Explainable Empirical Risk Minimization

for

Trustworthy AI

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Outline

- Empirical Risk Minimization
- What is an Explanation?
- Measuring Explainability
- Explainable Empirical Risk Minimization

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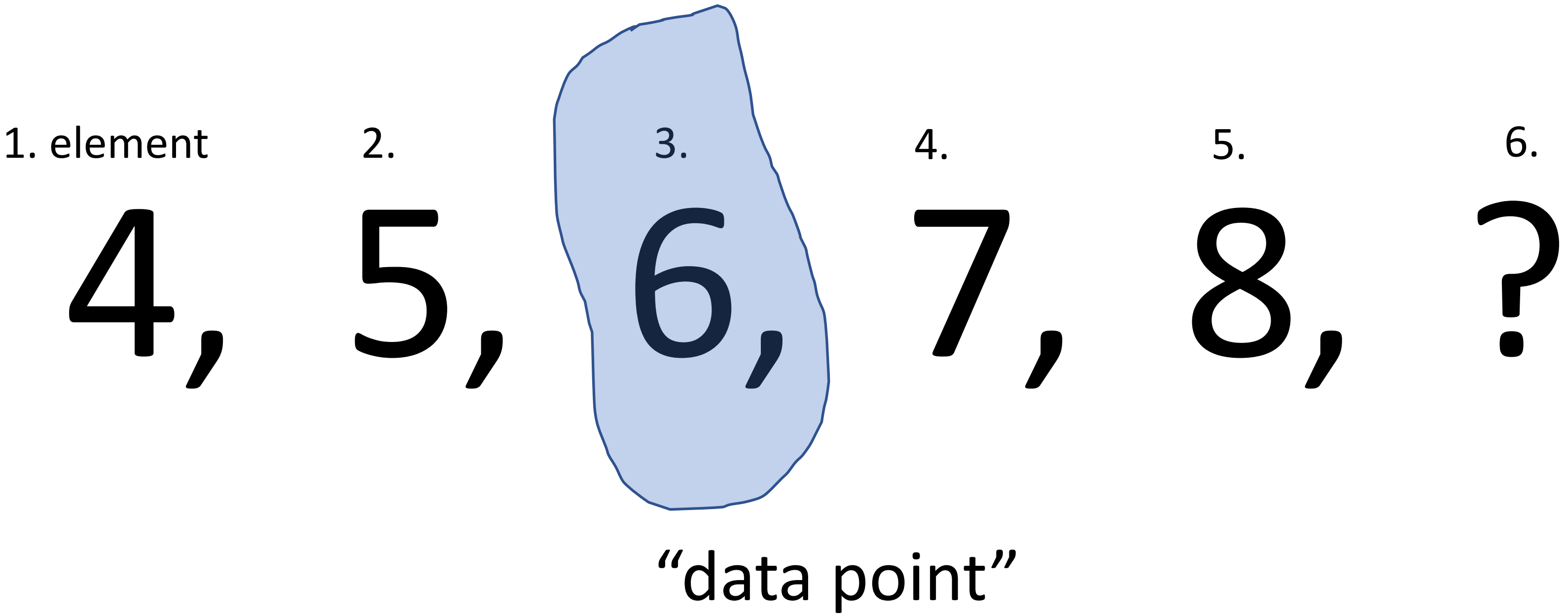
ML Principle (informal)

fit model to data to make accurate predictions or forecasts !

4, 5, 6, 7, 8, ?



1. element 2. 3. 4. 5. 6.

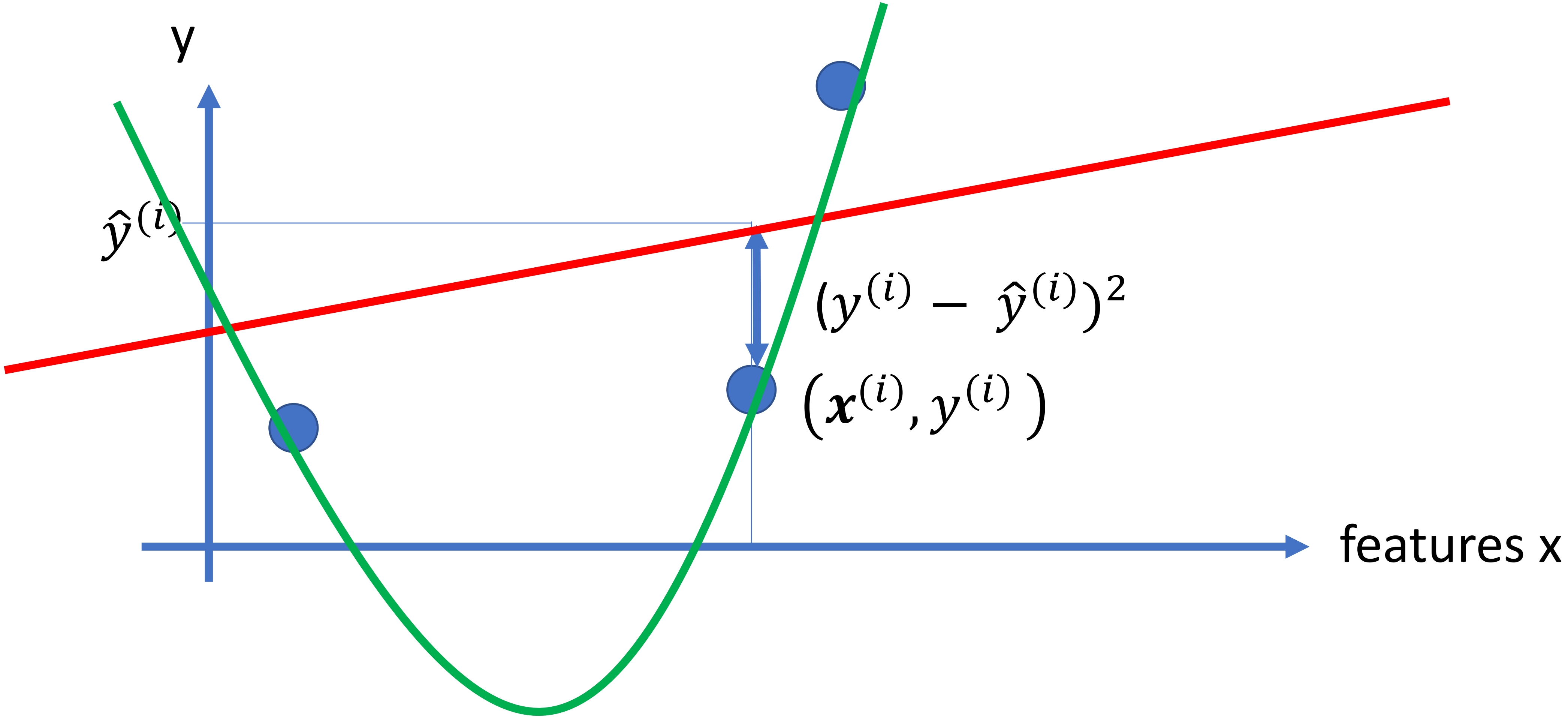
4, 5, 6, 7, 8, ?

“data point”

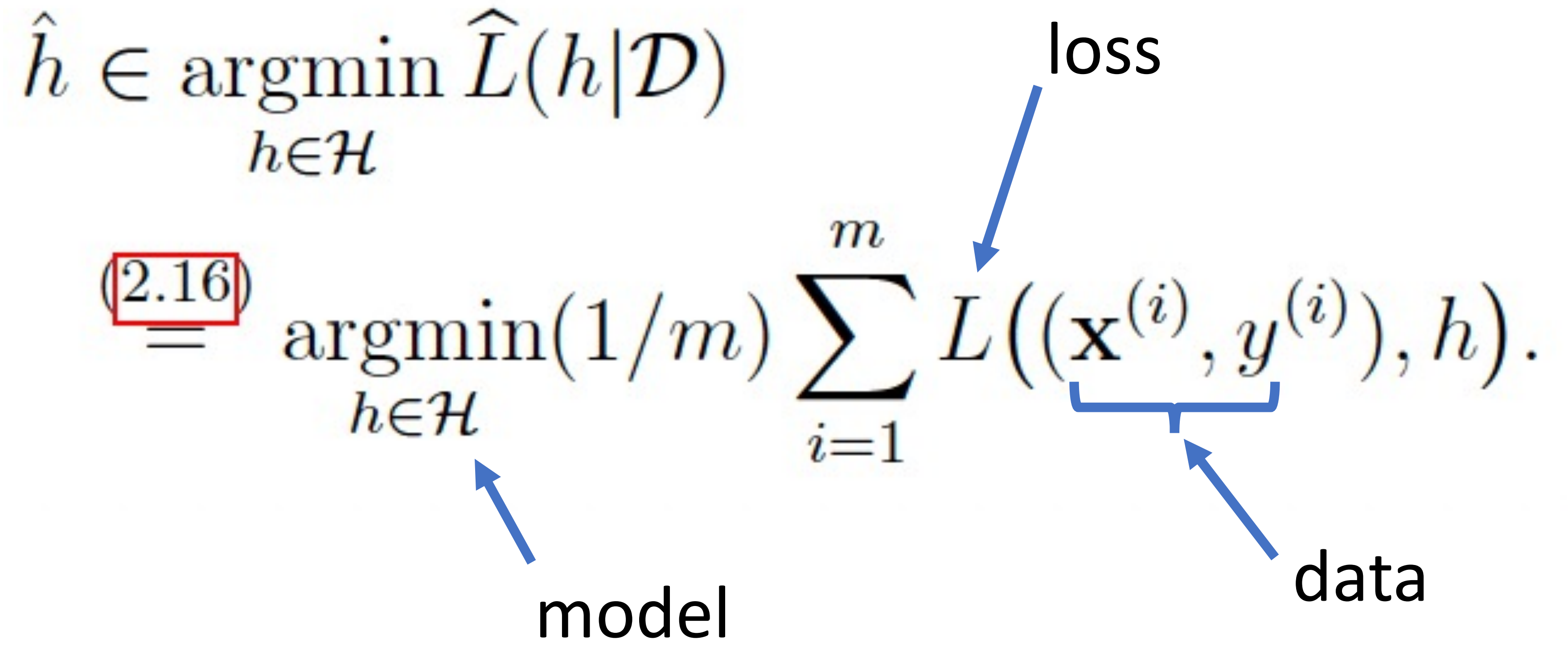
ML Principle (more formal)

learn hypothesis out of a hypothesis space (model) that allows to predict label of a data point from its features

