
Compare current application to similar application
E
Similarity
100%
50%
0%
Rejected
Accepted
72%
100%
Apply
Clear
Showing 202 out of 300 similar applications.
Similarity between #48641 and #38581
Attribute
Similarity of each attribute
0% 50% 100%
Applicant gender female
Applicant nationality Citizen
Email contact allowed NO
Has joint mortgage YES
Loan Purpose Vehicle
Loan repayment insured

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Results

- Participants found UI useful and easy to use
- Used UI to find problematic decisions through sorting/filtering on Predicted decision, Confidence, Comparison
- 20% of assessed decisions judged unfair, mostly honing in on Nationality
- When looking at Nationality, unfair was applied to 57.6% of accepted citizens, 14.4% for rejected foreigners
- 230 participants made weight changes to 3.71 applications on average
- Suggested weight changes improved DI to 0.814
  - 50% of participants increased DI (M=0.91), other half decreased it (M=0.63)

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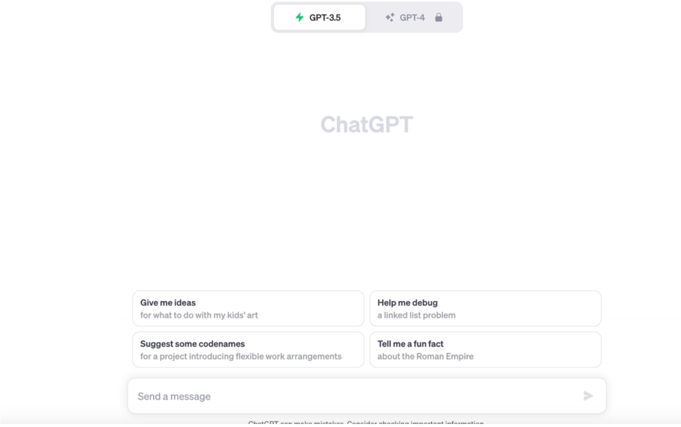
Transparency for other kinds of AI



Problems with current explanations for generative or autonomous AI

- Explanations are delivered in visual form – no good for certain situations or people
- Explanations are meant to be pondered – not sure how to integrate into real-time settings for human-AI collaboration
- Currently we have a narrow view of explanations – what do we mean by 'explanations' and what should be explained
  - Why was the model developed in the first place
  - What decisions about the AI were made during its development
  - What training data was used to develop the model
  - How was the model evaluated
  - How good is it
  - What biases or blind spots does it have

Model Cards [Mitchell et al. 2019]

• Model Details. Basic information about the model.

– Person or organization developing model

– Model date

– Model version

– Model type

– Information about training algorithms, parameters, fairness constraints or other applied approaches, and features

– Paper or other resource for more information

– Citation details

– License

– Where to send questions or comments about the model

• Intended Use. Use cases that were envisioned during development.

– Primary intended uses

– Primary intended users

– Out-of-scope use cases

• Factors. Factors could include demographic or phenotypic groups, environmental conditions, technical attributes, or others listed in Section 4.3.

– Relevant factors

– Evaluation factors

• Metrics. Metrics should be chosen to reflect potential realworld impacts of the model.

– Model performance measures

– Decision thresholds

– Variation approaches

• Evaluation Data. Details on the dataset(s) used for the quantitative analyses in the card.

• – Datasets

• – Motivation

• – Preprocessing

• Training Data. May not be possible to provide in practice. When possible, this section should mirror Evaluation Data. If such detail is not possible, minimal allowable information should be provided here, such as details of the distribution over various factors in the training datasets.

• Quantitative Analyses

– Unitary results

– Intersectional results

• Ethical Considerations

• Caveats and Recommendations

Summary

- Transparency is required and XAI has made some strides towards opening the black box
- However, ‘transparency’ is a very vague term and ‘explanations’ can come in different forms
- Need for a human-centred approach to transparency and explanations
- Consider what explanations are used/useful for

Resources

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- Thanks to Hima Lakkaraju and her tutorial on XAI!

Resources

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