

Applied Data Analysis (CS401)



Lecture 8
Learning from data:
Applied machine learning
5 Nov 2025

Announcements

- Homework H2: released **today!**
- Project milestone P2 due on **today 23:59**
- Friday's lab session:
 - Exercise on applied machine learning ([Exercise7](#))

Feedback

Give us feedback on this lecture here:

<https://go.epfl.ch/ada2025-lec8-feedback>

- What did you (not) like about this lecture?
- What was (not) well explained?
- On what would you like more (fewer) details?
- ...

Why an extra class on applied ML?

Machine Learning that Matters

Kiri L. Wagstaff

KIRI.L.WAGSTAFF@JPL.NASA.GOV

Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Drive, Pasadena, CA 91109 USA

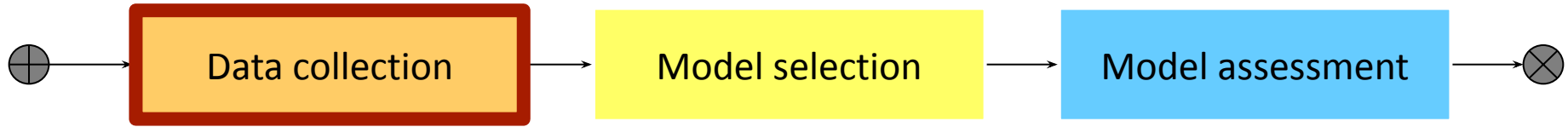
[link](#)

Classic ML
class

ADA

It is easy to sit in your office and run a Weka (Hall et al., 2009) algorithm on a data set you downloaded from the web. It is very hard to identify a problem for which machine learning may offer a solution, determine what data should be collected, select or extract relevant features, choose an appropriate learning method, select an evaluation method, interpret the results, involve domain experts, publicize the results to the relevant scientific community, persuade users to adopt the technique, and (only then) to truly have made a difference (see Figure 1). An ML researcher might well feel fatigued or daunted just contemplating this list of activities. However, each one is a necessary component of any research program that seeks to have a real impact on the world outside of machine learning.

Classification pipeline



Data collection

The first step is collecting data related to the classification task.

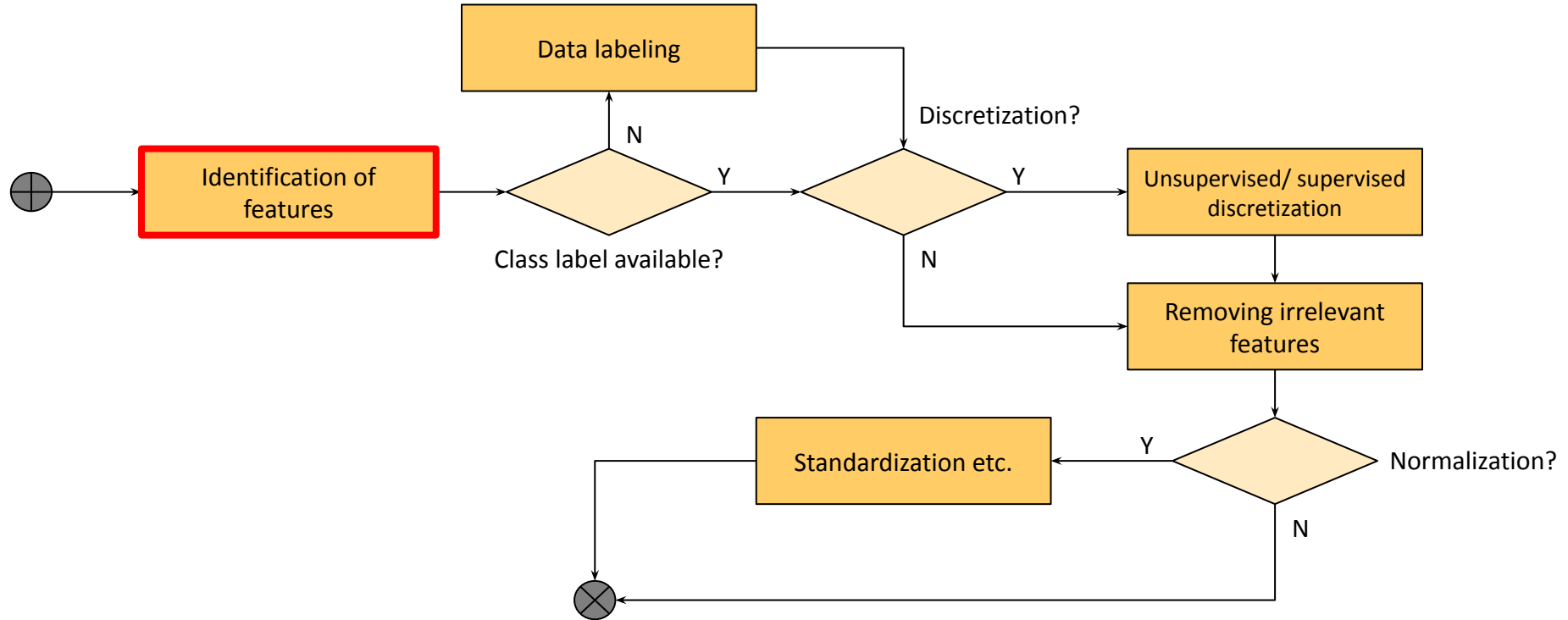
- Definition of the attributes (or features) that describe a data item and the class label.

Domain knowledge is needed.

What if assigning the class label would be too time-consuming or even impossible?

- **Unsupervised methods** (e.g., clustering); cf. next lecture!

Data collection



Features

Different types of features [\[more\]](#)

- Continuous (e.g., height, temperature ...)
- Ordinal (e.g., “agree”, “don’t care”, “disagree” ...)
- Categorical (e.g., country, gender ...)