Empirical Risk Minimization


y
$\hat{y}^{(i)}$
$(y^{(i)} - \hat{y}^{(i)})^2$
$(\boldsymbol{x}^{(i)}, y^{(i)})$
features x

Empirical Risk Minimization



$$\hat{h} \in \operatorname*{argmin}_{h\in\mathcal{H}} \widehat{L}(h|\mathcal{D})$$

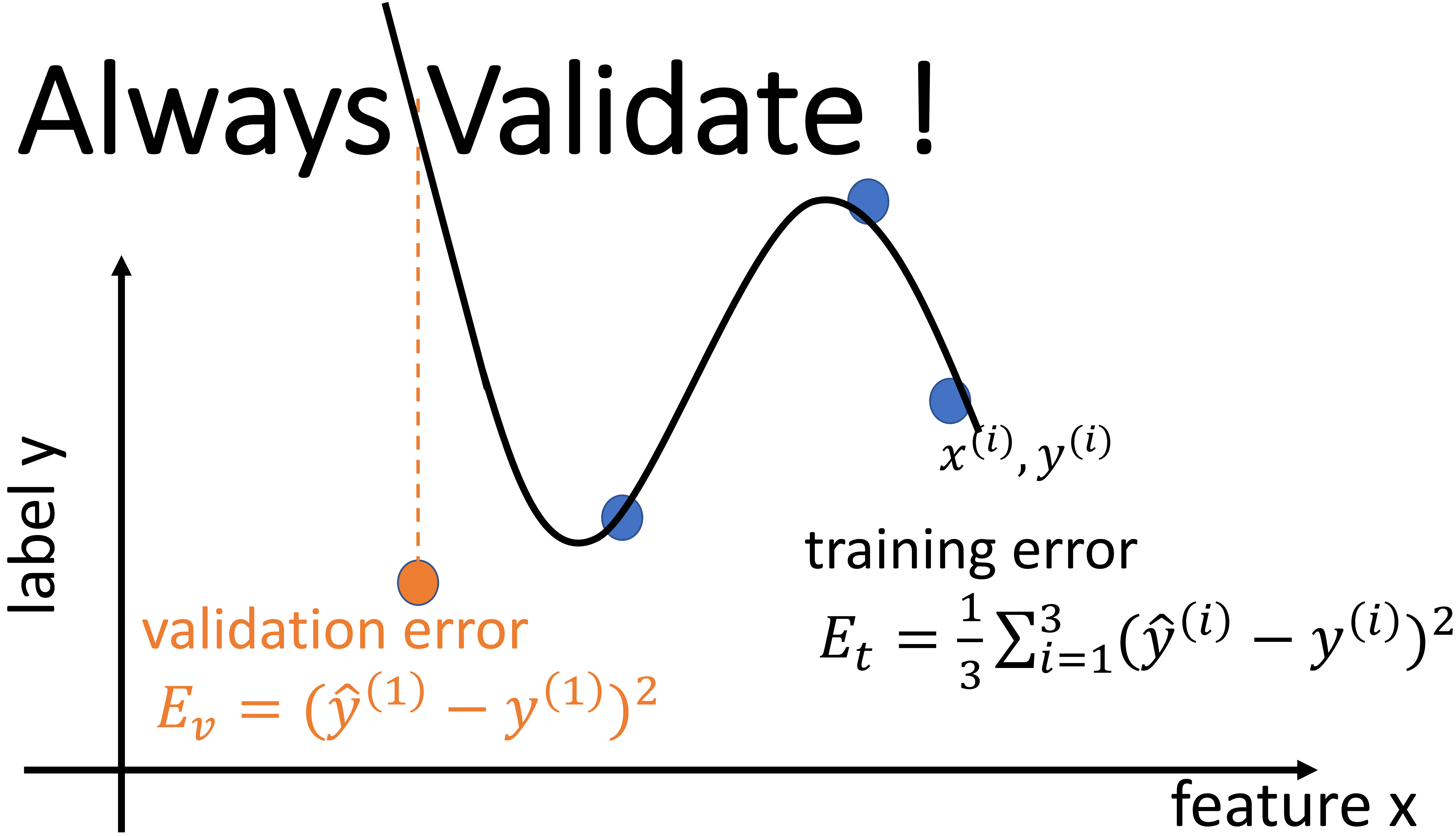
$$\overset{(\boxed{2.16})}{=} \operatorname*{argmin}_{h\in\mathcal{H}} (1/m) \sum_{i=1}^{m} L(\underbrace{(\mathbf{x}^{(i)}, y^{(i)})}, h).$$

loss

model

data

Always Validate !



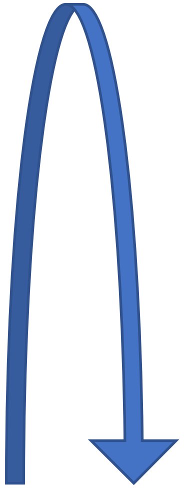
validation error

$$E_v = (\hat{y}^{(1)} - y^{(1)})^2$$

training error

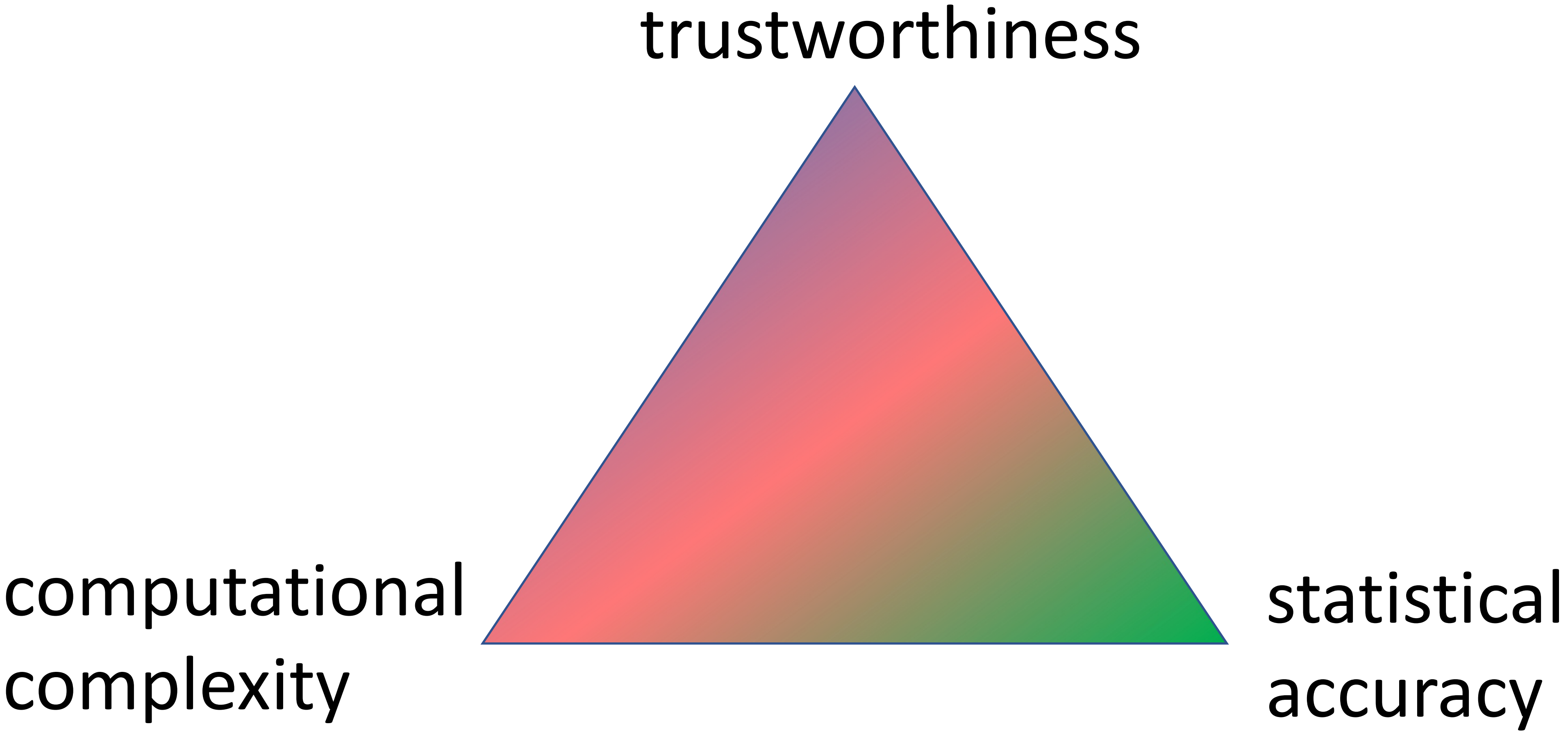
$$E_t = \frac{1}{3} \sum_{i=1}^{3} (\hat{y}^{(i)} - y^{(i)})^2$$

Life-Cycle of ML



- learn hypothesis h(x) via ERM (“train”)
- apply h(x) to new data (“validate”)
- measure error
- adapt ERM design choices and repeat

Design Choices: Data, Model, Loss.



trustworthiness

computational complexity

statistical accuracy

- **Human agency and oversight**
- **Technical robustness and safety**
- **Privacy and data governance**
- **Transparency**
- **Diversity, non-discrimination and fairness**
- **Societal and environmental wellbeing**
- **Accountability**

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Ethics Guidelines for Trustworthy AI

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https://ec.europa.eu/futurium/en/ai-alliance-consultation.1.html

Explainability.

