Invisible Users: Uncovering End-Users' Requirements for Explainable AI via Explanation Forms and Goals

Appendix: Literature Review, Visual Representations of Explanation Forms, Study Method and Material

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In this Appendix, we provide details on the literature review for the development of explanation forms in §1, the visual representations of each explanation form in §2, and the study method and participants' demographic information in §3. We attach the interview material at the end, including the tasks, explanation goals, and explanation forms.

Contents

1 Development of the End-User-Friendly Explanation Forms

The development of the end-user-friendly explanation forms is based on existing XAI techniques in the literature of AI, human-computer interaction (HCI), and information visualization (VIS). We develop the explanation forms by conducting a literature review and examining XAI surveys in the AI, VIS, and HCI domains.

For the literature review, we searched for XAI technique papers using "explainable/interpretable/ transparency/ black box" + "AI/machine learning/deep learning" in Google Scholar, IEEE Xplore Digital library, ACM Digital library, and arXiv.org in 2019, and excluded works that did not conduct evaluation on the proposed XAI algorithm.

For the papers included, we labelled the type of their output explanatory information, and identify the requisite technical literacy to understand the output explanatory information. We repeated the process until information "saturated", i.e., no new explanatory forms were identified.

A total of 66 papers were reviewed and analyzed. We extracted the following information from the included papers: algorithm name (if there is any); the inputs to generate the explanatory model (such as whether it needs access to the training data, the original model parameters); the original model to be explained (model-agnostic vs. model-specific; post-hoc vs. intrinsic); the brief description of the algorithm; the output explanatory information of the XAI model; visualization analysis of the explanatory information (including the explanatory data type, encoding method, and the screenshot of the visualization figures); the evaluation of the XAI method; whether it gives local or global explanations; whether it targets AI developers or/and end-users. The list of papers and their extracted information is in the following pages.

The labels revealed 12 primary types of explanatory information: feature attribution, feature shape, feature interaction, concept; decision tree, rule, counterfactual rule; instance, counterfactual instance, prototype, similar example, and clustering. We grouped them into three major categories: explaining based on features, examples, and rules. We also added input, output, performance, and dataset to the explanatory forms as necessary contextual information to make the explanation more complete.

After the primary development of the 12 end-user-friendly explanation forms, we also reviewed the up-to-date related XAI surveys in AI [20, 13, 25, 19, 18, 26, 21, 12, 5, 7], HCI [17, 14, 3, 11, 9], and VIS [4, 24]. Despite some surveys having similar taxonomies based on the explanation representation forms, none of the surveys explicitly summarize the XAI techniques based on end users' perspective. Therefore, we kept the original structure and categories of the 12 end-user-friendly explanation forms, and updated it with the latest XAI algorithms that can generate such a explanation form.

2 Visual Representations of the Explanation Forms

2.1 Feature-Based Explanation

2.1.1 Feature Attribution

Visual representation: Its visual representations largely depend on the feature data type. For image and text data, overlaying a **saliency map** or color map on the input is the most common visualization. It uses sequential colors to code the fine-grained feature importance score for each individual feature (could be a pixel for image input, a word for text data). For image/video input data, other popular visualizations include using *segmentation masks* or *bounding boxes* on important image objects/parts.

To visualize multiple feature attributions for tabular or text data, a **bar chart** is a typical choice. Variations of the bar chart include waterfall plot, treemap, wrapped bars, packed bars, piled bars, Zvinca plots, and tornado plot. Compared to a bar chart that shows a point estimation of feature importance, a *box plot* can be used to visualize the probabilistic distribution of the feature importance score. Its variations include violin plot and swarm plot that show more detailed data distribution and skewness.

Figure 1: Visual representations of feature attribution. The first column is the template with feature names shown by placeholders. The following columns are the visual representation cards used in the four tasks (House, Health, Car, Bird) in the user study. Different visual variations are shown in the second row.

2.1.2 Feature Shape

Visual representation: For a continuous feature (such as height, temperature, i.e.: measurement on a scale), a **line chart** is the most common visualization, depicting whether the relationship between the feature and outcome is monotonic, linear, or more complex. The line chart can be accompanied by a scatter plot detailing the position of individual data points.

For a categorical feature (such as gender, season), a *bar chart* can be used.

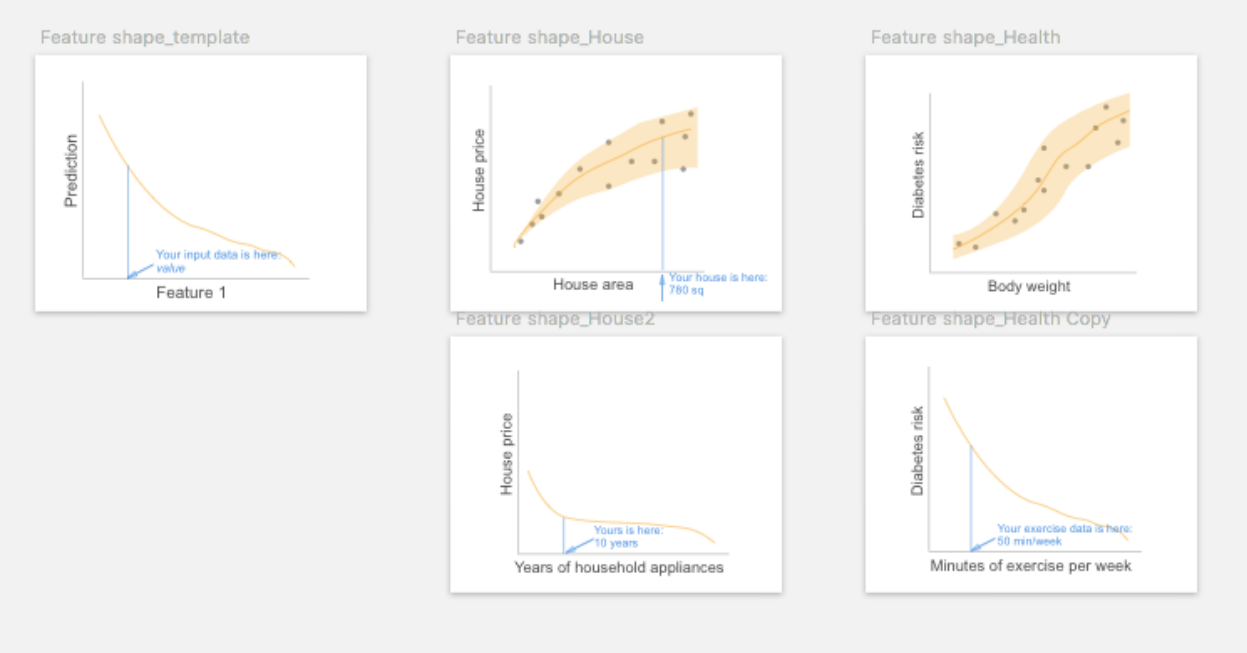

Figure 2: Visual representations of feature shape. The first column is the template with feature names shown by placeholders. The following columns are the visual representation cards used in the two tasks (House, Health) in the user study. Different visual variations are shown in the second row.

2.1.3 Feature Interaction

Visual representation: **2D or 3D heatmap** is usually used to visualize the combined effect of feature interactions on prediction. Limited by the visualization, a heatmap can show feature interactions for at most three features (using 3D heatmap). More complicated multiple paired feature-feature interactions can be visualized using matrix heatmap, node-link network, or contingency wheel.

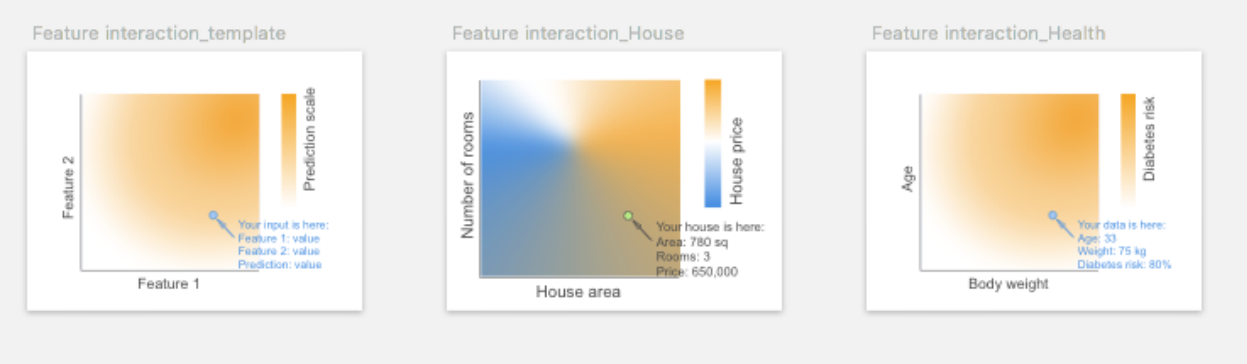

Figure 3: Visual representations of feature interaction. The first column is the template with feature names shown by placeholders. The following columns are the visual representation cards used in the two tasks (House, Health) in the user study.

2.2 Example-Based Explanation

2.2.1 Similar Example

The differences among similar, typical, and counterfactual examples are listed in Table A1: For a similar example, although it shares *similar features* with the query instance, their predictions may be *the same or different*. Whereas for a counterfactual example, it not only shares *similar features* with the query instance, but also has a *different prediction*. For a typical example, it has *the same prediction* as the query instance, regardless of their features.

Explanation Form	Features	Prediction
Similar Example	similar	the same or different
Typical Example	similar or different	the same
Counterfactual Example	similar	different

Table A1: **Distinctions among the three example-based explanation forms** by comparing their features and prediction with the query instance.

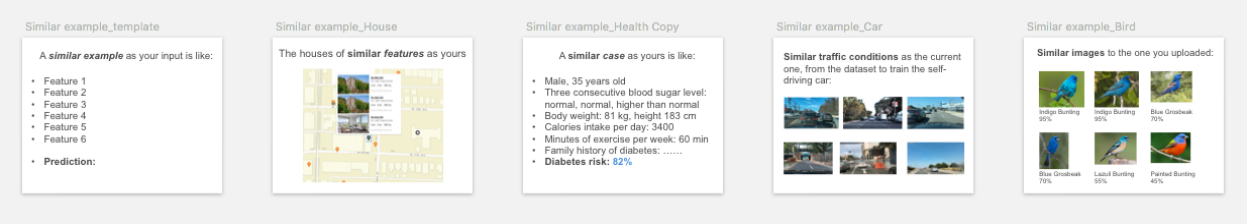

Figure 4: Visual representations of similar example. The first column is the template with feature names shown by placeholders. The following columns are the visual representation cards used in the four tasks (House, Health, Car, Bird) in the user study.