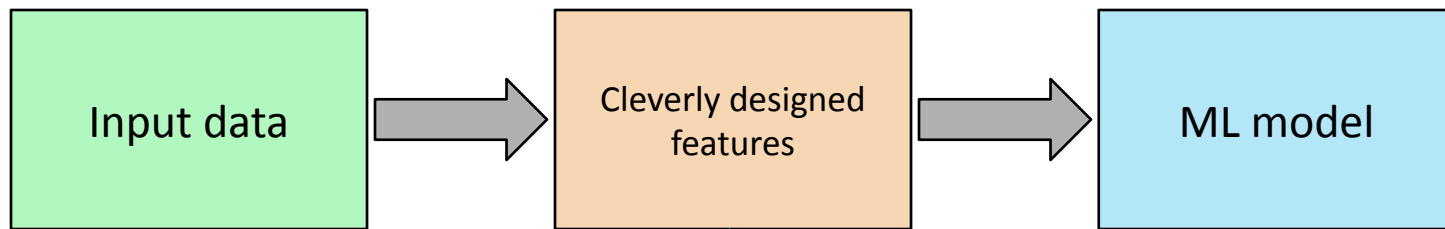
New features can be generated from **simple stats**

- *Feature engineering* is considered a form of art, therefore it is often useful to find what other people did for similar problems

Some classifiers require categorical features => **discretization**

ML before 2012*

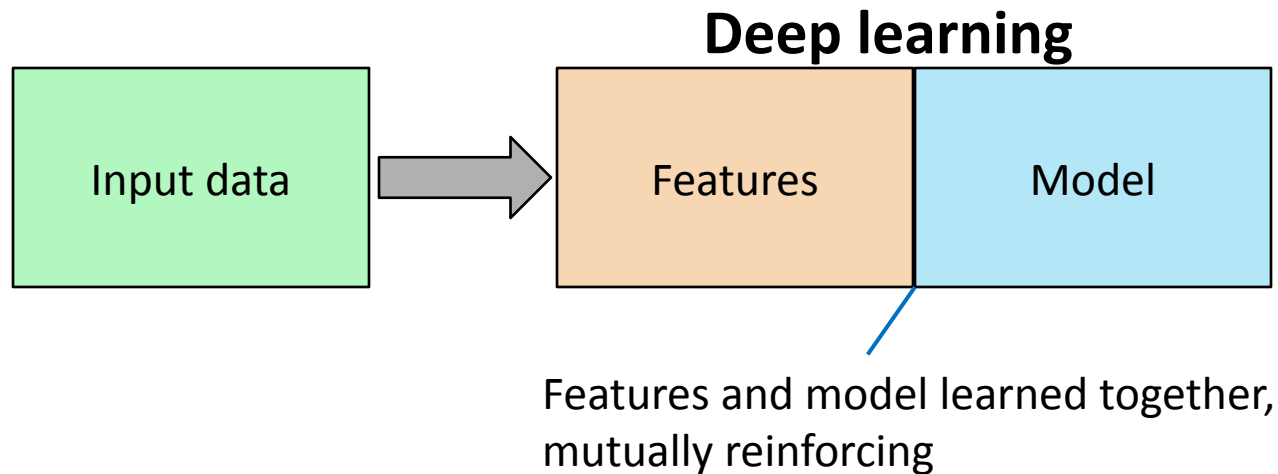
(but still very common today)



Much of the “heavy lifting” in here.
Final performance only as good as the
feature set.

* Before publication of Krizhevsky et al.’s ImageNet CNN [paper](#)

A typical ML approach after 2012



EE-559: Deep learning

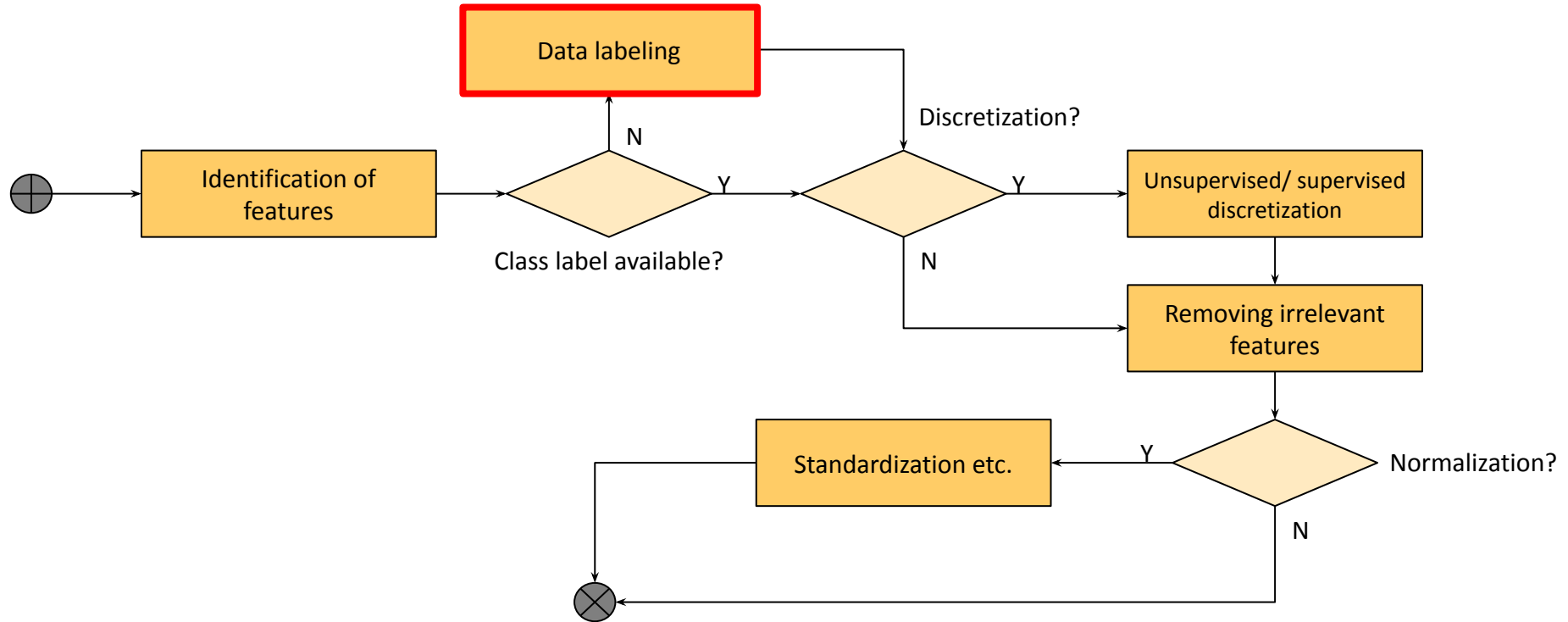
CS552: Modern natural language processing