“…Technical explainability requires that the decisions made by an AI system can be understood and traced by human beings. Moreover, trade-offs might have to be made between enhancing a system's explainability (which may reduce its accuracy) or increasing its accuracy (at the cost of explainability)...”

Two Key Questions

- what is an explanation ?

- how to measure explainability ?

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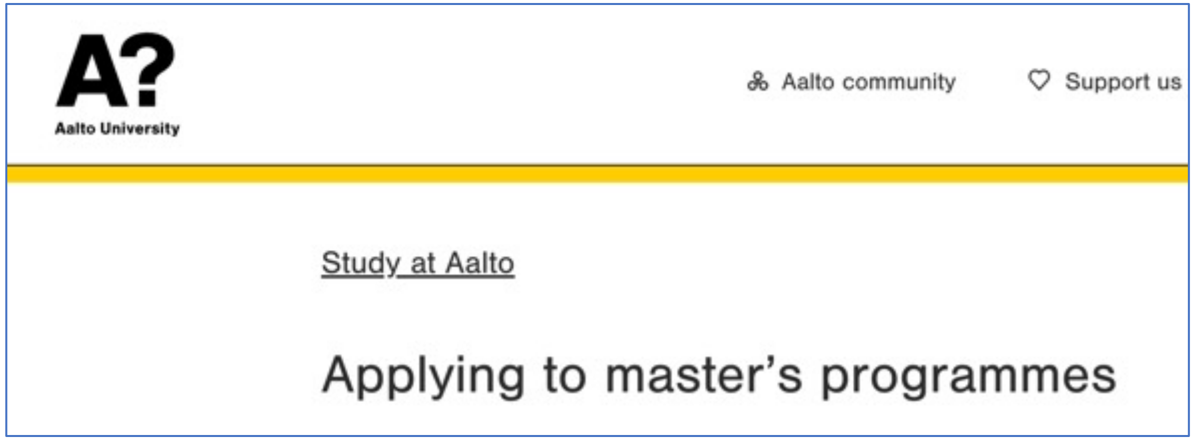
- Explainable Empirical Risk Minimization

ISO/IEC TR 24028

"…An explanation is always an attempt to communicate understanding. The effectiveness of an explanation can be improved by tailoring ..to...level of understanding it aims to convey…"

Premium Version of Explanations …



Study at Aalto

Applying to master's programmes

Among my students,

explaining a ML method could amounts to

- specification of data format and source
- specification of model (hypothesis space)
- specification of loss function

Explanation for a ML Method.

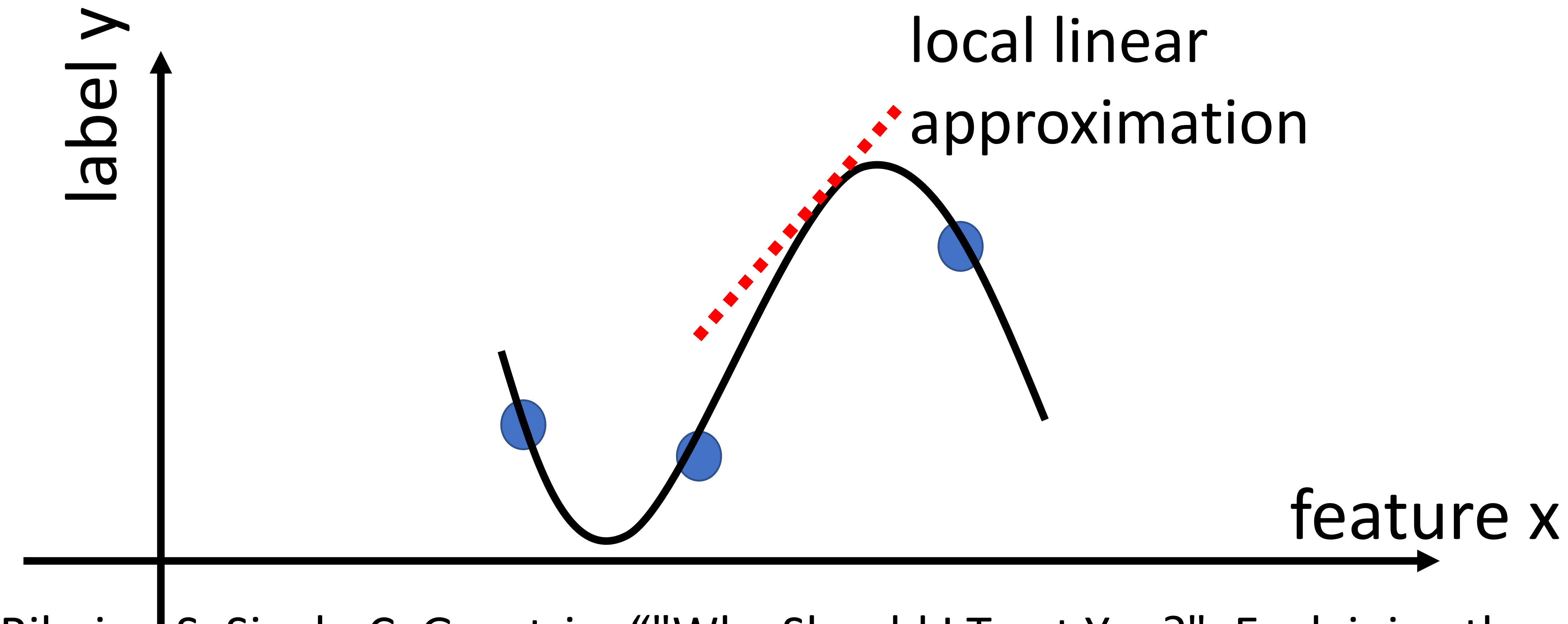
“linear regression learns a linear hypothesis by minimizing the average squared error on training set”

Explaining Prediction of Linear Model.

provide information about how the prediction h(x) is computed for a given data point with features x

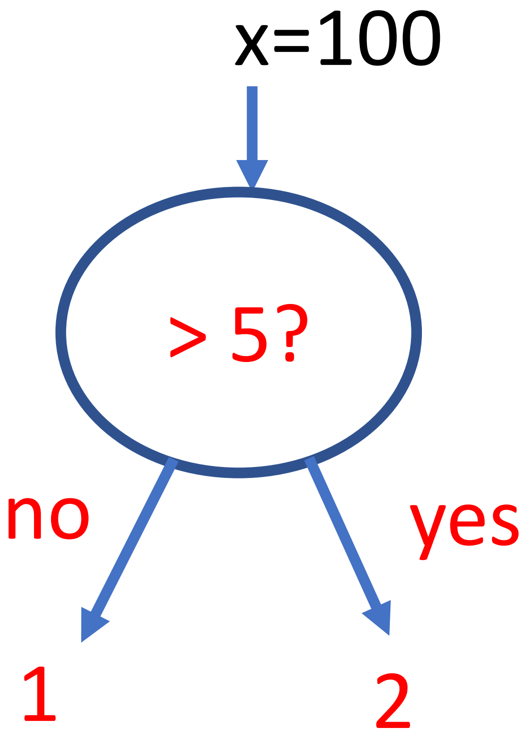
e.g., “the prediction is obtained since x=4 for this data point and we use a linear hypothesis h(x) = w1*x1+w2*x2 with weights w1 = 10 and w2=4”

LIME - Local Interpretable Model-Agnostic

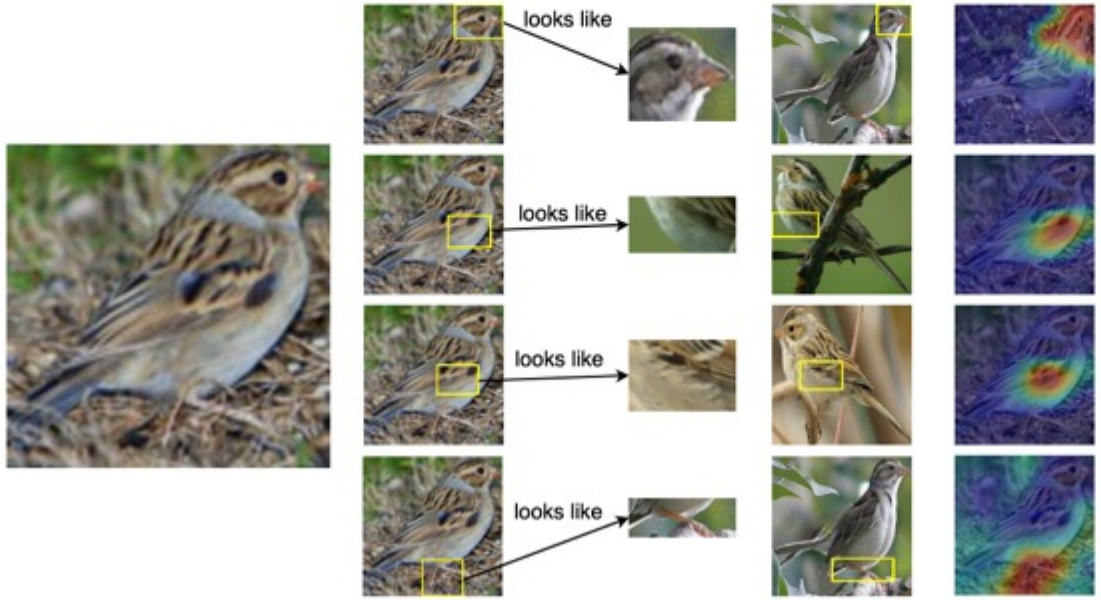


M. Ribeiro, S. Singh, C. Guestrin, “"Why Should I Trust You?": Explaining the Predictions of Any Classifier”, <i>arXiv e-prints</i>, 2016.