2.2.2 Typical Example

Visual representation: For similar and typical examples, it is straightforward to show several examples with their corresponding predictions.

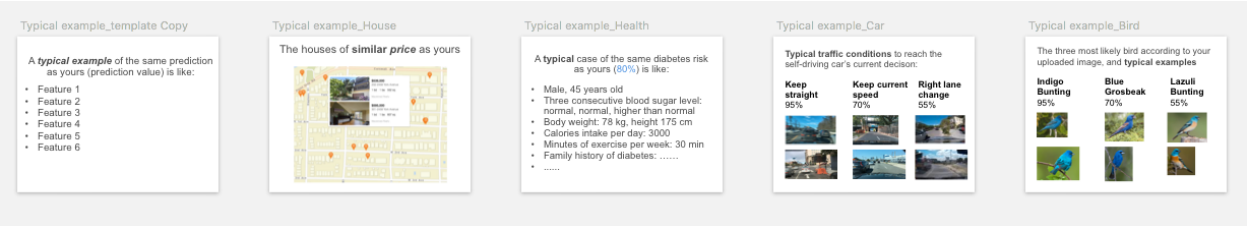

Figure 5: Visual representations of typical example. The first column is the template with feature names shown by placeholders. The following columns are the visual representation cards used in the four tasks (House, Health, Car, Bird) in the user study.

2.2.3 Counterfactual Example

We noted that counterfactual explanations can also be expressed as counterfactual features or rules. However, a counterfactual feature/rule can not be a standalone explanation in an XAI system, they must reside within a certain context by assuming all other features are constant. To make the explanation information complete, we include the counterfactual explanation in the form of example.

Visual representation: Counterfactual examples can be shown as two instances and their predictions, with their **counterfactual/contrasting features highlighted**, or a **transition** from one instance to the other by gradually changing the counterfactual features.

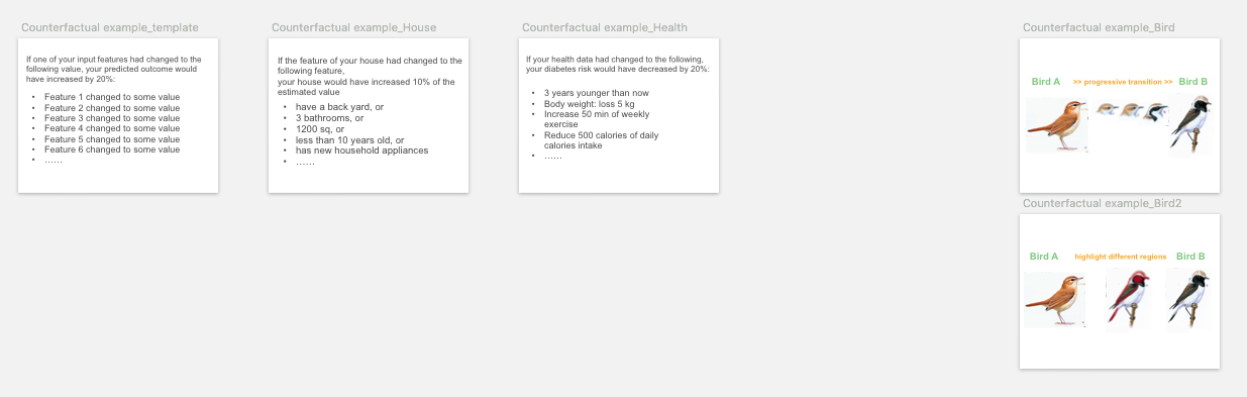

Figure 6: Visual representations of counterfactual example. The first column is the template with feature names shown by placeholders. The following columns are the visual representation cards used in the three tasks (House, Health, Bird) in the user study. We did not include a counterfactual example for the Car task, therefore we leave the column black. Different visual variations are shown in the second row.

2.3 Rule-Based Explanation

We note decision rule and decision tree actually carry similar explanation information. However, since they are usually generated by different XAI algorithms, and their representation formats (text vs. diagram) are different to users, we included them as two separate explanation forms.

2.3.1 Decision Rule

Visual representation: Decision rules are usually represented using **text**. Other representing formats include table [8] or matrix [16] to align, read, and compare rule clauses more easily.

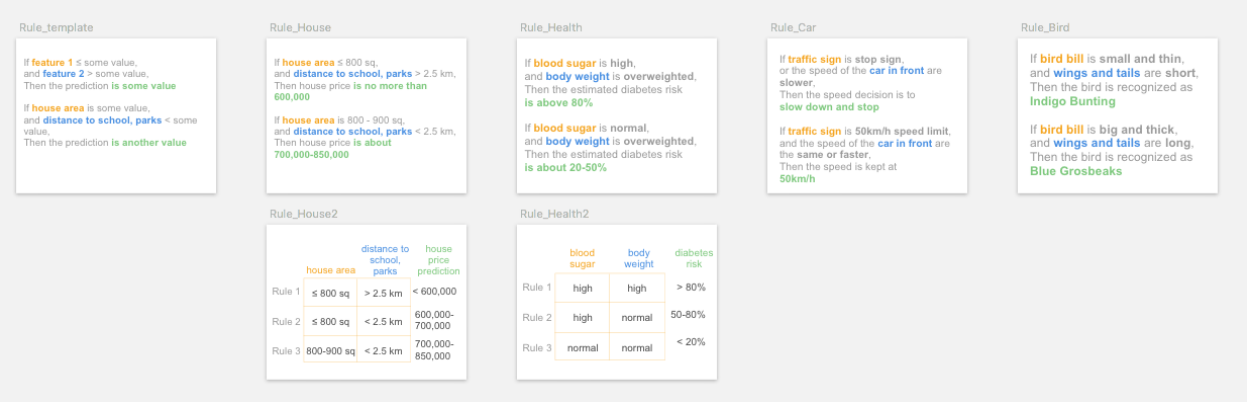

Figure 7: Visual representations of decision rule. The first column is the template with feature names shown by placeholders. The following columns are the visual representation cards used in the four tasks (House, Health, Car, Bird) in the user study. Different visual variations are shown in the second row.

2.3.2 Decision Tree

Visual representation: The most common representation is to use a node-link **tree diagram**. Other visual representations to show the hierarchical structure include treemap, cladogram, hyperbolic tree, dendrogram, and flow chart.

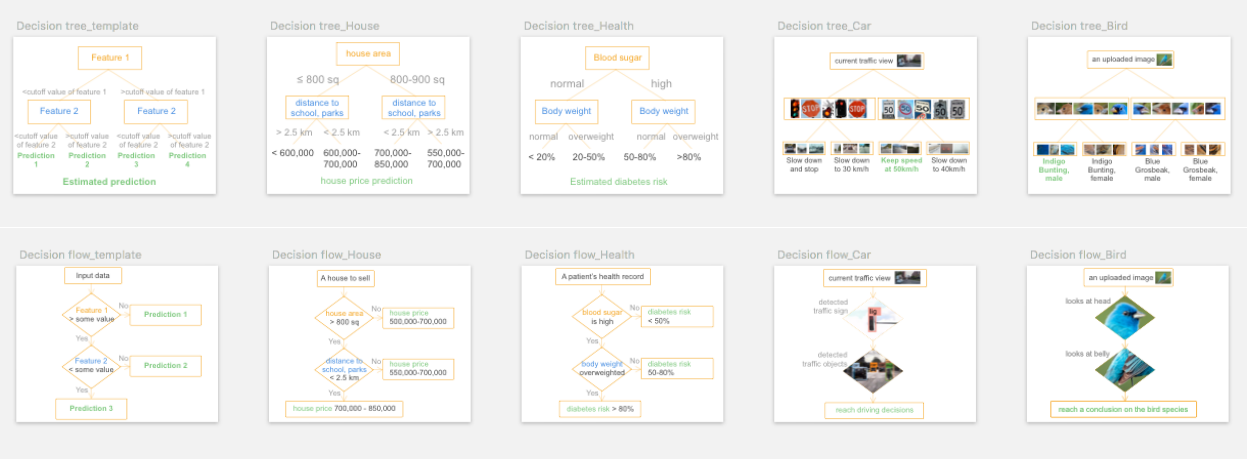

Figure 8: Visual representations of decision tree (1st row) and decision flow (2nd row). The first column is the template with feature names shown by placeholders. The following columns are the visual representation cards used in the four tasks (House, Health, Car, Bird) in the user study.

2.4 Contextual information

To provide necessary context and background for a more complete explanation, we additionally include contextual information in the end user-friendly explanation forms, include:

Input x.

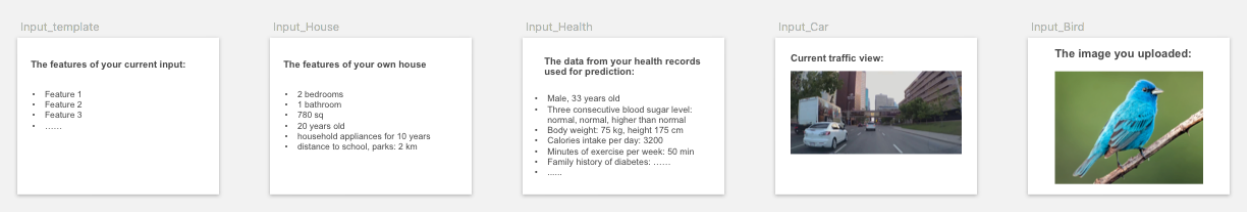

Figure 9: Visual representations of input. The first column is the template with feature names shown by placeholders. The following columns are the visual representation cards used in the four tasks (House, Health, Car, Bird) in the user study.