CS-502: Deep learning in biomedicine

CS-456: Deep reinforcement learning

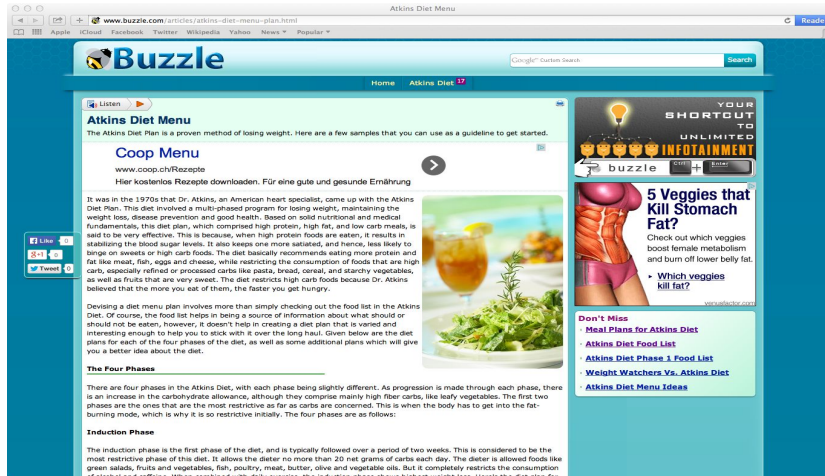
etc

Data collection



Labels

Collecting a lot of data (features) is often easy.
Labeling data is time consuming, difficult, and
sometimes even impossible.



Label: “Is page credible?”
Human dietary expert is needed

Potential labelers

- You
- Older days:
 - Undergraduate students
 - Domain experts (\$\$\$)
- Now: **crowdsourcing**
 - Can get both amateurs (~ undergrad students) and experts



"Is this webpage
credible?"

Crowdsourcing
platform



2. Accept task



Crowd workers



Requester

1. Submit task

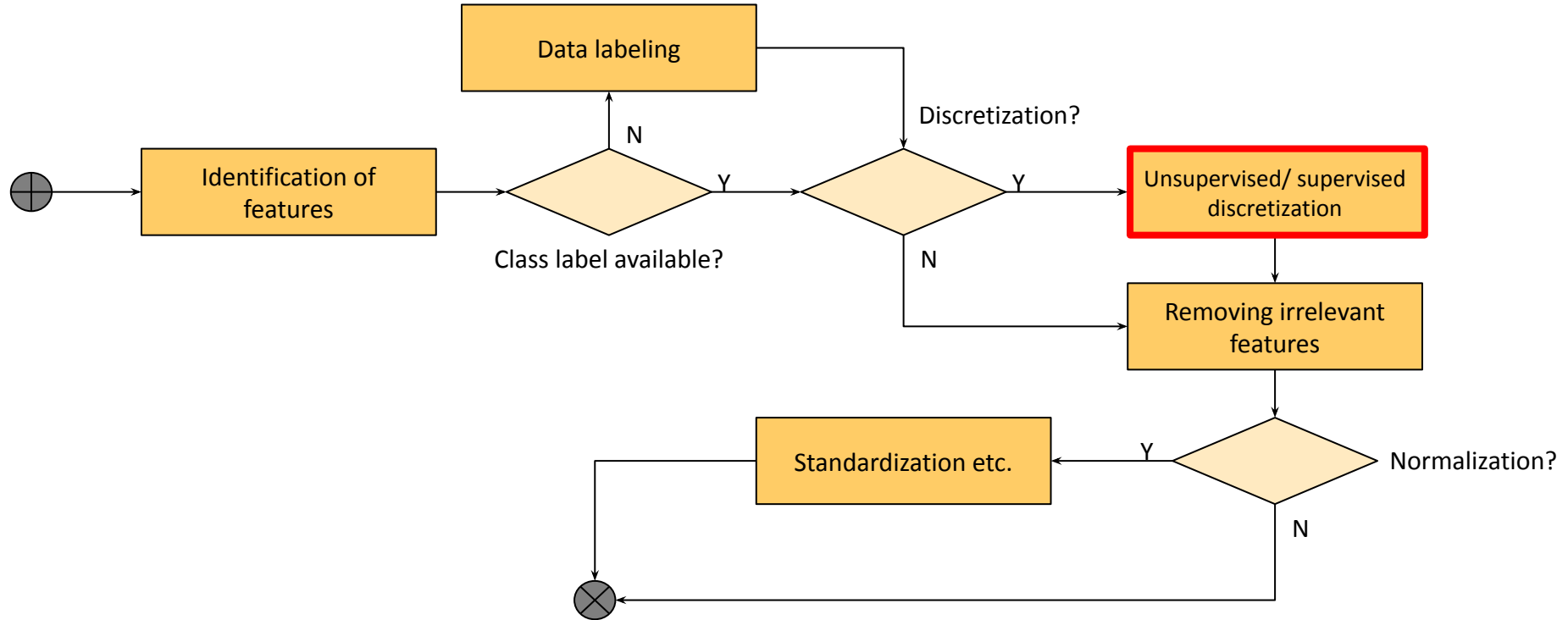
4. Collect answers



Credible
Credible
Not credible
Credible
Not credible

3. Return answers

Data collection



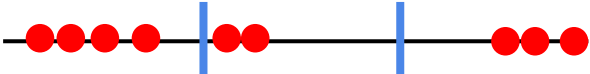
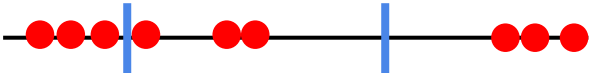
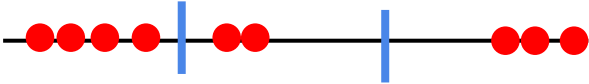
Discretization