Explaining Decision Tree Prediction.



Explaining a Prediction.

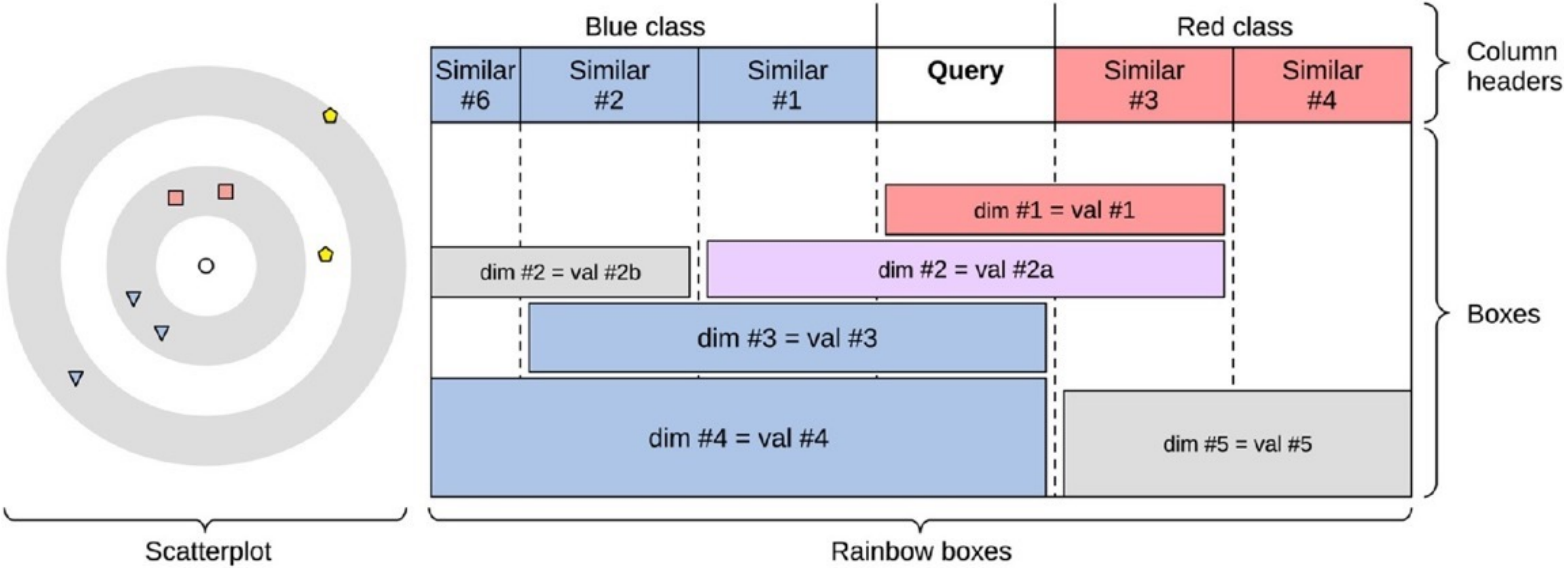


Leftmost: a test image of a clay-colored sparrow
Second column: same test image, each with a bounding box generated by our model -- the content within the bounding box is considered by our model to look similar to the prototypical part (same row, third column) learned by our algorithm
Third column: prototypical parts learned by our algorithm
Fourth column: source images of the prototypical parts in the third column
Rightmost column: activation maps indicating how similar each prototypical part resembles part of the test bird

Figure 1: Image of a clay colored sparrow and how parts of it look like some learned prototypical parts of a clay colored sparrow used to classify the bird’s species.

*Chaofan Chen, Oscar Li, Daniel Tao, Alina Barnett, Cynthia Rudin, Jonathan K. Su “***This Looks Like That: Deep Learning for Interpretable Image Recognition”, Neurips 2019**

Case-Based Reasoning.



Lamy et.al., “Explainable artificial intelligence for breast cancer: A visual case-based reasoning approach,” Artificial Intelligence in Medicine, Volume 94, 2019.

Towards a Definition.

“ explanation is an artefact “e” that is revealed to a user “u” who is also served the prediction $\hat{y} = h(\boldsymbol{x})$ *for a data point with features* $\boldsymbol{x}$*”*

A Precise Definition.

since we serve explanations for predictions on unlabelled data, explanation is a (stochastic) function of features only,

data point

e(x)

features x, y

restrict function e(.) to belong to feasible set $\mathcal{F}$ (similar to a hypothesis space!)

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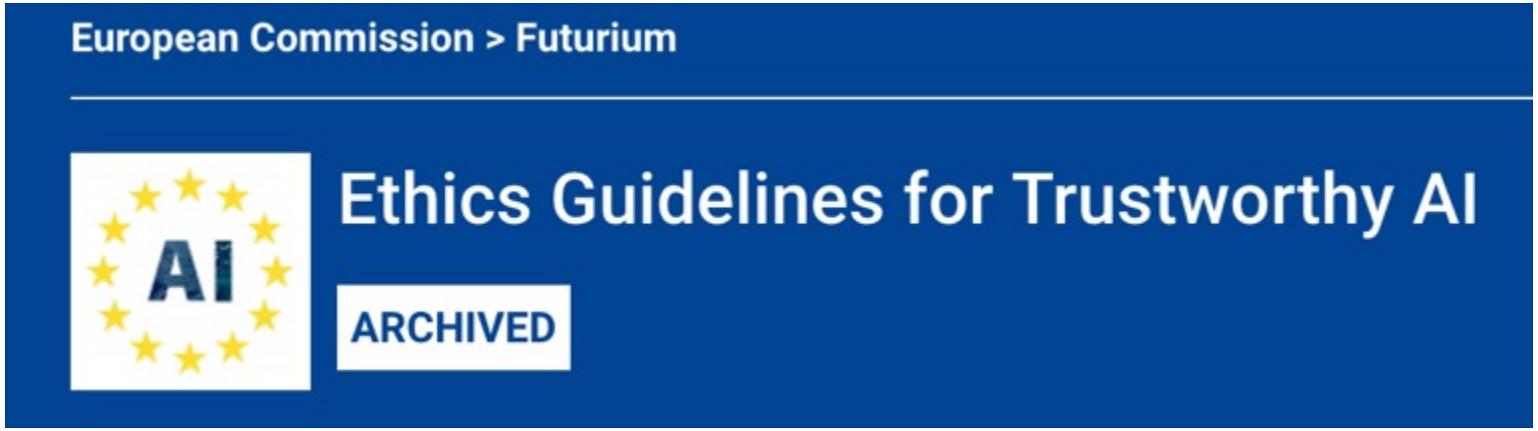
Explainability is Subjective.

"… explanation should be timely and adapted to the expertise of the stakeholder concerned (e.g. layperson, regulator or researcher)…."



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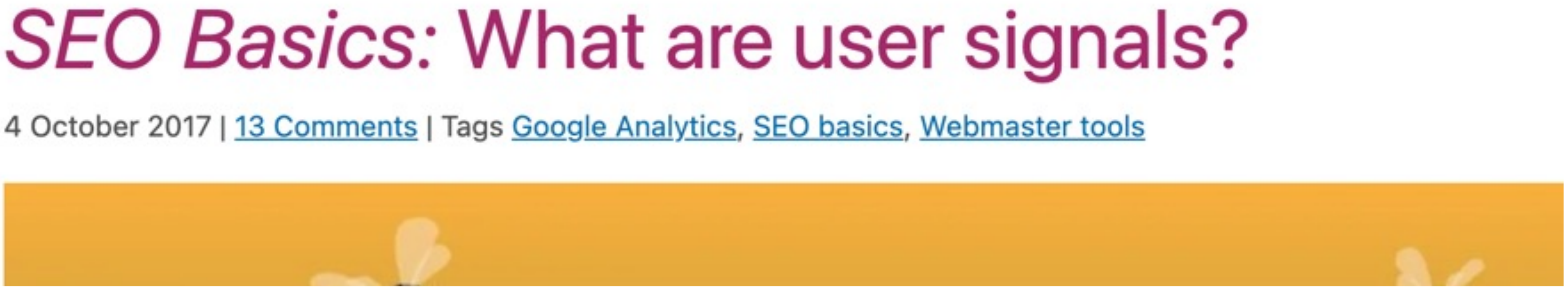
What is Subjective?