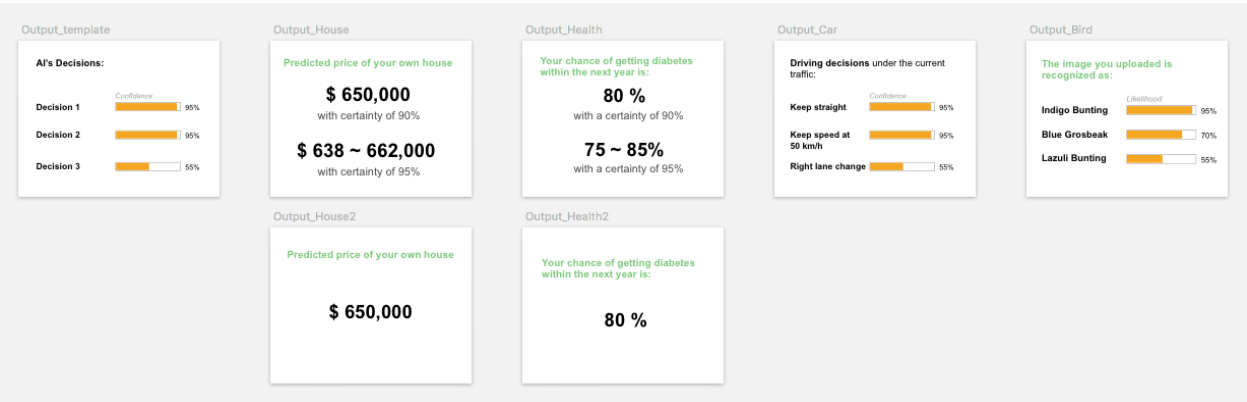

Figure 10: Visual representations of output. The first column is the template shown using placeholders. The following columns are the visual representation cards used in the four tasks (House, Health, Car, Bird) in the user study. Different visual variations are shown in the second row.

Output y.

Performance: Model's performance metrics (such as prediction accuracy, confusion matrix, ROC, mean squared error) help end users to judge a model's overall decision quality and set a proper expectation on model's capability.

Dataset: It is the proper description of the training and validation dataset, such as data distribution, and how the data were collected.

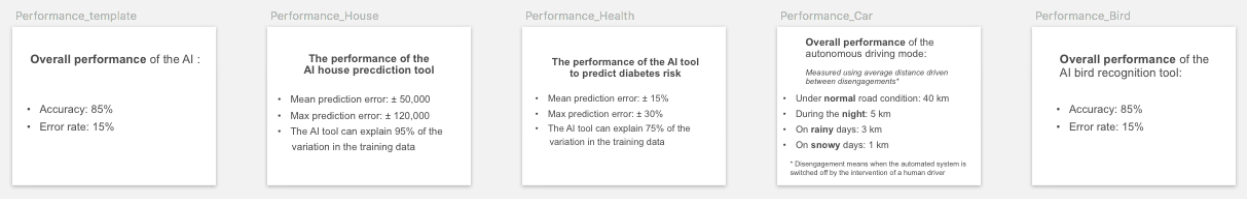

Figure 11: Visual representations of performance. The first column is the template. The following columns are the visual representation cards used in the four tasks (House, Health, Car, Bird) in the user study.

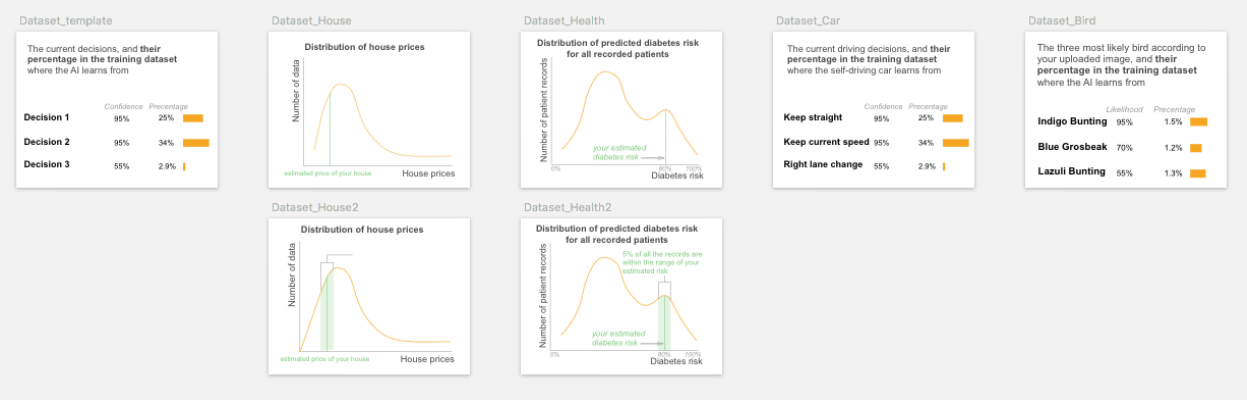

Figure 12: Visual representations of dataset. The first column is the template shown using placeholders. The following columns are the visual representation cards used in the four tasks (House, Health, Car, Bird) in the user study. Different visual variations are shown in the second row.

3 User Study Method

3.1 The Interview Instrument

3.1.1 Critical Decision-Making Tasks

We focus the scope of the study on AI-assisted critical decision-support tasks, where explanations have high utility as shown in previous research [6, 15, 10], and AI could not be delegated to have full automation because of the high-stakes nature of the tasks and the liability issue. In this study phase, we did not included domain experts. Therefore, we deliberately designed the tasks so that decisions can be made based on common sense without requiring domain knowledge. We designed four decision-making tasks reflecting the diversity of AI-supported critical decision-making. They are:

1. **House** task: users use AI to get a proper estimate of their house price.
2. **Health** task: users use AI to predict his/her diabetes risk.
3. **Car** task: users decide whether to buy an autonomous driving vehicle.
4. **Bird** task: users use AI bird recognition tool to prepare for an important biology exam.

The four tasks are critical decision-making scenarios, because their decisions have significant consequences on one's health and life (Health and Car Task), finance (House Task), or education (Bird Task). The corresponding datasets of the four tasks are publicly available (Table A2), so that the resultant low-fidelity paper-based AI prototypes from this user study can be actualized as high-fidelity functional prototypes for task-specific studies in future work.

AI-Assisted Critical Decision-Making Tasks		**HOUSE TASK** **Sell a house**	**HEALTH TASK** **Check diabetes risk**	**CAR TASK** **Buy a self-driving car**	**BIRD TASK** **Prepare for exam**
					
Explanation Goals	**Calibrate Trust**	You doubt whether to trust the AI tool or not	You doubt whether to trust the software prediction on your diabetes risk	n/a	You don't know whether to trust the results from the website or not
	Ensure Safety	n/a	n/a	You need to know whether the autopilot mode is safe and reliable	n/a
	Detect Bias	n/a	You doubt whether the software will perform the same among people with different gender, age, or ethnicity group	You want to know if the autopilot mode performs robustly under varying road, weather, and light conditions.	n/a
	Unexpected Prediction: Disagreement with AI	AI's prediction aligns/does not align with your own estimation	You maintain good health with no major diseases or a family history of diabetes/Diabetes tends to run in your family, and you're afraid of getting it someday, and AI predicts your chance of getting diabetes is low/high	You notice the car sometimes drives much slower than the expected speed limit	The results sometimes do not align with your knowledge
	Differentiation Similar Instances	n/a	n/a	n/a	In the exam, you need to write a short statement to differentiate different birds
	Learn from AI	n/a	n/a	n/a	Is it a good tool to improve your learning and help you know more about bird taxonomy?
	Improve the Predicted Outcome	You need to decide whether to do a renovation or replacement of appliances to increase your house value, and which action is the most cost-effective	You want to know how to adjust your lifestyle accordingly to lower the risk of diabetes	n/a	n/a
	Communicate with Stakeholders	You need to communicate your decision with your family	You need to need to inform family members and consult your doctor	You need to communicate with your family about your judgment on the car's safety	n/a
	Generate Reports	n/a	n/a	n/a	In the exam, you need to write a short statement on how you recognize the bird as such a species
	Multi-Objectives Trade-Off	n/a	You're aware that the insurance company may use such a prediction from the software to determine your insurance premium and benefits	You're easy to get motion sickness, and you notice you seem to get car sick more frequently in autopilot mode	n/a
ML problem type		Regression	Regression	Classification	Classification
Input data type		Tabular data	Tabular/sequential data	Image/video data	Image data
Available dataset		Boston housing [2]	Diabetes dataset [1]	BDD100K [23]	CUB-200 dataset [22]

Table A2: **The four tasks and their explanation goals used in the user study.**

3.1.2 End Users' Explanation Goals

Even for the same user and task, end users' explanation goals, i.e.: the trigger point or motivation to check the explanation of an AI system, may vary in different contexts or usage scenarios. In our study, we aim to capture the fine-grained details of end users' requirements for different explanation goals. We instantiated the identified explanation goals for each task, trying to cover as many explanation goals as we can. Table A2 shows the explanation task and their accompanying scenarios describing an explanation goal.

3.1.3 Creating Visual Representation Cards from Explanation Forms

We instantiated the explanation forms as low-fidelity visual cards for each task, based on their visual representations. We illustrate this process below:

1. **Create visual card templates** We started by creating visual representation templates of the explanation forms. We selected the most common visualizations, based on the summarized visual representations in Section 2. For example, we used bar chart and color map to visualize feature attribution for tabular and image data respectively. Each individual card shows one visual representation of an explanation form. For some explanation forms (such as feature attribution and counterfactual example), we created multiple cards with different variations of their visual representations.

2. **Extract features as content placeholder** We then manually extracted several interpretable features given the AI task. For instance, in the house price prediction task, we extracted features of house size, age, etc. In the self-driving car task, we extracted saliency objects such as traffic signs, road markers, cars, and pedestrians. As a quick prototyping, the feature content may not necessarily reflect the real content generated by XAI algorithms. They mainly serve as content placeholders.

3. **Fill the visual card templates with content placeholders** The extracted features were then used to fill in the visual card templates. The final visual representation cards are shown as figures in Section 2.

After interviewing the first five participants, we revised some visual cards based on participants' feedback. For instance, we indicated the position of the input data point on the feature shape and feature interaction cards. We also removed several variations of the cards (such as using a table to represent rules) since participants found them difficult to interpret.

