

Explainable ML for Customer Satisfaction Data

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Customer Satisfaction Data

Tells the companies what their customers think about their products or services

Fundamental for informed business decisions and roadmap planning

Can be collected in multiple ways: surveys, social media, online review platforms

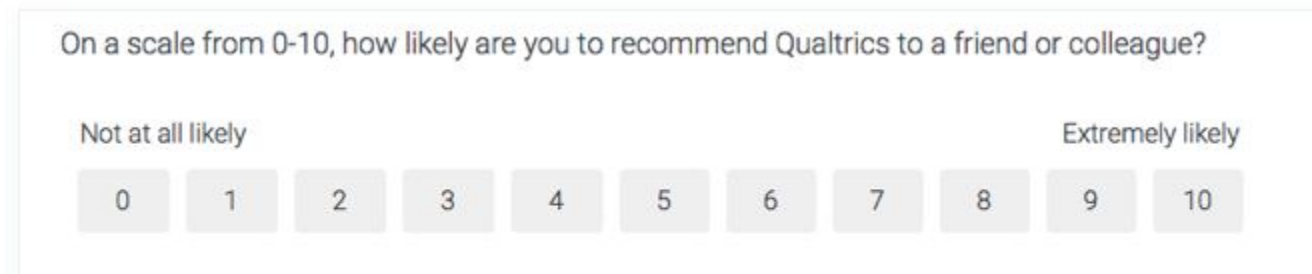
Qualtrics helps companies in collecting, analyzing, and understanding of the Customer Satisfaction (CSAT) Data

- **Qualtrics** was named the leader in the 2021 Gartner's report for the Voice of the Customer



Net Promoter Score

Measures customer perception based on one simple likelihood-to-recommend (**LTR**) question



On a scale from 0-10, how likely are you to recommend Qualtrics to a friend or colleague?

Not at all likely Extremely likely

0 1 2 3 4 5 6 7 8 9 10

The image shows a screenshot of a survey question. The question is 'On a scale from 0-10, how likely are you to recommend Qualtrics to a friend or colleague?'. Below the question is a horizontal scale with 11 buttons labeled 0 through 10. The text 'Not at all likely' is positioned above the 0 button, and 'Extremely likely' is positioned above the 10 button. The scale is currently empty, with no selection made.

Often accompanied by additional open-ended or so-called “driver” questions.

**Detractors**

(score 0-6) are unhappy customers who can damage your brand and impede growth through negative word-of-mouth

**Passives**

(score 7-8) are satisfied but unenthusiastic customers who are vulnerable to competitive offerings.

**Promoters**

(score 9-10) are loyal enthusiasts who will keep buying and fuel growth by referring others.

$$\text{😊 \%} - \text{😡 \%} = \text{NPS®}$$

Follow Up Questions

The **LTR** question is very often accompanied by follow up questions measuring the customer satisfaction in various dimensions. Examples

- How satisfied were you with the **website experience**?
- How satisfied were you with the **delivery**?
- How would you rate the **price for value** of the product?
- How satisfied were you with **food and beverages** served during the flight?

These questions help in **understanding** which customer satisfaction aspects have the biggest impact on **NPS**. This information together, often accompanied with financial data, is crucial in making informed business decisions.

Example

	LTR	Admission Process	In Room Experience	Food and Beverage	Attendees Experience	Doctors Experience	Nursing Services	Overall Staff	Discharge Process
0	9	4.000000	4.00	3.00	3.666667	4.00	4.00	4.000000	4.000000
1	10	4.000000	4.00	4.00	4.000000	4.00	4.00	4.000000	4.000000
2	7	3.333333	3.00	3.00	3.666667	4.00	4.00	4.000000	3.333333
3	10	4.000000	3.50	3.75	3.333333	4.00	3.75	3.333333	3.333333
4	10	4.000000	4.00	4.00	4.000000	4.00	4.00	4.000000	4.000000
5	10	4.000000	4.00	3.75	4.000000	4.00	3.50	4.000000	4.000000
6	10	1.666667	3.25	3.50	4.000000	4.00	4.00	3.000000	3.333333
7	9	3.333333	3.00	3.00	2.666667	4.00	4.00	4.000000	3.333333
8	9	4.000000	3.75	2.75	3.000000	4.00	4.00	4.000000	4.000000
9	10	4.000000	3.50	3.75	3.666667	3.75	3.75	4.000000	2.333333

Which dimensions are **the most important** drivers of LTR/NPS?

Machine Learning to the Rescue!