SEO Basics: What are user signals?

4 October 2017 | 13 Comments | Tags Google Analytics, SEO basics, Webmaster tools

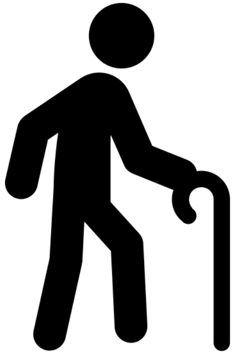
"User signals are behavioral patterns…. The most important user signals are the bounce rate and the click-through rate (CTR)"

https://yoast.com/what-are-user-signals/

User Signal.

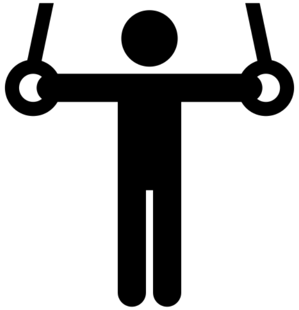
data point

features x,
label y



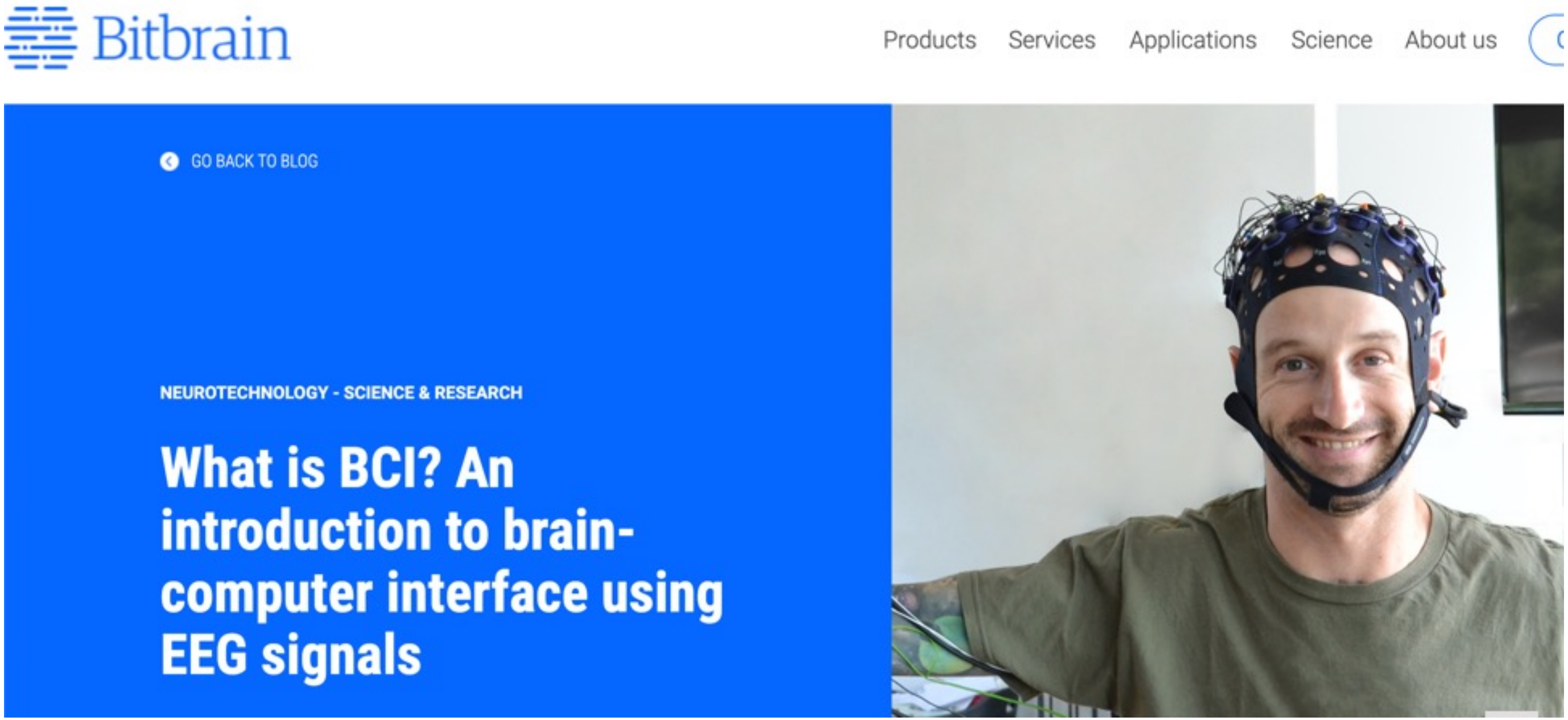
user 1

user 2



user 3

User Brain Signal.



NEUROTECHNOLOGY - SCIENCE & RESEARCH

What is BCI? An introduction to brain-computer interface using EEG signals

User Psychological Signal

What do you see ?

https://www.tutordale.com/what-do-you-see-pictures-psychology/

User Signal via Interpretable Representation (Features)

“…Lime explains those classifiers in terms of interpretable representations (words), even if that is not the representation actually used by the classifier.…”

https://homes.cs.washington.edu/~marcotcr/blog/lime/

Abstract User Signal.

some user-specific quantity e associated with a data point

might interpret e as user-specific feature or label

A Simple Probabilistic Model

data point
features “x”, label y

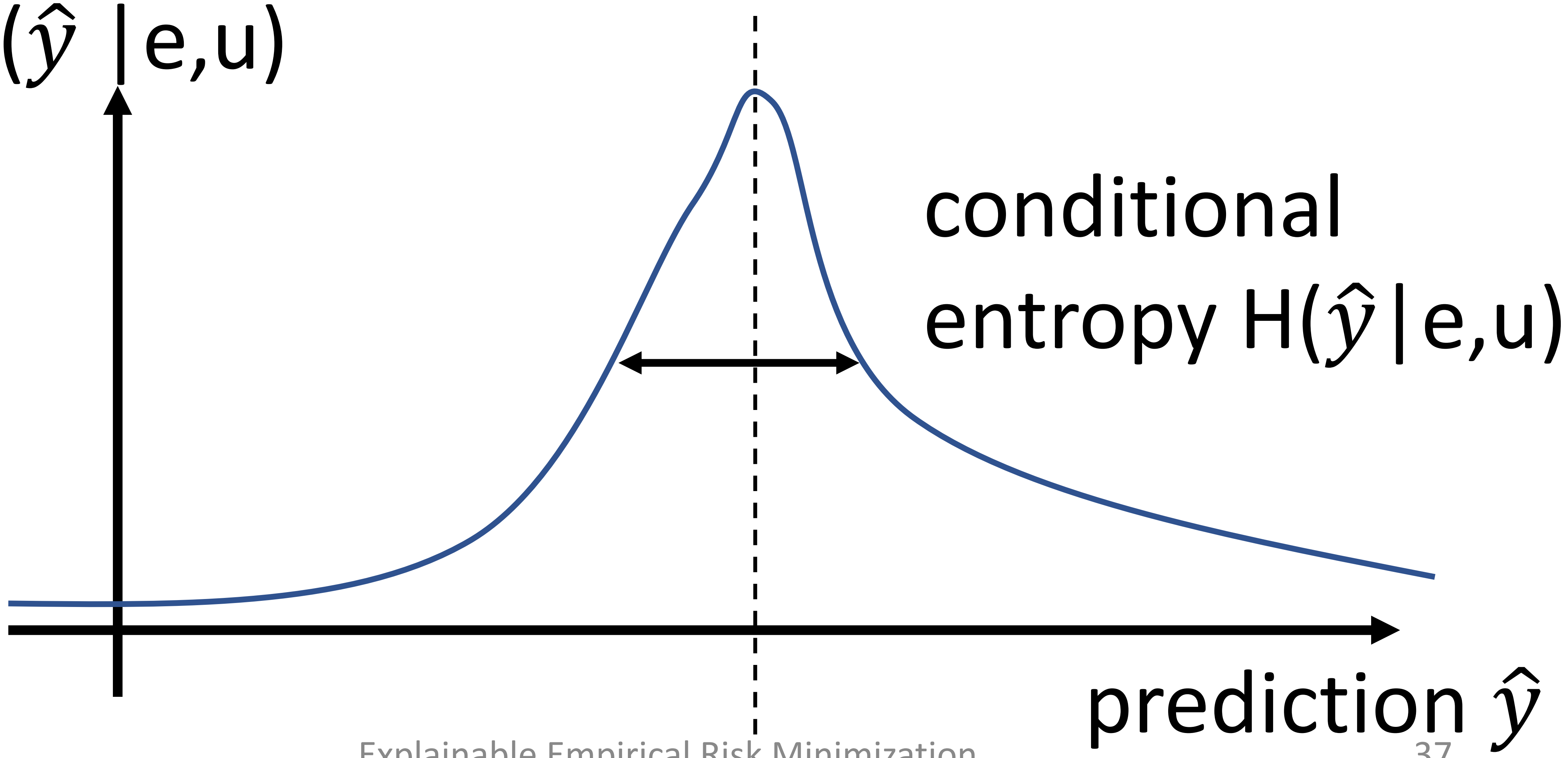
joint distribution
p(x,e, $\hat{y}$,u)

user
summary “u”

explanation e(x)

predicted yield “$\hat{y} = h(x)$ ”

Explainability = Predictability



My Information-Theory Slide.

conditional entropies

$$I(e;\hat{y}|u) = H(\hat{y}|u) - H(\hat{y}|e,u)$$

conditional mutual information

see Chapter 8 of

T. Cover, J. Thomas, "Elements of Information Theory", Wiley, 2005

Computing Explanations

$$I(e^{*};\hat{y}|u) = \sup_{e \in \mathcal{F}} I(e;\hat{y}|u)$$

set of ”allowed” explanations

optimal explanation varies for different users u !

expersonalized explanations !