3.2 Study Procedure

The study procedure consists of two rounds. **Round 1** is to familiarize participants with the tasks and explanation goals, and to understand end users' explanation goals for XAI before showing them the visual cards of the explanation forms. **Round 2** is the selection & ranking to understand users' interpretations and requirements for the explanation forms.

3.2.1 Round 1: Interview on Explanation Goals

We began the user study by introducing the researchers and the aim of the study, and went through the study consent form with the participant. The interview started after gaining the participant's written consent.

Task We first introduced an AI-assisted task to participants. The choice of the task was determined by a pre-generated random sequence. The task was presented as a storyboard color-printed on paper. Fig. 13 shows an example of the storyboard of the Health task. The researcher asked the participant to assume s/he was the character in the story context, and went through the task context with the participant by reading the text on the storyboard.

Explanation Goal After confirming that the participant had no questions and fully understood the current task, the research then randomly selected an explanation goal under the task context. The explanation goal was also shown as a storyboard picture, and the researcher read the text on the picture to introduce the explanation goal. Figure 14 gives an example of an explanation goal of unexpected. For each explanation goal, the researcher asked the participants whether they accept AI as decision-support, and need

Figure 13: The interview storyboard of the Health task in the user study

Figure 14: The explanation goal of unexpected in the Health task context. The end user may expect to have a high risk of diabetes due to family history. However, AI predicts the risk is only 10% which may not align with the user's expectation.

AI to explain its decision. If explanations were needed, the researcher then asked what explanations/further information they request.

After discussing all explanation goals for one task, the participant entered Round 2: card selection & ranking, which is detailed in the next subsection.

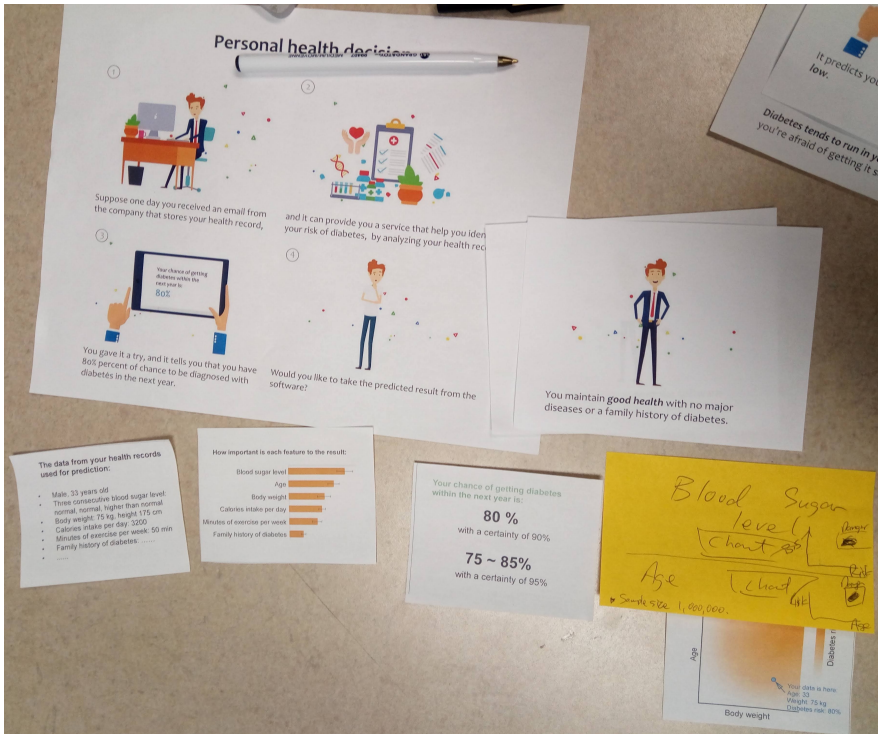

Figure 15: **The card selection & ranking result from one participant**. Given the task and explanation goal, the participant selected and ranked the visual cards from left to right according to their usefulness to the given explanation goal. She also sketched to improve the last card on feature interaction.

After completing one task, if the duration of the interview was less than 30 minutes, the participants were assigned to another task and underwent the same two-round interview procedure. At the end of the interview, the participants filled out a demographic questionnaire (Section 3.4). The study session duration is 67.9 ± 18.8 (Mean $\pm$ SD) minutes (Median: 67 min, Range: 41 - 120 min, each participant's specific data are detailed in Table 3.3). We audio-recorded the interviews, made observational notes on the card selection & ranking process, and took pictures of the card selection & ranking results. All study materials including the storyboards of tasks and explanation goals, and visual representation cards of explanation forms are listed at the end of this document.

3.2.2 Round 2: Card Selection and Ranking on Explanation Forms

For each decision-making task, the participants first revisited the task. Then the researcher gave a short tutorial of the explanation forms by walking through the visual cards and explaining the information on a card. In this process, the participant could ask questions if s/he did not understand or needed clarification. S/he could also comment on each card. Before moving on to the next step, we asked the participant and made sure they had no questions on these cards.

After confirming the participant fully understand the content of the cards, for each explanation goal, the researcher asked participants to select, rank, and combine the visual cards that they found were the most useful ones and could meet their current explanation goals. The participants could comment on any card anytime during this process. They could also modify the existing cards, or sketch on blank cards to create new visual cards, and add the newly created/modified cards to the card selection & ranking. After ranking the cards, they were asked to comment on why they selected or did not select a card, and their rationals for making such a ranking. After the card selection & ranking, they were asked whether the combination of cards would fulfill their explanation goals.

3.3 Participants' Information

Participant number	Age	Sex	Education level	Major or Industry	AI familiarity	AI attitudes	Tasks	Interview duration (min)
P01	38	M	Bachelor	computer science	program but not in AI	interested	House; Health; Car; Bird	120
P02	26	M	PhD	HCI	program but not in AI	concerned; interested; excited	Health; Bird	90
P03	29	F	PhD	HCI	use AI (Google) to reminders/navigation/daily use/play music or video etc.	interested	House; Car	74
P04	28	M	Master	HCI	program but not in AI	concerned; interested; excited	House; Car	94
P05	40	F	Trade	editing	heard	concerned; interested; excited	Car; Bird	46
P06	21	F	Some college credit	psychology	use AI (Google home) to play music	concerned; skeptical; interested	Health; Bird	76
P07	62	M	Bachelor				House; Car	64
P08	22	F	High school	computer science	program but not write AI code	excited	Health; Bird	55
P09	40	M	Bachelor	Business development and sales (IT)	use AI (Google navigator) to traffic and directions	excited	Car; Bird	51
P10	19	M	High school	cooking	heard	neutral	House; Bird	54
P11	30	F	Bachelor	IT	program but not write AI code	interested	House; Bird	76
P12	48	F	High school		heard	neutral	House; Bird	74
P13	53	M	Bachelor	customer service	heard	concerned; skeptical	Health; Car	69
P14	47	M	Some college credit	healthcare-sterilization work	never	interested	House; Bird	55

Participant number	Age	Sex	Education level	Major or Industry	AI familiarity	AI attitudes	Tasks	Interview duration (min)
P15	73	M	Professional	retired	heard	skeptical	Car	81
P16	34	F	Professional	law	heard	concerned; interested; excited	Health	67
P17	70	M	Bachelor	retired	heard	neutral	Health; Car	47
P18	27	M	Some college credit	General studies and legal studies	heard	skeptical; neutral; excited	Bird	41
P19	35	F	Bachelor	Government or social services (employment services for indigenous peoples)	heard	concerned; skeptical; interested; excited	House; Car	42
P20	30	M	Bachelor	Food industry	heard	concerned; skeptical; interested; excited	House	58
P21	26	F	Bachelor	Interior designer	use AI (chatting with clients)	concerned; interested; excited	Car	60
P22	23	F	Some college credit	Student (RMT); Work (hospitality (restaurant)	heard	concerned; skeptical; excited	Health	69
P23	31	M	Master	Accountant	use AI (google Home) to preferred music/movie	excited	Health	72
P24	41	M	Bachelor	Financial industry	use AI (investment software) to help drive investment decisions	excited	Health	69
P25	72	M	Master	retired	heard	concerned; interested; excited	Health	112
P26	70	F	Bachelor	retired	heard	skeptical; interested	Bird	52
P27	28	F	Bachelor	hospitality	heard	interested	Car	45
P28	28	M	Trade	Marlcotins sale	heard	interested	Health	88

Participant number	Age	Sex	Education level	Major or Industry	AI familiarity	AI attitudes	Tasks	Interview duration (min)
P29	43	F	Bachelor	Project management in construction (currently no job)	heard	concerned; interested; excited	House	67
P30	24	F	Master	Computer science	program but not write AI code	concerned	House	83
P31	25	F	Bachelor	psychology office worker	heard	interested	Health	65
P32	39	F	Bachelor	car insurance	heard	excited	Car	59

3.4 Demographic Questionnaire

1. Your age: _____
☐ prefer not to disclose

2. Your gender:
☐ Female
☐ Male
☐ Other

3. What is the highest degree or level of school you have completed or currently enrolled?
☐ No schooling completed
☐ Nursery school to 8th grade
☐ Some high school, no diploma
☐ High school graduate, diploma or the equivalent (for example: GED)
☐ Some college credit, no degree
☐ Trade/technical/vocational training
☐ Bachelor's degree
☐ Master's degree
☐ Professional degree (e.g. MD, JD)
☐ Doctorate degree (PhD)

4. If you are a student, what is your major? If you are working, what is your current work industry?

5. What is your understanding of artificial intelligence (AI)?
☐ I have never heard of AI before
☐ I only hear of AI from the news, friends, etc.
☐ I use AI in my work or life. If so, please specify what kind of AI do you use: _____ , to accomplish what tasks:_____
☐ I can program, but I can not write AI code
☐ I can write AI code

6. What is your opinion on incorporating AI technology into our everyday decision-making scenarios? (you can select multiple choices)
☐ I am not interested in AI, and I do not pay attention to it
☐ I am concerned about the prevalence of AI (e.g.: it will take over many people's job; it's a threat to human beings)
☐ I am skeptical of the incorporation of AI technology, but I would like to learn more about it
☐ I am neutral regarding the incorporation of AI technology

☐ I am interested in the incorporation of AI, and willing to know more about it
☐ I am excited to use AI to improve my work and life

3.5 Interview Material

We attach the interview material used in the study at the end of the Appendix, including:

1. The four tasks shown as storyboards;
2. The explanation goals shown as storyboards;
3. The explanation forms shown as cards.