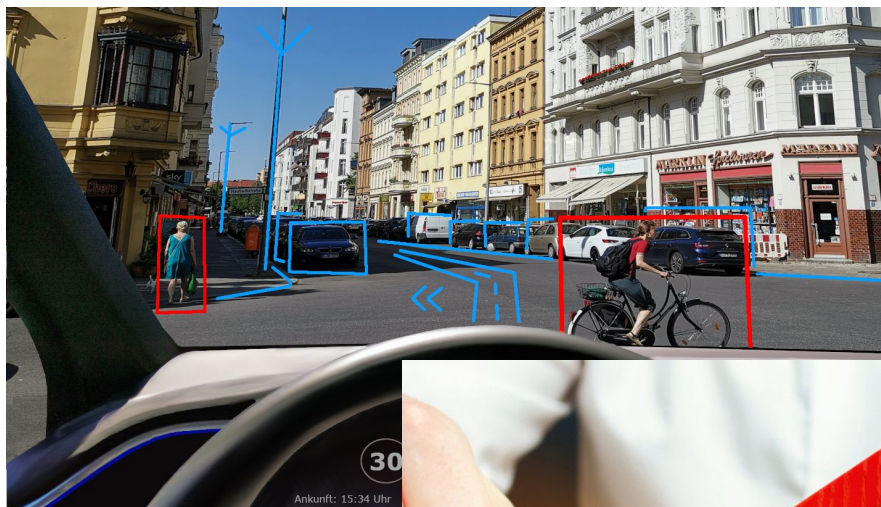
ML models are great at picking patterns in the data

Understanding what a model deems important provides insights into the data

- **Explainable ML** makes the behavior and predictions of machine learning systems understandable to humans

“Statistical models are lenses through which you look at your data” by Scott Zeger

ML is becoming **ubiquitous** in our lives



European Union Regulations on Algorithmic Decision Making and a “Right to Explanation”

Bryce Goodman, Seth Flaxman

■ We summarize the potential impact that the European Union’s new General Data Protection Regulation will have on the routine use of machine-learning algorithms. Slated to take effect as law across the European Union in 2018, it will place restrictions on automated individual decision making (that is, algorithms that make decisions based on user-level predictors) that “significantly affect” users. When put into practice, the law may also effectively create a right to explanation, whereby a user can ask for an explanation of an algorithmic decision that significantly affects them. We argue that while this law may pose large challenges for industry, it highlights opportunities for computer scientists to take the lead in

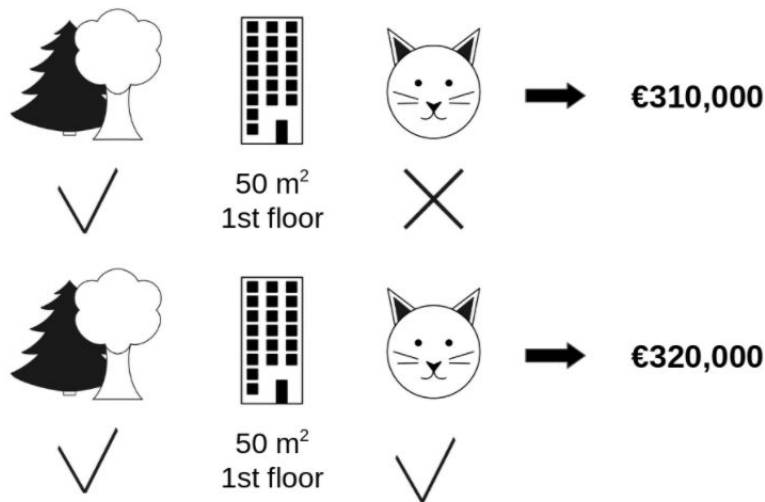
In April 2016, for the first time in more than two decades, the European Parliament adopted a set of comprehensive regulations for the collection, storage, and use of personal information, the General Data Protection Regulation (GDPR)¹ (European Union, Parliament and Council 2016). The new regulation has been described as a “Copernican Revolution” in data-protection law, “seeking to shift its focus away from paper-based, bureaucratic requirements and towards compliance in practice, harmonization of the law, and individual empowerment” (Kuner 2012). Much in the regulations is clearly aimed at perceived gaps and inconsistencies in the European Union’s (EU) current approach to data protection. This includes, for example, the codification of the “right to be forgotten” (Article 17), and

Explainability vs. Accuracy

	Explainable	Accurate
Complex model (Random Forest, Deep neural net)	✗	✓
Simple model (linear regression, decision tree)	✓	✗

SHAP (SHapley Additive exPlanations)

SHAP, proposed by Lundberg and Lee [1], is a method to explain individual predictions. SHAP is based on the game theoretically optimal Shapley Values.





Time for an exercise

Available at <https://github.com/gchlebus/explainable-ml-talk>