Towards an Algorithm.

$$I(e^{*};\hat{y}|u) = \sup_{e \in \mathcal{F}} I(e;\hat{y}|u)$$

- estimate $\mathrm{h}(\hat{y}|e,u)$ using i.i.d. training set $\left(x^{(1)},u^{(1)},\hat{y}^{(1)}\right)$… $\left(x^{(m)},u^{(m)},\hat{y}^{(m)}\right)$
- choose tractable explanation space $\mathcal{F}$
- apply your favourite solver

The story so far…

- measure (lack of) eplainability via $\mathrm{H}(\hat{y}|e,u)$
- construct map *e(x)* to minimize $\mathrm{H}(\hat{y}|e,u)$
- we could also skip explanation and minimize $\mathrm{H}(\hat{y}|u)$ learning a simpler (interpretable) predictor $\hat{y} = h(x)$

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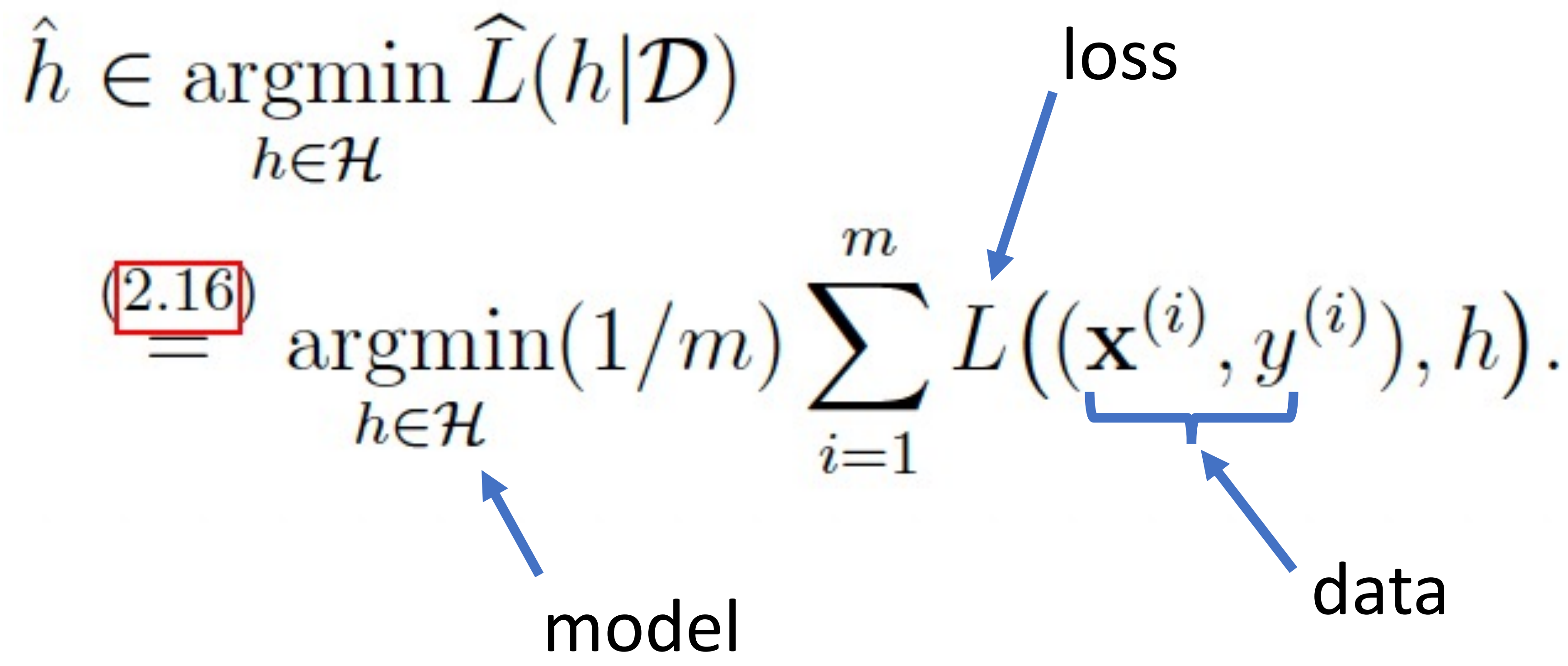
Recall the ERM Principle



$$\hat{h} \in \operatorname*{argmin}_{h\in\mathcal{H}} \widehat{L}(h|\mathcal{D})$$

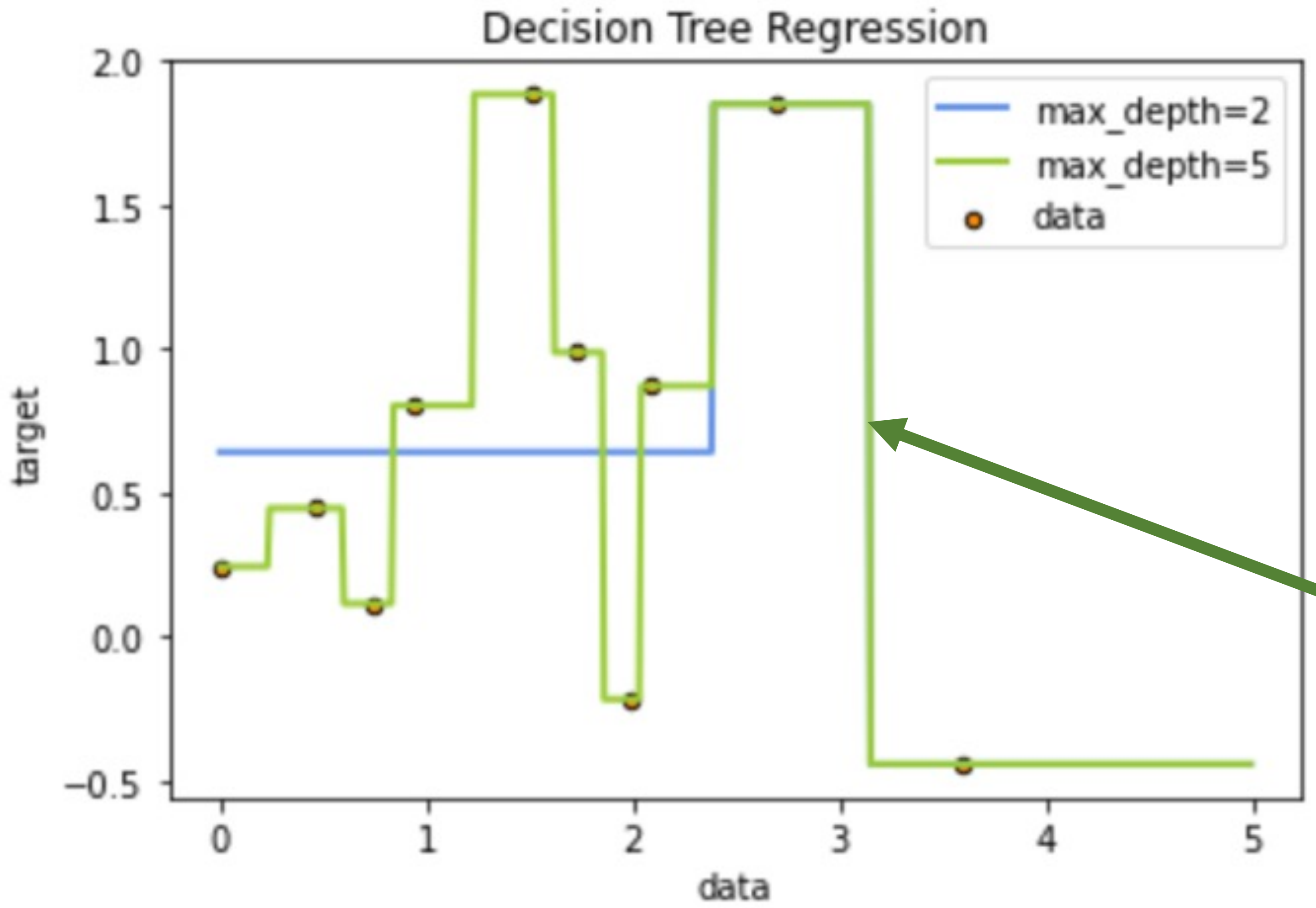
$$\overset{(\boxed{2.16})}{=} \operatorname*{argmin}_{h\in\mathcal{H}} (1/m) \sum_{i=1}^{m} L((\underbrace{\mathbf{x}^{(i)}, y^{(i)}}), h).$$