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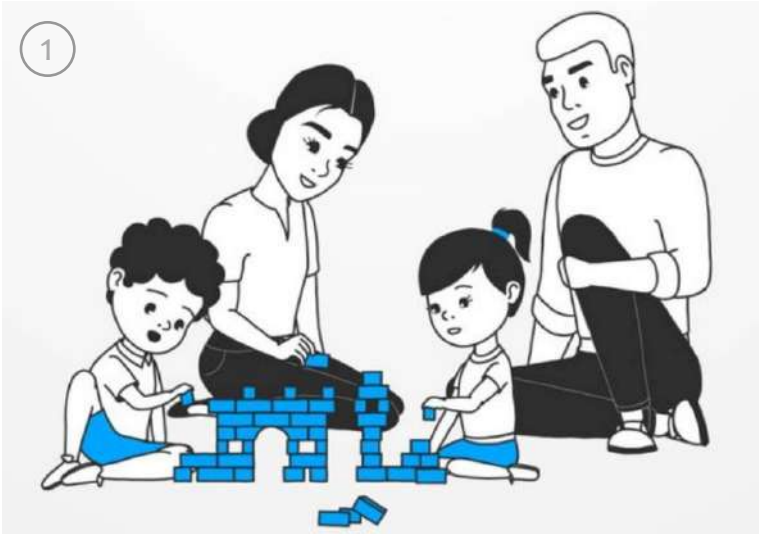
Selling your house

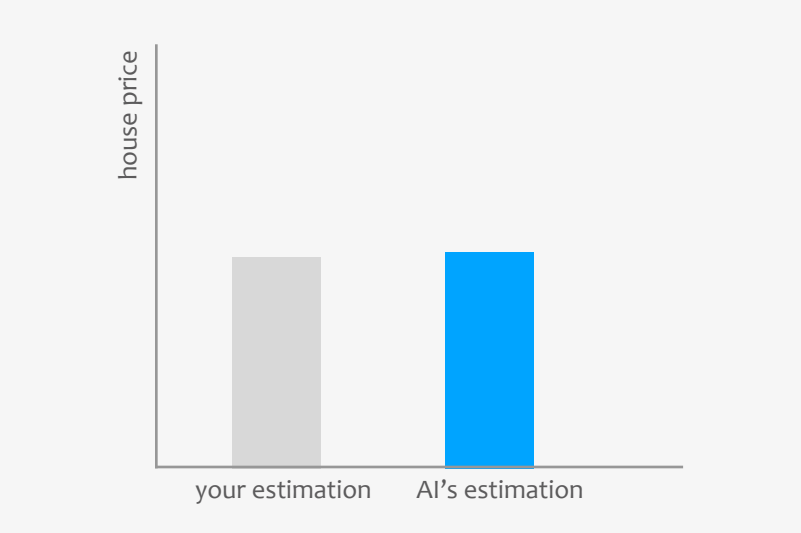


Suppose your family is expanding

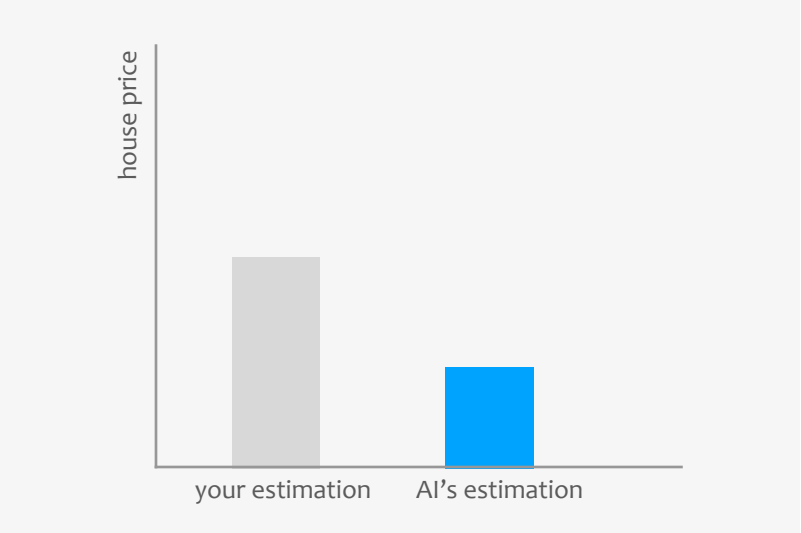
and you need to sell your current house, for a bigger one.

Since your budget is limited, you need to sell your current house at a really good price

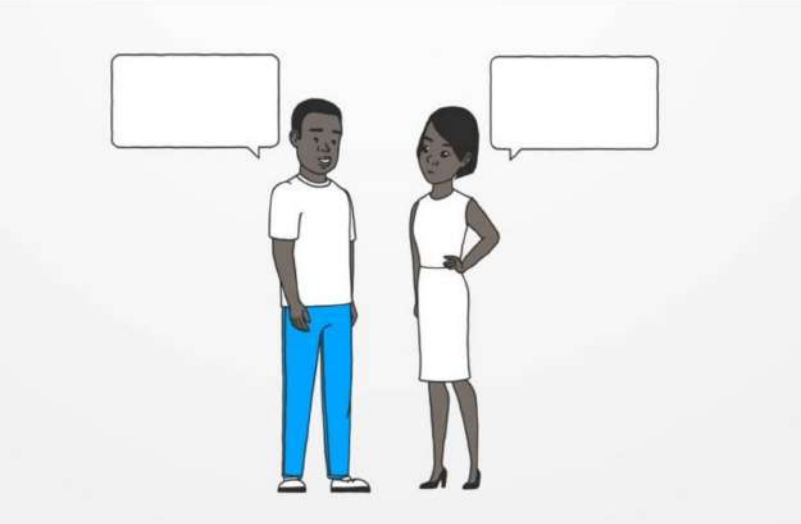
You get to know there is an **aritifical intelligence (AI)** tool that can **predict house price**. It may help you to get a propoer estimate of your house.



AI's prediction ***aligns*** with your own estimation



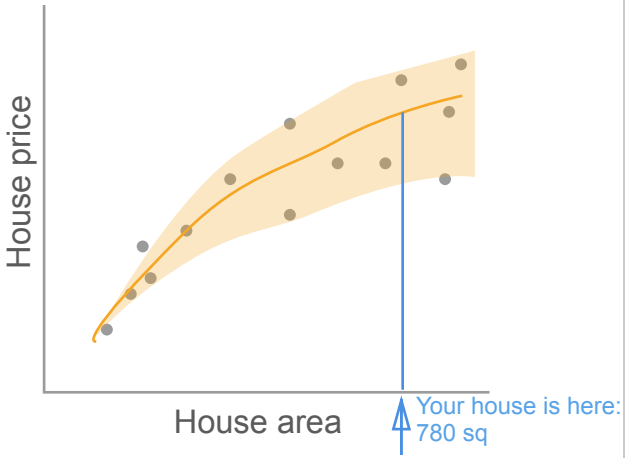
AI's prediction does ***not align*** with your estimation

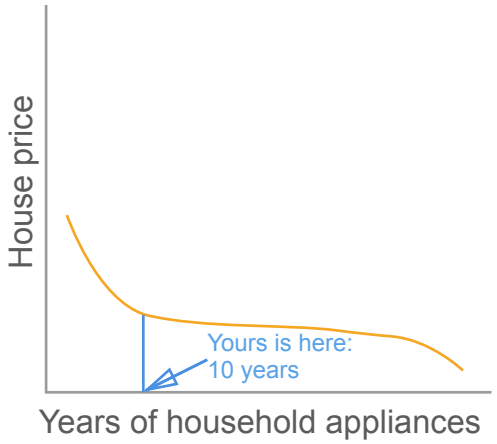


You need to ***communicate*** your decision with your family

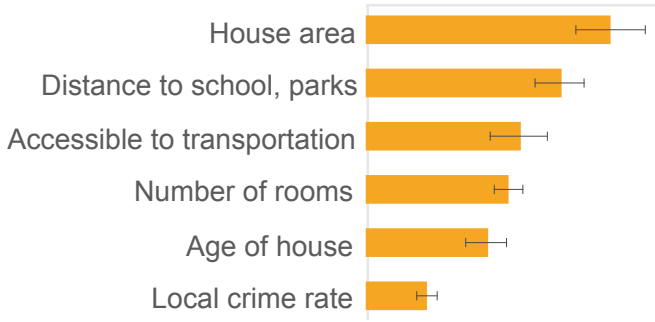
You doubt whether to ***trust*** the AI tool or not

You need to decide whether to do a renovation or replacement of appliances to increase your house value, and ***which action*** is the most cost-effective.