Why? 🤔

- Some classifiers want discrete features (e.g., simplest kinds of decision trees)
- Discrete features let a linear classifier learn non-linear decision boundaries
- Certain feature selection methods require discrete (or even binary) features

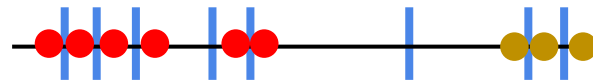
Discretization

Unsupervised

- **Equal width** 
 - Divide the range into a predefined number of bins (bad for skewed data, e.g., from a power law)
- **Equal frequency** 
 - Divide the range into a predefined number of bins so that every interval contains the same number of values
- **Clustering** 

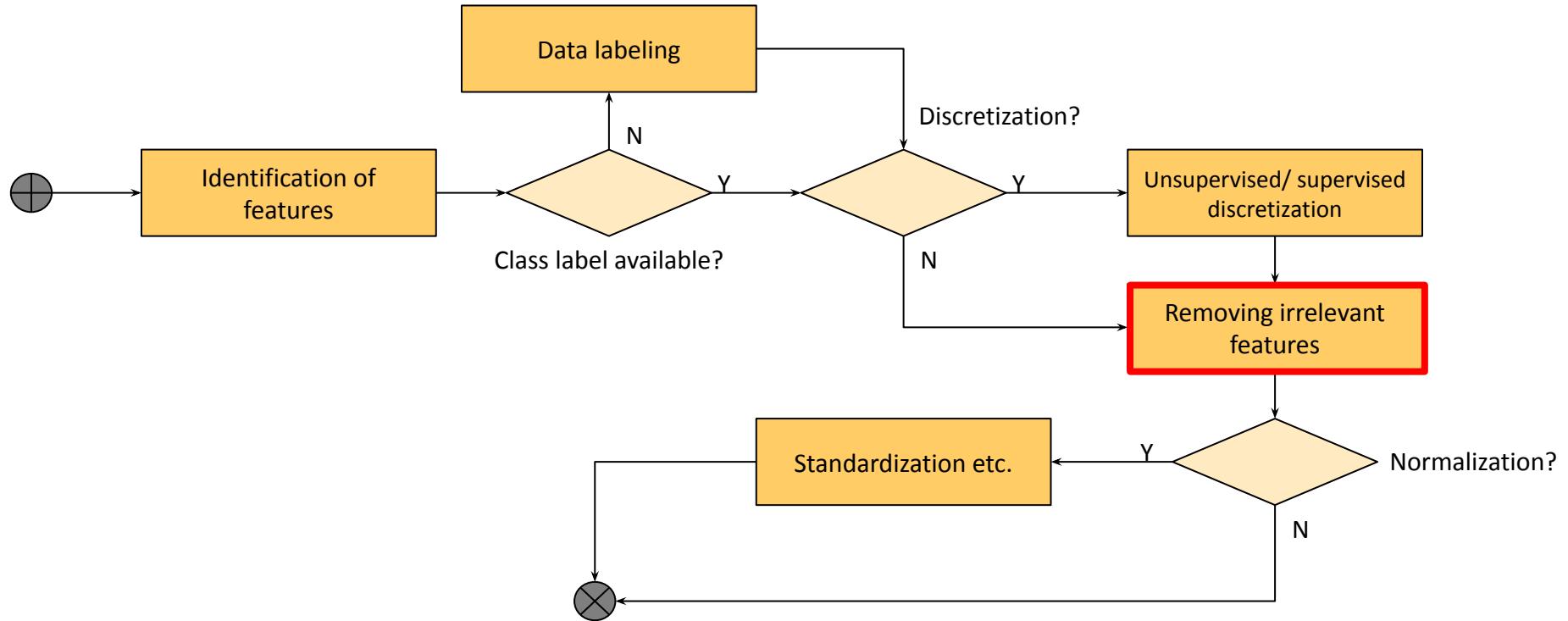
Discretization

Supervised



- Start with very fine-grained discretization
- Test the hypothesis that membership in two adjacent intervals of a feature is independent of the class
- If they are independent, they should be merged
- Otherwise they should remain separate
- Independence test: χ^2 test (“chi-squared test”) [[example](#)]
- Continue recursively

Data collection



Removing irrelevant features: Feature selection

- **Goal:** reduce set of N features to a subset of the best size $M < N$
- **Why?**
 - More interpretability
 - Less danger of overfitting
 - More efficient training
- **Problem:** There are 2^N possible subsets
- **Solutions:**
 - Filtering as preprocessing (“offline”)
 - Iterative feature selection (“online”)

Offline feature selection

Rank features according to their individual predictive power; then select the best ones

Pros:

- Independent of the classifier (performed only once)

Cons:

- Independent of the classifier (ignore interaction with the classifier)
- Assumes features are independent

Ranking of features

Continuous features (and ideally labels):

- Pearson's correlation coefficient (capturing strength of linear [!] dependence)

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

Categorical features and labels:

- Mutual information (goes beyond linear dependence)

$$I(F; C) = H(C) - H(C | F) = H(F) + H(C) - H(F, C)$$

$$H(F) = - \sum_i P(f_i) \log_2 P(f_i)$$

$$H(F, C) = - \sum_i \sum_j P(f_i, c_j) \log_2 P(f_i, c_j)$$

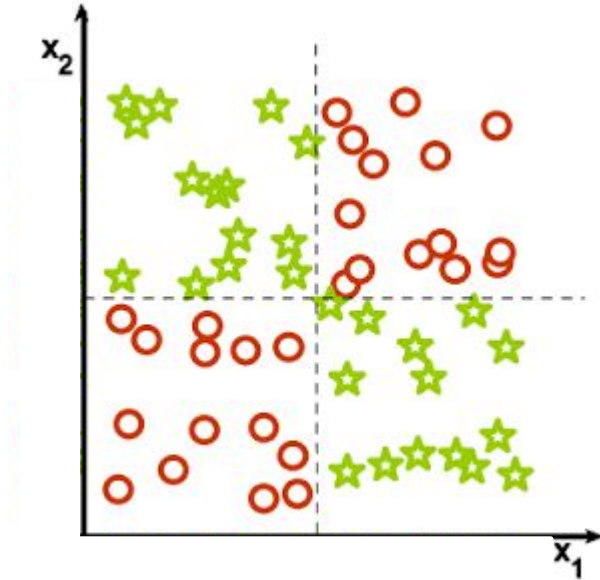
Ranking of features

Categorical features and labels (cont'd):