loss

model

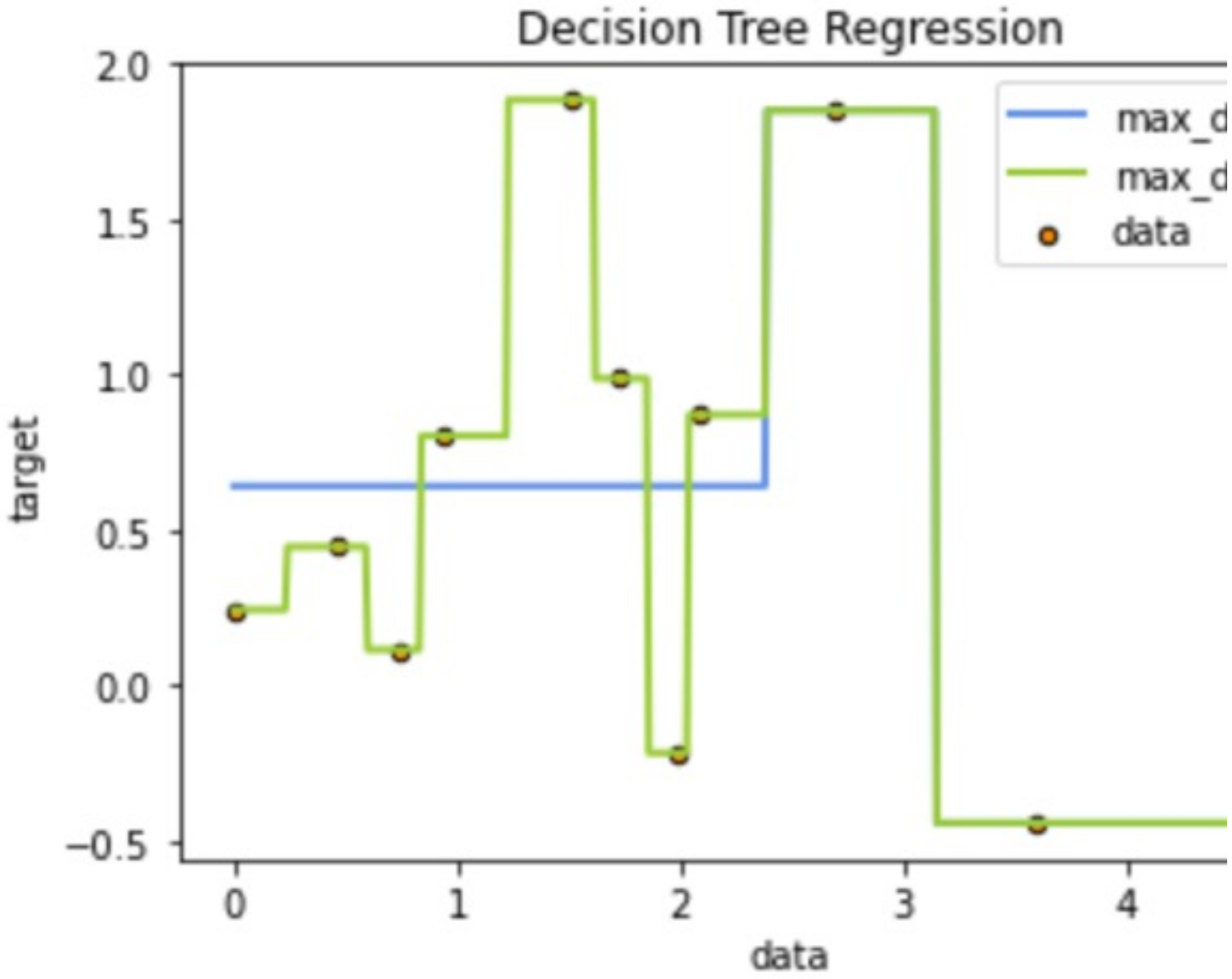
data

Overfitting.



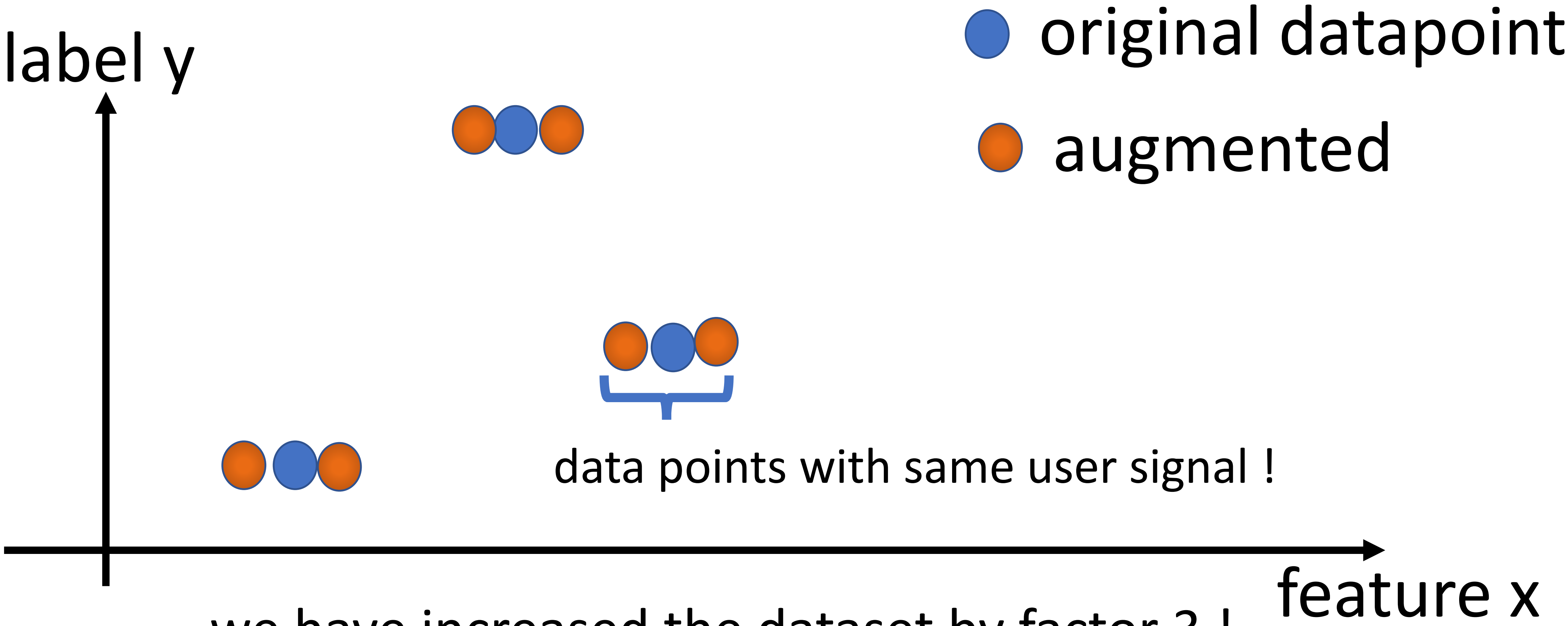
do you like this learnt hypothesis which achieves ZERO empirical risk ?

Avoid Overfitting by Regularization.



learnt hypothesis should be nearly constant for data points whose feature values are within distance 0.5

Regularization via Augmentation.



data points with same user signal !

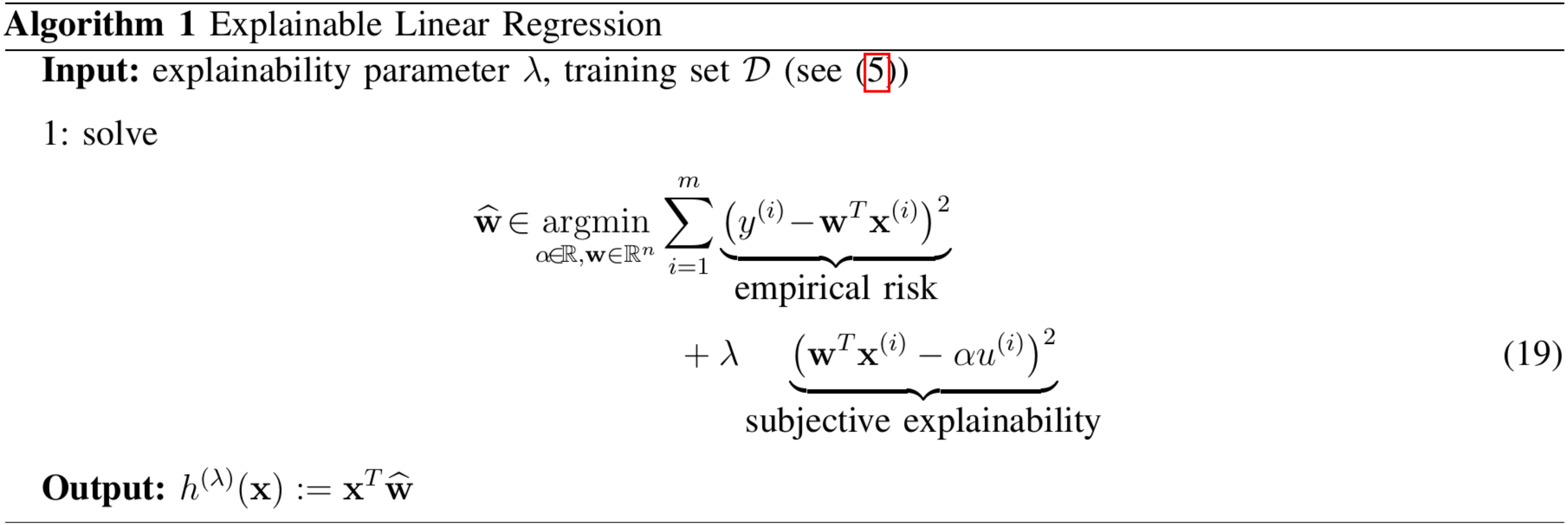
we have increased the dataset by factor 3 !