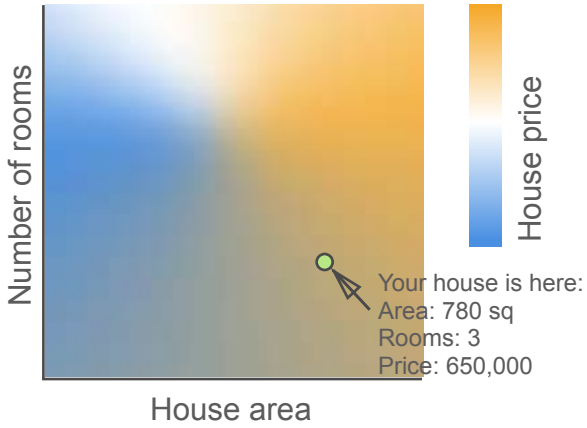




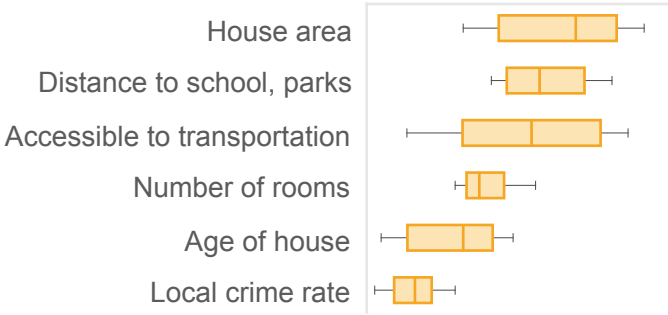
How important is each feature to the result:



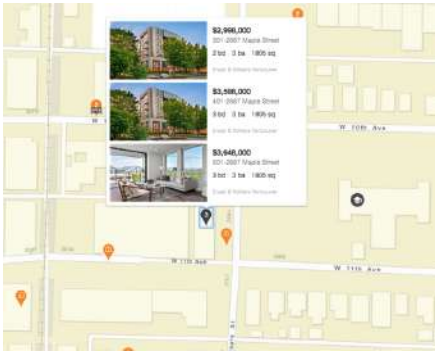
The houses of **similar *price*** as yours



Feature importance score



The houses of **similar *features*** as yours



A **typical** house to sell at the estimated price as yours is like:

In your neighbourhood:

- 2 bedrooms
- 2 bathrooms
- 1000 sq
- 20 years old
- ……

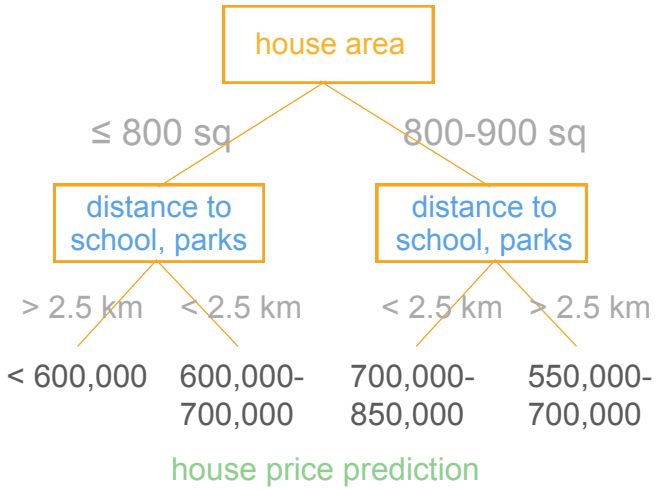
If the feature of your house had changed to the following feature,
your house price would have increased by 10%:

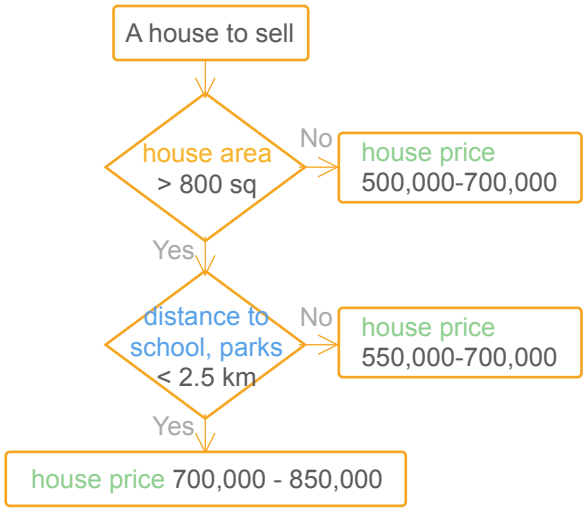
- have a back yard, or
- 3 bathrooms, or
- 1200 sq, or
- less than 10 years old, or
- has new household appliances
- ……

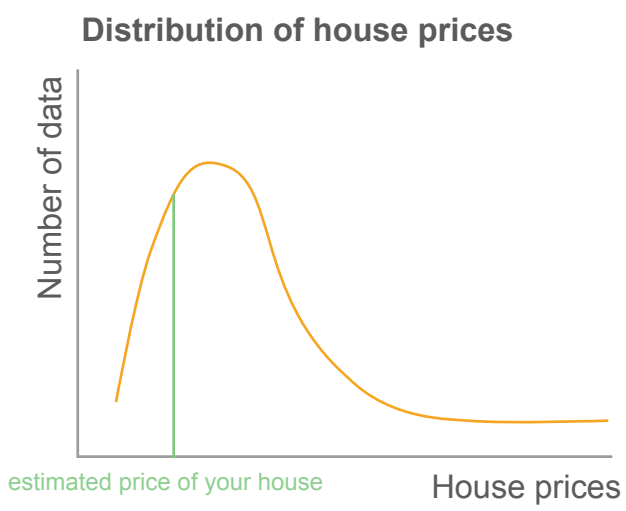
If **house area** ≤ 800 sq,
and **distance to school, parks** > 2.5 km,
Then house price **is no more than 600,000**

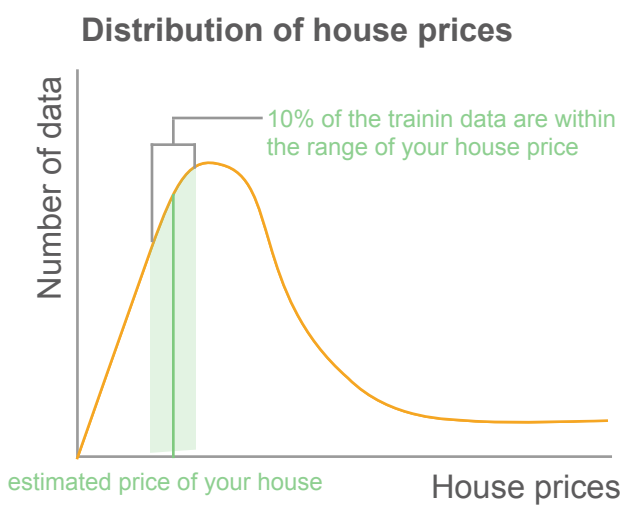
If **house area** is 800 - 900 sq,
and **distance to school, parks** < 2.5 km,
Then house price **is about 700,000-850,000**

	house area	distance to school, parks	house price prediction
Rule 1	≤ 800 sq	> 2.5 km	< 600,000
Rule 2	≤ 800 sq	< 2.5 km	600,000-700,000
Rule 3	800-900 sq	< 2.5 km	700,000-850,000









The features of your own house

- 2 bedrooms
- 1 bathroom
- 780 sq
- 20 years old
- household appliances for 10 years
- distance to school, parks: 2 km

Predicted price of your own house

$ 650,000

Predicted price of your own house

$ 650,000

with certainty of 90%

$ 638 ~ 662,000

with certainty of 95%

The performance of the AI house precdiction tool

- Mean prediction error: ± 50,000
- Max prediction error: ± 120,000
- The AI tool can explain 95% of the variation in the training data

Personal health decision

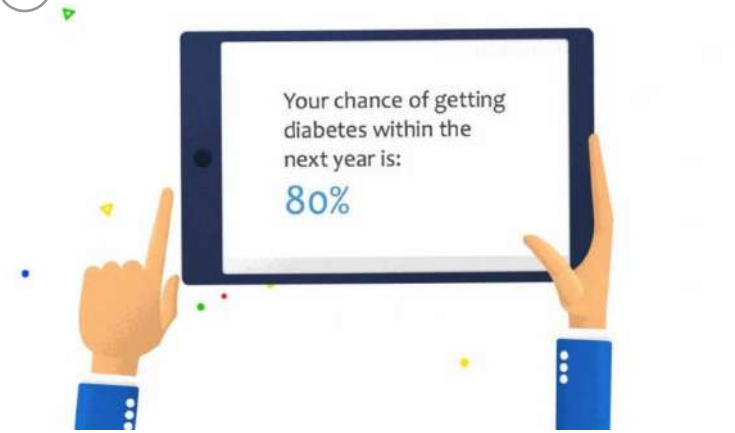
1

Suppose one day you received an email from the company that stores your health record,

2

and it can provide you a service that help you identify your risk of diabetes, by analyzing your health records.

3



You gave it a try, and it tells you that you have 80% percent of chance to be diagnosed with diabetes in the next year.

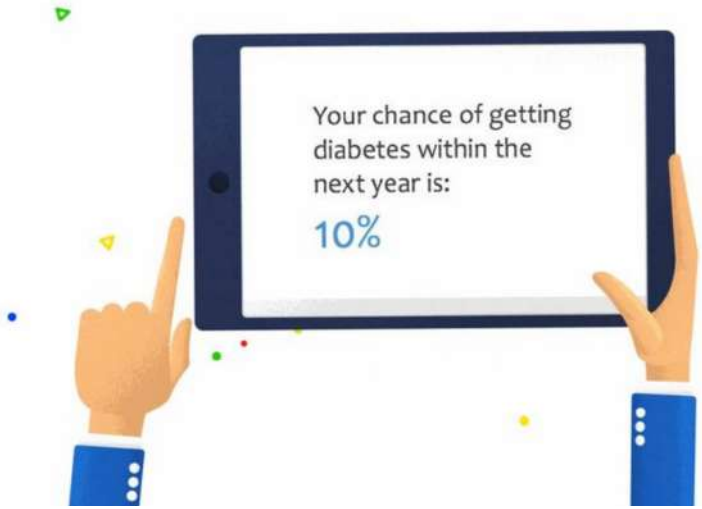
4

Would you like to take the predicted result from the software?

You doubt whether to ***trust*** the software prediction on your diabetes risk.

You want to know how to ***adjust your lifestyle*** accordingly to lower the risk of diabetes.

You need to need to inform ***family*** members and consult your ***doctor***.



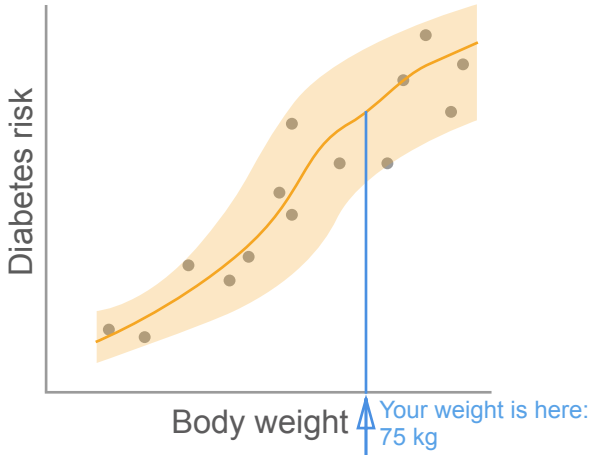
It predicts your chance of getting diabetes is ***low***.