- **χ^2 method** (“chi-squared”)
 - Similar to χ^2 method for feature discretization
 - Test whether feature is independent of label
 - Difference w.r.t. mutual information: the χ^2 test checks the independence of the class and the feature, without indicating the strength or direction of any existing relationship (you just get a significance, a.k.a. p -value)

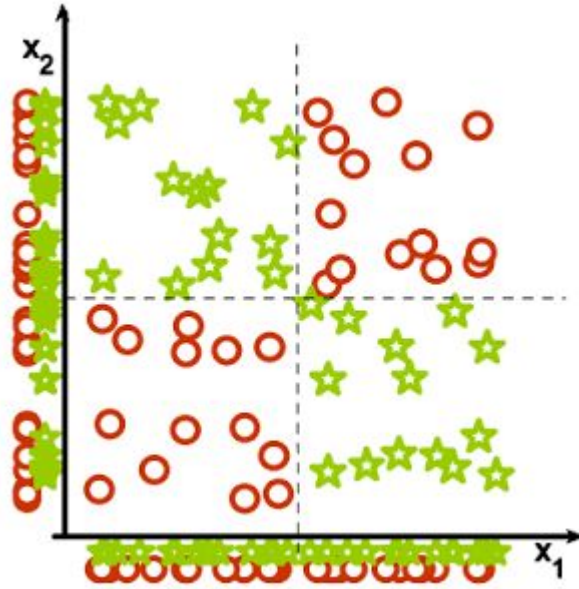
Ranking of features

Beware: collectively relevant features may look individually irrelevant!



Ranking of features

Beware: collectively relevant features may look individually irrelevant!



Online feature selection

Forward feature selection: greedily **add** features; evaluate on validation dataset; stop when no improvement

Pros

- Interact with the classifier
- No feature-independence assumption

Cons

- Computationally intensive

Online feature selection

Backward feature selection: greedily **remove** features; evaluate on validation dataset; stop when no improvement

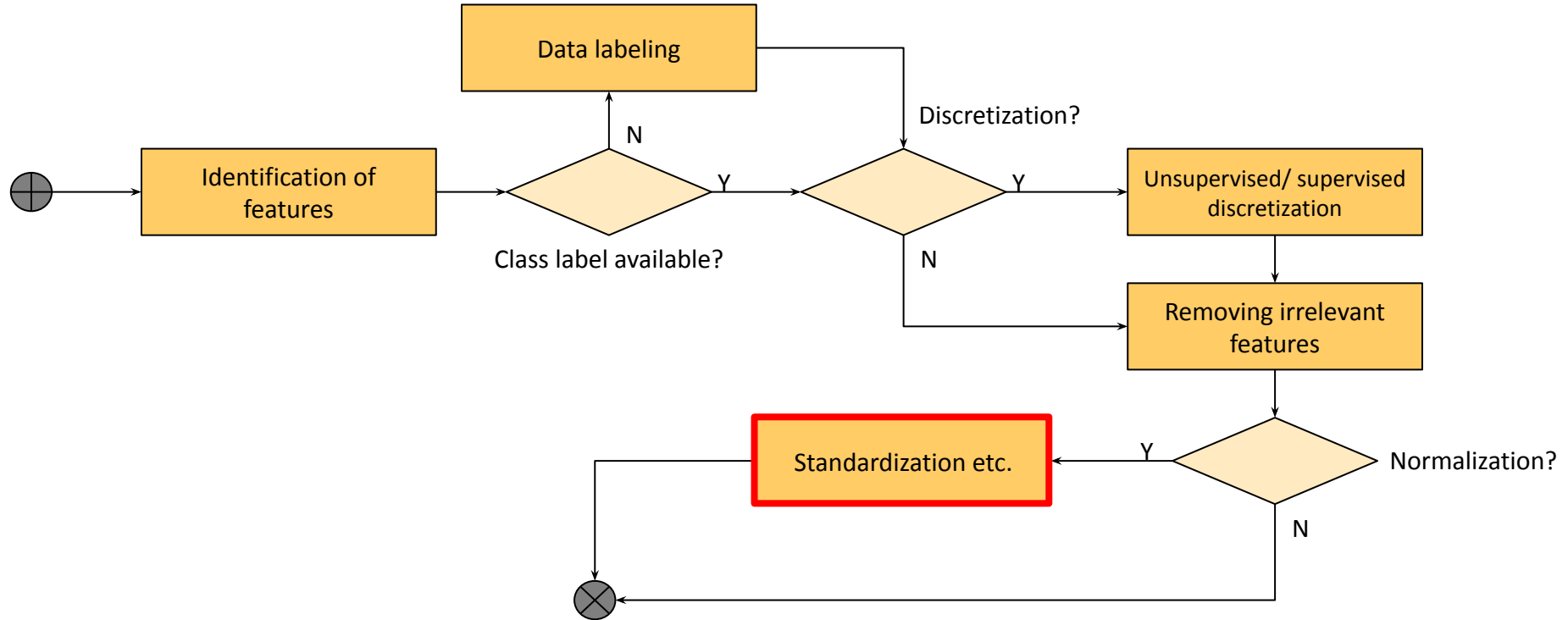
Pros

- Interact with the classifier
- No feature-independence assumption

Cons

- Computationally intensive

Data collection



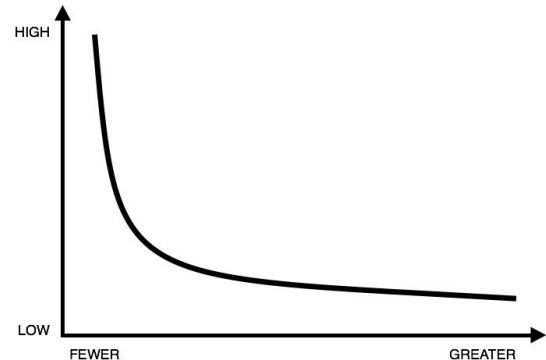
Feature normalization

- Some classifiers can't easily handle features with very different scales, e.g.,
 - Revenue in CHF: 10,000,000
 - # of employees: 300
- Features with large values dominate the others, and the classifier tends to over-optimize for them
- Even single feature may span many orders of magnitude
 - e.g., city size (most cities small, some huge)
 - Too little resolution where data is dense, too much resolution where data is sparse