Explainable ERM (EERM)

$$\min_{h \epsilon \mathcal{H}} \frac{1}{m} \sum_{i=1}^{m} L\left(\left(x^{(i)}, y^{(i)}\right), h\right) + \lambda H(h|u)$$

- $H(h|u)$ measures (lack of) subj. explainability
- $h(x)$ similar for data points with similar user signal u
- EERM design choices: $\mathcal{H}$ and loss L

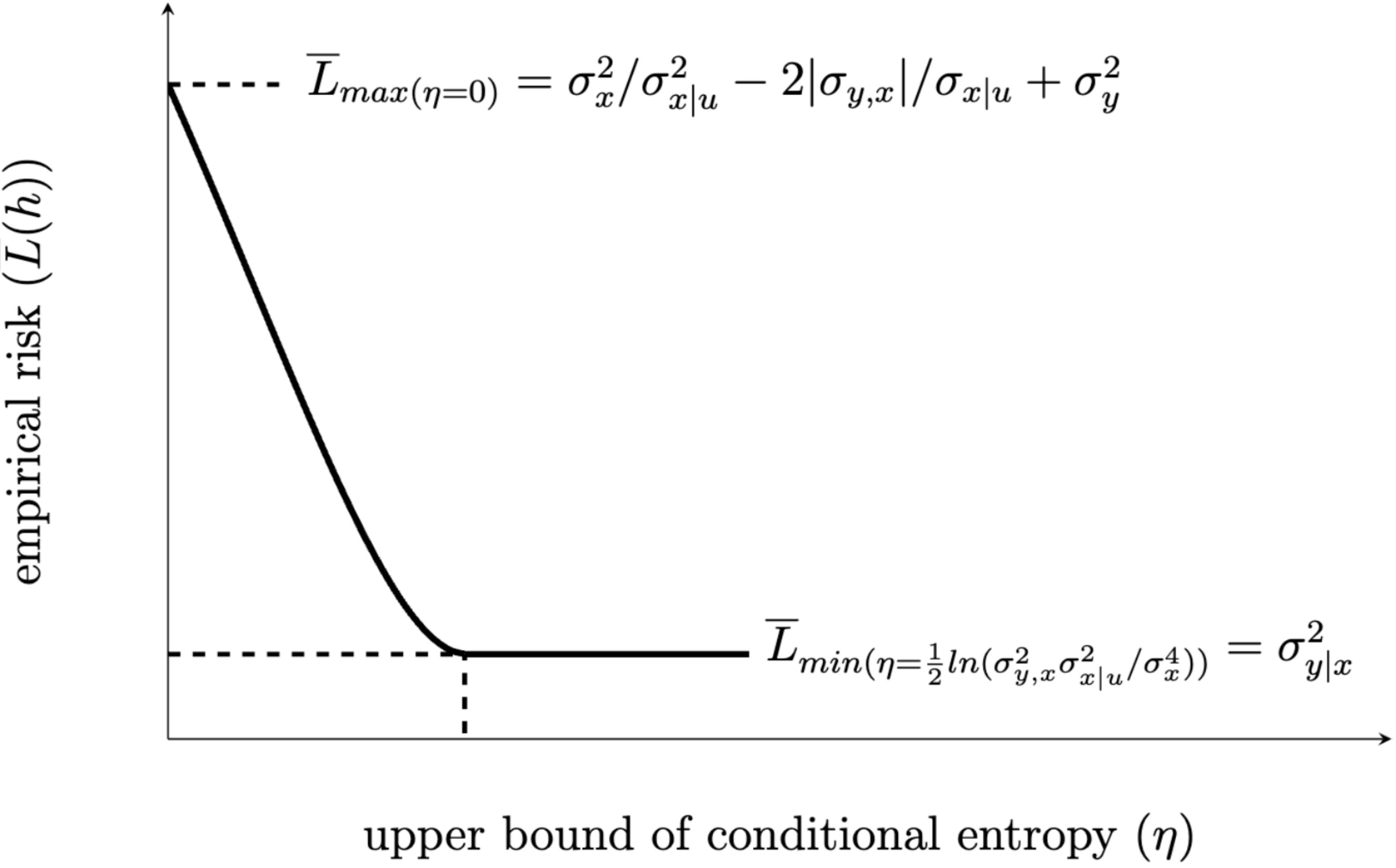
Explainable Linear Regression



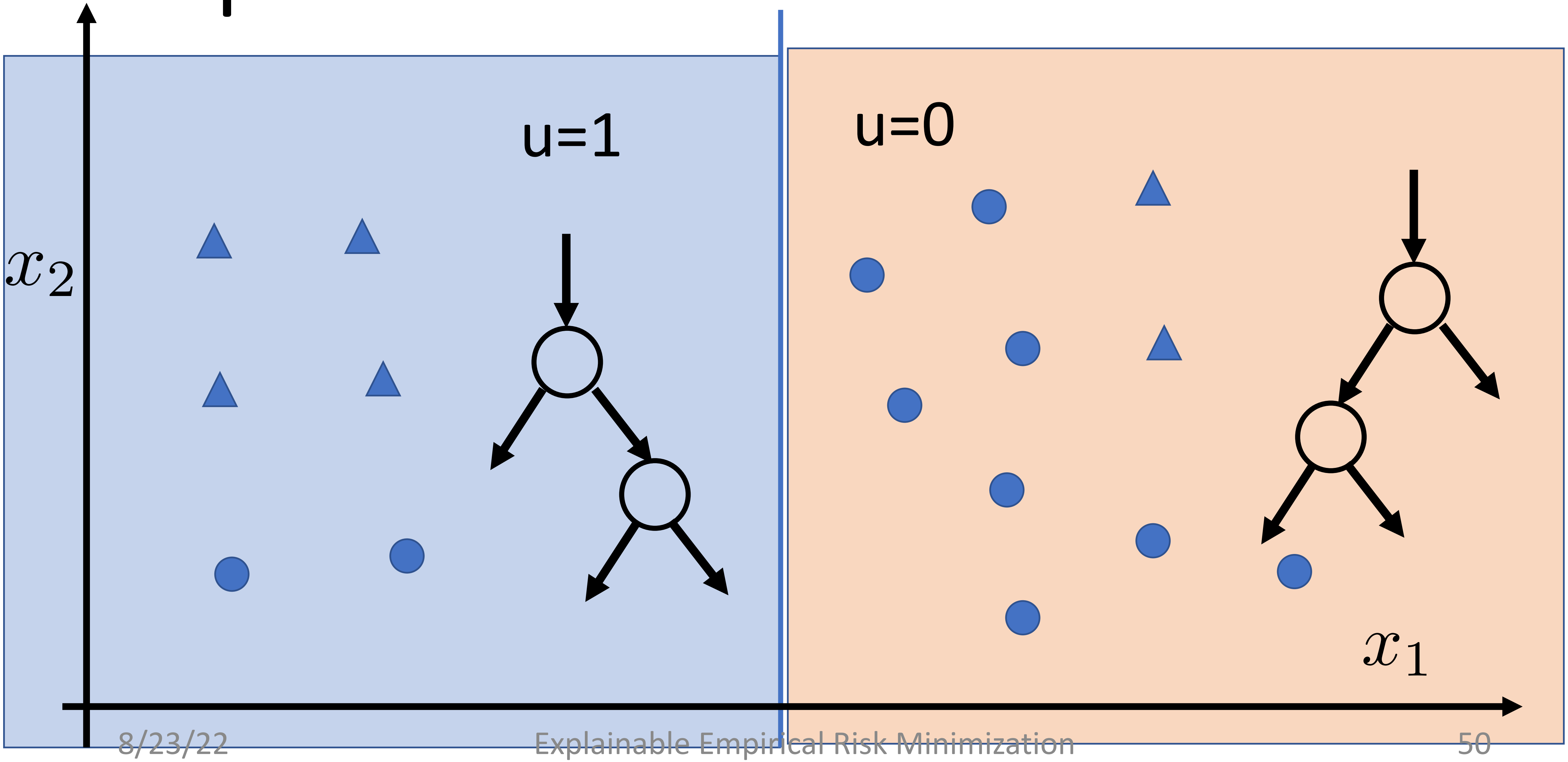
Algorithm 1 Explainable Linear Regression

```
Input: explainability parameter $\lambda$, training set $\mathcal{D}$ (see (5))
1: solve
   $\widehat{\mathbf{w}} \in \operatorname*{argmin}_{\alpha \in \mathbb{R}, \mathbf{w} \in \mathbb{R}^n} \sum_{i=1}^{m} \underbrace{\left(y^{(i)} - \mathbf{w}^T \mathbf{x}^{(i)}\right)^2}_{\text{empirical risk}} + \lambda \underbrace{\left(\mathbf{w}^T \mathbf{x}^{(i)} - \alpha u^{(i)}\right)^2}_{\text{subjective explainability}} \quad (19)$
Output: $h^{(\lambda)}(\mathbf{x}) := \mathbf{x}^T \widehat{\mathbf{w}}$
```

Explainability vs. Risk



Explainable Decision Trees



EERM vs. LIME

$$\min_{h \epsilon \mathcal{H}} \frac{1}{m} \sum_{i=1}^{m} L\left(\left(x^{(i)}, y^{(i)}\right), h\right) + \lambda \, \mathrm{H}(h|u)$$

$$\xi(x) = \operatorname{argmin}_{g \in G} \; \mathcal{L}(f, g, \Pi_x) + \Omega(g)$$

- EERM and LIME essentially solve a regularized ERM
- LIME solves separate regularized ERM for each feature value x
- “empirical risk” in LIME based on faithfulness to given ML method

References

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