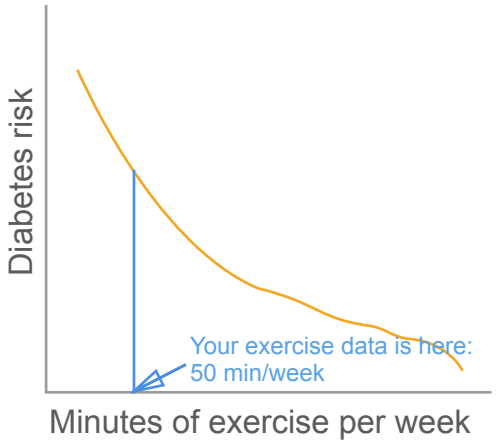
Diabetes tends to run in your family, and you're afraid of getting it someday.

You maintain ***good health*** with no major diseases or a family history of diabetes.

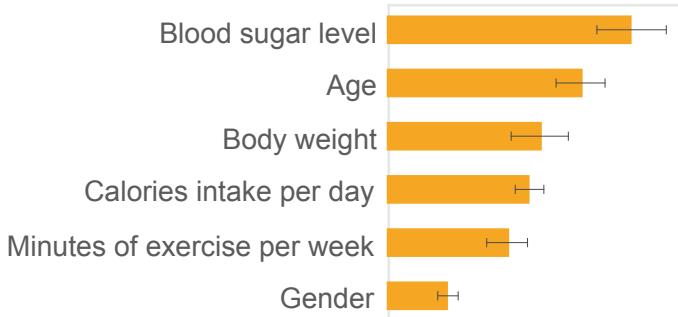
You're aware that the insurance company may use such a prediction from the software to ***determine your insurance fee and benefits***.

You doubt whether the software will perform the same among people with ***different gender, age, or ethnicity group***.



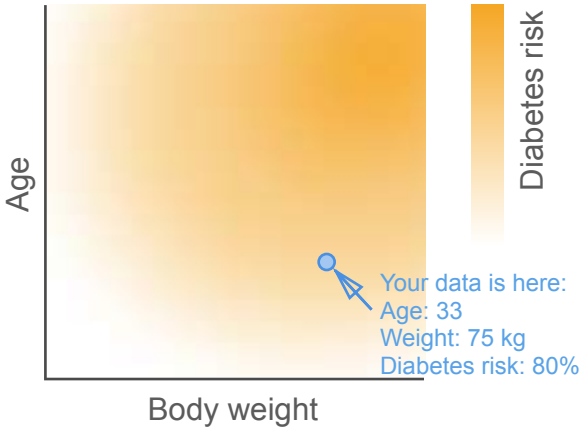


How important is each feature to the result:

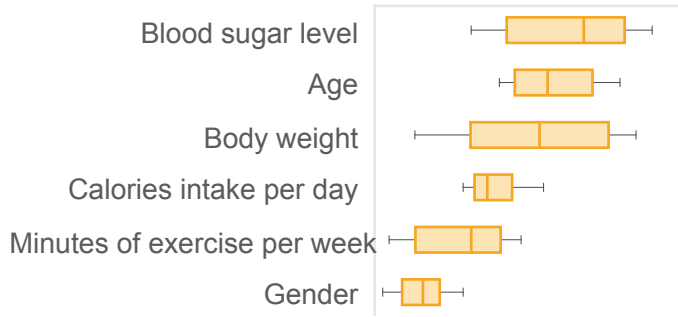


The case that has the **similar *diabetes risk*** as yours:

- Male, 32 years old
- Three consecutive blood sugar level: higher than normal, higher than normal, normal
- Body weight: 80 kg, height 178 cm
- Calories intake per day: 2900
- Minutes of exercise per week: 30 min
- Family history of diabetes: ……
- .....



Feature importance score



The case that has **similar *features*** as yours:

- Male, 35 years old
- Three consecutive blood sugar level: normal, normal, higher than normal
- Body weight: 81 kg, height 183 cm
- Calories intake per day: 3400
- Minutes of exercise per week: 60 min
- Family history of diabetes: ……
- .....

A **typical** case of the same diabetes risk as yours is like:

- Male, 45 years old
- Three consecutive blood sugar level: normal, normal, higher than normal
- Body weight: 78 kg, height 175 cm
- Calories intake per day: 3000
- Minutes of exercise per week: 30 min
- Family history of diabetes: ……
- .....

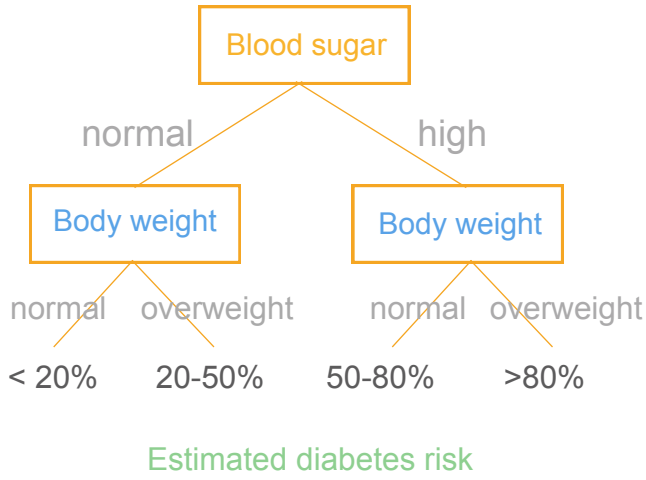
If your health data had changed to the following, your diabetes risk would have decreased by 20%:

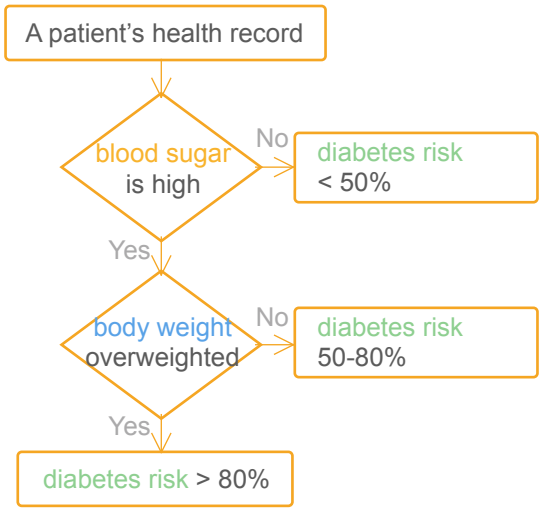
- 3 years younger than now
- Body weight: loss 5 kg
- Increase 50 min of weekly exercise
- Reduce 500 calories of daily calories intake
- ……

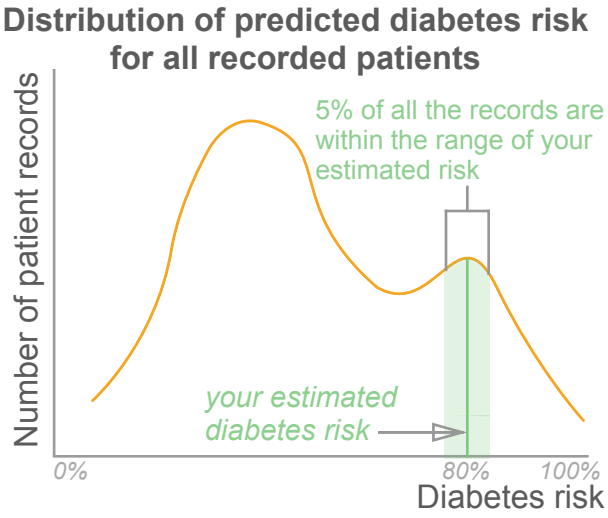
If **blood sugar** is **high**,
and **body weight** is **overweighted**,
Then the estimated diabetes risk
is above 80%

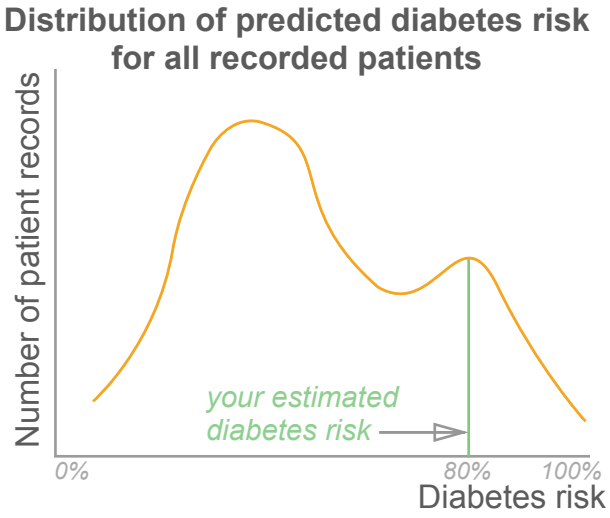
If **blood sugar** is **normal**,
and **body weight** is **overweighted**,
Then the estimated diabetes risk
is about 20-50%

	blood sugar	body weight	diabetes risk
Rule 1	high	high	> 80%
Rule 2	high	normal	50-80%
Rule 3	normal	normal	< 20%









The data from your health records used for prediction:

- Male, 33 years old
- Three consecutive blood sugar level: normal, normal, higher than normal
- Body weight: 75 kg, height 175 cm
- Calories intake per day: 3200
- Minutes of exercise per week: 50 min
- Family history of diabetes: ……
- .....

Your chance of getting diabetes within the next year is:

80 %

Your chance of getting diabetes within the next year is:

80 %

with a certainty of 90%

75 ~ 85%

with a certainty of 95%

The performance of the AI tool to predict diabetes risk

- Mean prediction error: ± 15%
- Max prediction error: ± 30%
- The AI tool can explain 75% of the variation in the training data

Buying an autonomous driving vehicle

1

You're test-driving an autonomous driving vehicle

2

Equipped with sensors and artificial intelligence (AI) system, the car can drive on its own.

3

Your main concern is the safety issue.

4

You need to decide whether to buy the car or not.