Logarithmic scaling

$$x'_i = \log(x_i)$$

- Consider order of magnitude, rather than direct value
- Good for heavy-tailed features (e.g., from power laws)



Min-max scaling

$$x'_i = (x_i - m_i) / (M_i - m_i)$$

where M_i and m_i are the max and min values of feature x_i respectively

The new feature x'_i lies in the interval $[0,1]$

Standardization

$$x'_i = (x_i - \mu_i) / \sigma_i$$

where μ_i is the mean value of feature x_i , and σ_i is the standard deviation

The new feature x'_i has mean 0 and standard deviation 1

Dangers of standardization and scaling

Standardization:

- Assume that the data has been generated by a Gaussian
- Uses mean and std → not meaningful for heavy-tailed data (may be mitigated by log-scaling)

Min-max scaling:

- If the data has outliers, they scale the typical values to a very small interval

Commercial break

NETFLIX

loyd have been invited to
ate questions on Tuesday's

e District 2 seat are Harry
ayne Biggs, Harold Haines,
lliott, Bill R. Vandegriff,
es.

Comedy

wall High School drama
esent a three act comedy,
e Girls," Monday at 7:30
hool auditorium.

evolves around three main
rying to catch a killer and
o discover the true culprit.

includes Korina Bushnell,
well, Lore Reagh, Sylidia
erri Teel, Tonja Kelley,
ano, and Johnna Winton.
kup is club sponsor and

is \$1 adults and 50 cents for

Mike Tommeizer said blast victim's death poem away, to make the poem
ready to be primed and painted.

SUNDAY APRIL 28 1985

Unsolved, violent crimes haunt Ada

By DOROTHY HOGUE

The Norman man entered the convenience store about 9 a.m. that Saturday and stood at the checkout counter waiting for someone to come wait on him. He noticed school books were open behind the counter, a cigarette was burning in an ashtray, the cash drawer was open and empty. He looked around for the clerk but found no one. After a few minutes the police were

remind local citizens of the murder of another young local woman but police say they seriously doubt there could be any connection between the Haraway case and that of Debbie Carter.

It has been almost 2½ years since Carter was brutally murdered in her apartment, located only a few blocks from the East Central University campus. Det. Dennis Smith said police have narrowed their focus to one

precinct
Precinct 25 — Arm
Arlington and Country
Precinct 31 (2) —
Center, Fourth and O
Precinct 33 (2) — O
Church, 523 N. Oak.
Precinct 34 (2) —
825 W. 10th.
Precinct 42 — Ad
Room 101.
Precinct 43 (2) — V
600 W. 17th.
Precinct 44 (2) —
Church, 15th and Ash
Precinct 45 — A
auditorium.

Willard
continu

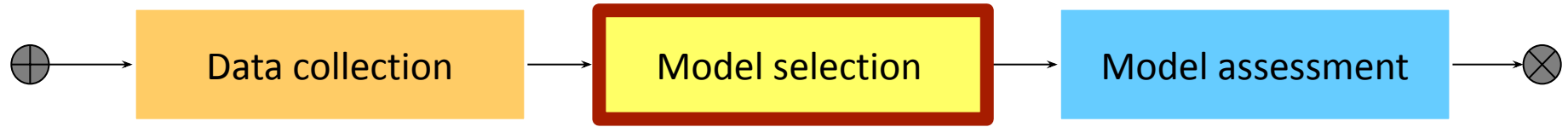
44:14



The Innocent Man S1:E1 Debbie and Denice



Classification pipeline



Model selection: high level

Need to choose type of model

- k-NN?
- Decision trees?
- Random forest?
- Boosted decision trees?
- Logistic regression?
- Deep learning?
- ...

Model selection: low level

Usually a classifier has some “hyperparameters” to be tuned

- Set of features to include
- Distance function (e.g., k-NN)
- Number of neighbors (e.g., k-NN)
- Number of trees (e.g., random forest)
- Decision threshold (e.g., logistic regression)
- Regularization parameter
- Learning rate (for gradient descent algorithms)

Loss function (more of them later!)

Categorical output

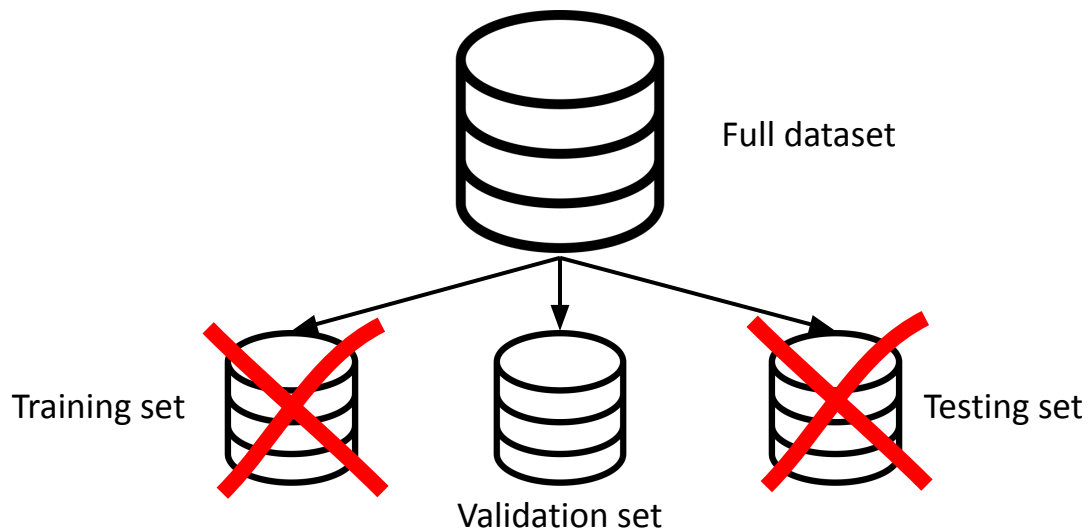
- e.g., 0-1 loss function, risk (= 1 minus accuracy):

$$J = \frac{1}{n} \sum_{i=1}^n \#(y \neq f(x_i))$$

Real-valued output

- e.g., squared error: $J = \frac{1}{n} \sum_{i=1}^n (y_i - f(x_i))^2$
- e.g., absolute error: $J = \frac{1}{n} \sum_{i=1}^n |y_i - f(x_i)|$

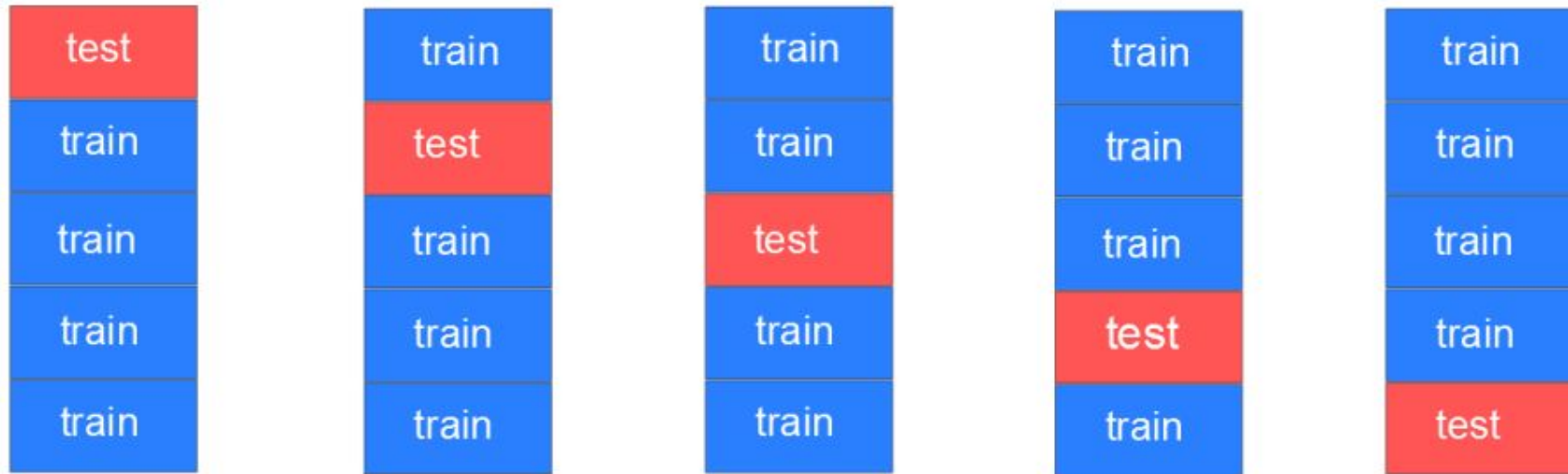
Model selection: on what data to evaluate?



What if you can't afford a 3-way split because you have too little data?

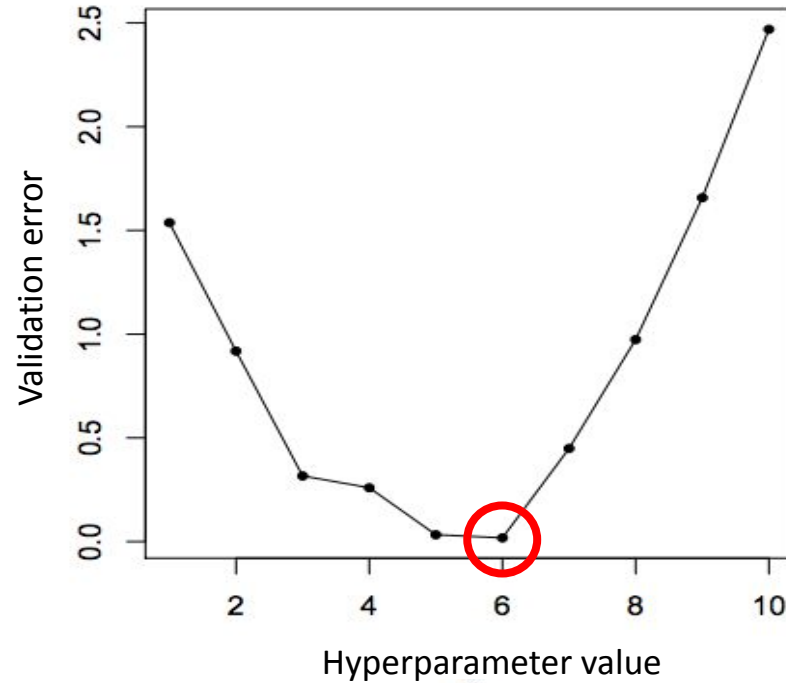
→ **Cross-validation!** (p.t.o.)

Cross-validation



- Last lecture: [leave-one-out cross-validation](#) == N -fold cross-validation (where N is #data points)
- More efficient: m -fold cross-validation (in above picture: $m = 5$)
- Average performance over the m red portions → validation error
- Repeat procedure for all candidate models and pick the one with the lowest validation error

Model selection



Performance metrics for binary classification

For categorical binary classification, the usual metrics are based on the **confusion matrix**, which has 4 values:

- True Positives (positive examples classified as positive)
- True Negatives (negative examples classified as negative)
- False Positives (negative examples classified as positive)
- False Negatives (positive examples classified as negative)

		Class	
		Pos	Neg
Classified	Pos	TP	FP
	Neg	FN	TN

Accuracy

		Class	
		Pos	Neg
Classified	Pos	TP	FP
	Neg	FN	TN

$$A = \frac{TP+TN}{TP+TN+FP+FN} = \frac{TP+TN}{N}$$

Appropriate metric when

- classes are not skewed
- errors (FP, FN) have the same importance

Accuracy (skewed example)

Classifier 1		Class	
		Fraud	¬Fraud
Classified	Fraud	5	10
	¬Fraud	5	80

$$\text{Accuracy} = 85/100 = 85\%$$

Always ¬Fraud		Class	
		Fraud	¬Fraud
Classified	Fraud	0	0
	¬Fraud	10	90

$$\text{Accuracy} = 90/100 = 90\%$$

Poll time

Which classifier is better?