You notice the car sometimes drives much ***slower than the expected speed limit.***

You're easy to get motion sickness, and you notice you seem to get ***car sick*** more frequently ***in autopilot mode.***

You need to ***communicate*** with your family about your judgement on the car's safety.

You want to know if the autopilot mode performs equally ***under different road, weather*** conditions, and during the ***night.***

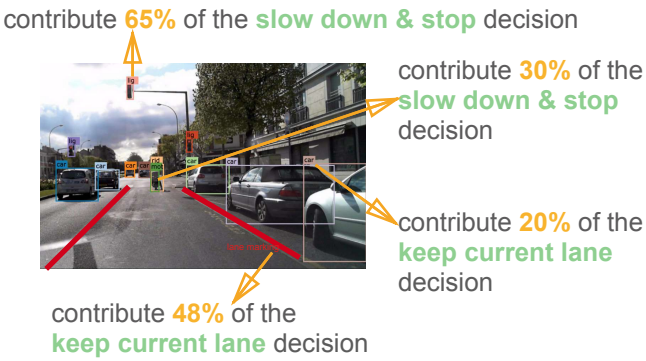
You need to know whether the autopilot mode is ***safe*** and ***reliable.***

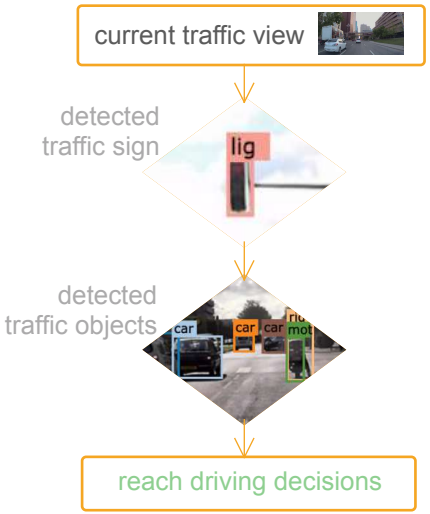
Similar traffic conditions as the current one, from the dataset to train the self-driving car:

Typical traffic conditions to reach the self-driving car's current decison:

Keep straight 95%	**Keep current speed** 70%	**Right lane change** 55%

Important objects detected for the self-driving car's judgement:

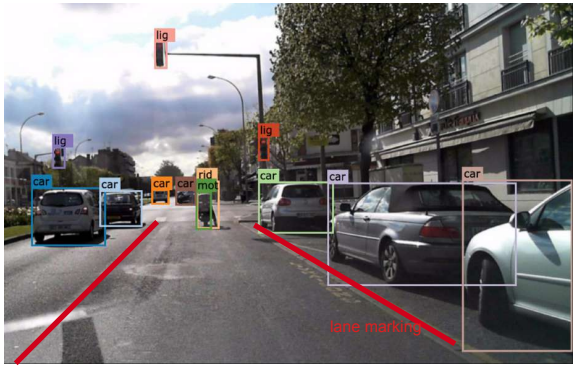




The current driving decisions, and **their percentage in the training dataset** where the self-driving car learns from

	Confidence	*Precentage*
Keep straight	95%	25%
Keep current speed	95%	34%
Right lane change	55%	2.9%

Important objects detected for the self-driving car's judgement:



Current traffic view:

Driving decisions under the current traffic:

	Confidence
Keep straight	95%
Keep speed at 50 km/h	95%
Right lane change	55%

Overall performance of the autonomous driving mode:

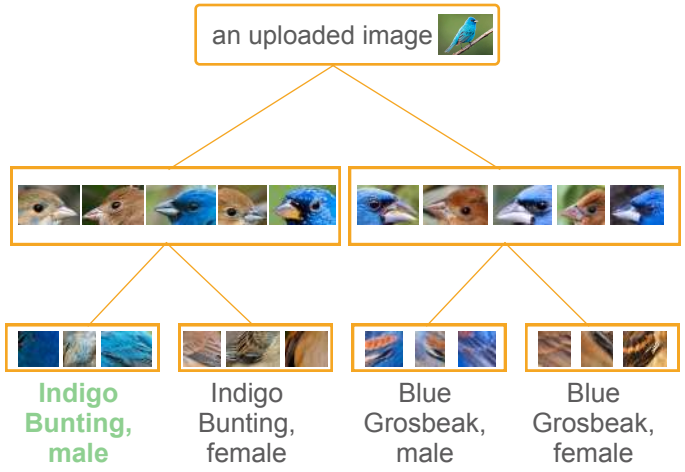
*Measured using average distance driven between disengagements**

- Under **normal** road condition: 40 km
- During the **night**: 5 km
- On **rainy** days: 3 km
- On **snowy** days: 1 km

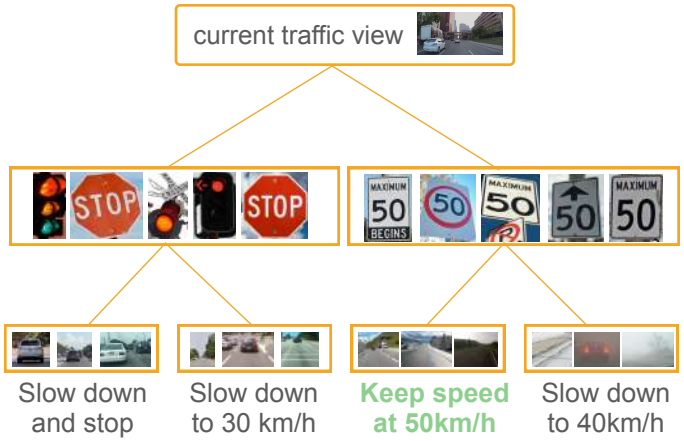
* Disengagement means when the automated system is switched off by the intervention of a human driver

If **bird bill** is **small and thin**,
and **wings and tails** are **short**,
Then the bird is recognized as
Indigo Bunting

If **bird bill** is **big and thick**,
and **wings and tails** are **long**,
Then the bird is recognized as
Blue Grosbeaks



Bird A **>> progressive transition >>** **Bird B**



Bird A **highlight different regions** **Bird B**

If **traffic sign** is **stop sign**,
or the speed of the **car in front** are
slower,
Then the speed decision is to
slow down and stop

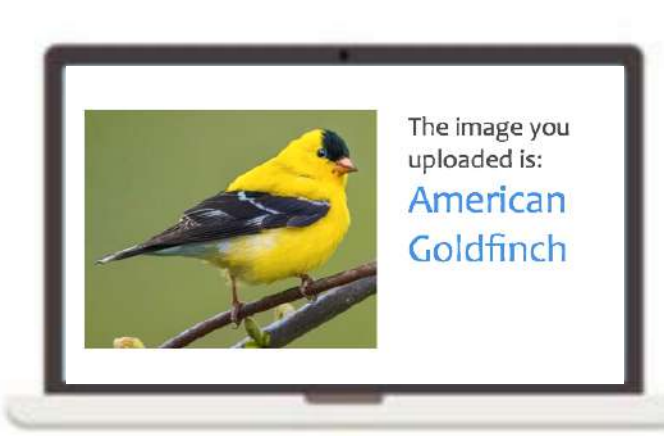
If **traffic sign** is **50km/h speed limit**,
and the speed of the **car in front** are
the **same or faster**,
Then the speed is kept at
50km/h

Learning bird species

Suppose you're a biology student, and are studying over the weekend to prepare for exam on bird species.

You get to know a bird taxonomy website that can automatically recognize the bird images you upload.

So you give it a try by uploading a bird image, and it gives you the most likely bird species.



Will you use the website to help you prepare for the exam?

You don't know whether to ***trust*** the results from the website or not.

The results sometimes does ***not align*** with your knowledge.

In the exam, you need to **write a short statement** on how you **recognize** the bird as such species.

In the exam, you need to **write *a short statement*** to ***differentiate different birds.***

Is it a good tool to improve your ***learning*** and help you know more about bird taxonomy?

Similar images to the one you uploaded:


Indigo Bunting
95%


Indigo Bunting
95%


Blue Grosbeak
70%


Blue Grosbeak
70%


Lazuli Bunting
55%


Painted Bunting
45%

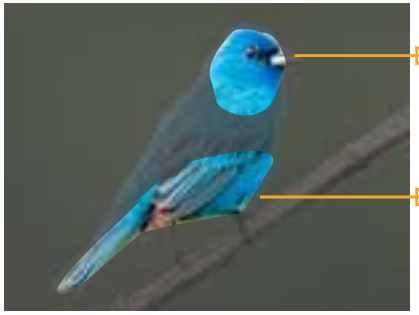
The three most likely bird according to your uploaded image, and **typical examples**

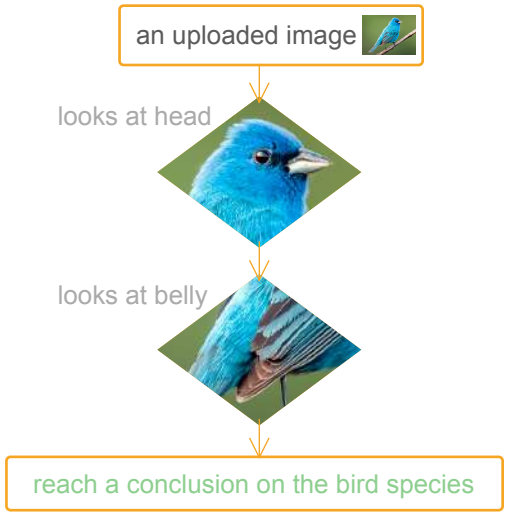
Indigo Bunting
95%

Blue Grosbeak
70%

Lazuli Bunting
55%

Important regions (highlighted) for AI's bird recognization:





The three most likely bird according to your uploaded image, and **their percentage in the training dataset** where the AI learns from

	Likelihood	*Precentage*
Indigo Bunting	95%	1.5%
Blue Grosbeak	70%	1.2%
Lazuli Bunting	55%	1.3%

Important regions (highlighted) for AI's bird recognization:

The image you uploaded:

The image you uploaded is recognized as:

	Likelihood
Indigo Bunting	95%
Blue Grosbeak	70%
Lazuli Bunting	55%

Overall performance of the AI bird recognition tool:

- Accuracy: 85%
- Error rate: 15%