- Classifier 1
- Classifier 2
- Both are equally good

		Class	
		Cancer	¬Cancer
Classified	Cancer	45	20
	¬Cancer	5	30

100 data points

		Class	
		A	B
Classified	Cancer	40	10
	¬Cancer	10	40

100 data points



POLLING TIME

- Scan QR code or go to <https://go.epfl.ch/ada2025-lec8-poll>



Poll time

		Class	
		Cancer	¬Cancer
Classified	Cancer	45	20
	¬Cancer	5	30

		Class	
		Cancer	¬Cancer
Classified	Cancer	40	10
	¬Cancer	10	40

Which classifier is better?

- Classifier 1
- Classifier 2
- Both are equally good

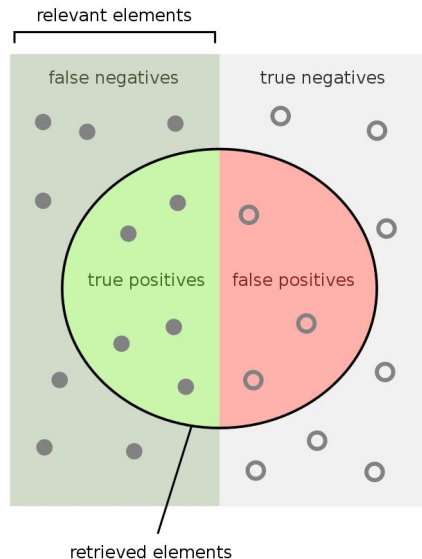
Precision and recall

Precision: what fraction of positive predictions are actually positive?

$$P = \frac{TP}{TP + FP}$$

Recall: what fraction of actually positive examples did I recognize as such?

$$R = \frac{TP}{TP + FN}$$

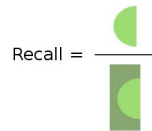


How many retrieved items are relevant?



Precision =

How many relevant items are retrieved?



Recall =

[\[source\]](#)

Precision and recall

Classifier 1		Class	
		Cancer	¬Cancer
Classified	Cancer	45	20
	¬Cancer	5	30

$$P_1 = 45/65 = 0.69$$

$$R_1 = 45/50 = 0.9$$

Classifier 2		Class	
		Cancer	¬Cancer
Classified	Cancer	40	10
	¬Cancer	10	40

$$P_2 = 40/50 = 0.8$$

$$R_2 = 40/50 = 0.8$$

Everybody has cancer		Class	
		Cancer	¬Cancer
Classified	Cancer	50	50
	¬Cancer	0	0

$$P = 50/100 = 0.5$$

$$R = 50/50 = 1$$

F-score

$$P = \frac{TP}{TP + FP}$$

$$R = \frac{TP}{TP + FN}$$

Sometimes it's necessary to have a single metric to compare classifiers

F-score (or F1-score): harmonic mean of precision and recall

$$F1 = 1 / (0.5 * (1/P + 1/R)) = 2 \cdot \frac{P \cdot R}{P + R}$$

Precision and recall can be **differently weighted**, if one is more important than the other

Precision and recall

Classifier 1		Class	
		Cancer	¬Cancer
Classified	Cancer	45	20
	¬Cancer	5	30

$$F_1 = 2 * (0.69 * 0.9) / (0.69 + 0.9) = 0.78$$

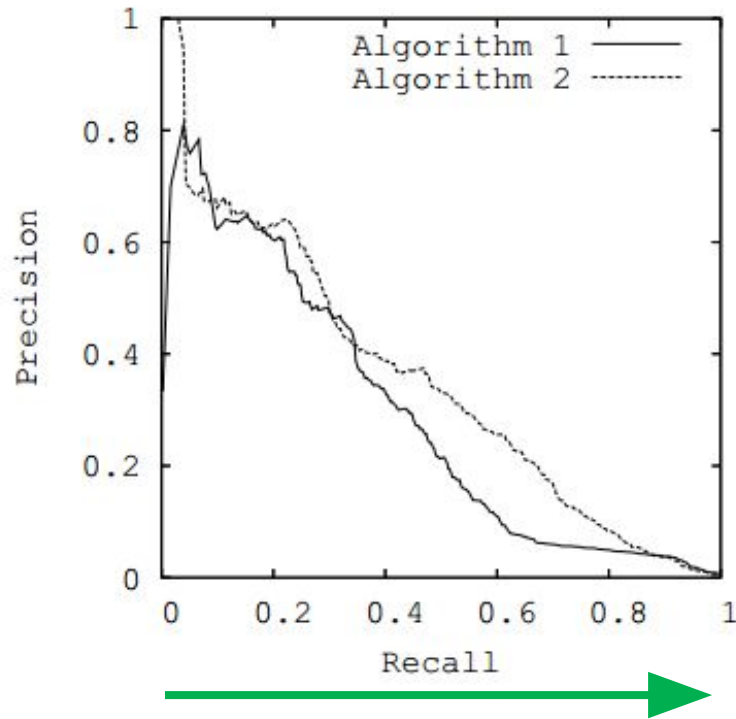
Classifier 2		Class	
		Cancer	¬Cancer
Classified	Cancer	40	10
	¬Cancer	10	40

$$F_2 = 2 * (0.8 * 0.8) / (0.8 + 0.8) = 0.8$$

Everybody has cancer		Class	
		Cancer	¬Cancer
Classified	Cancer	50	50
	¬Cancer	0	0

$$F = 2 * (0.5 * 1) / (0.5 + 1) = 0.66$$

Precision/recall curve



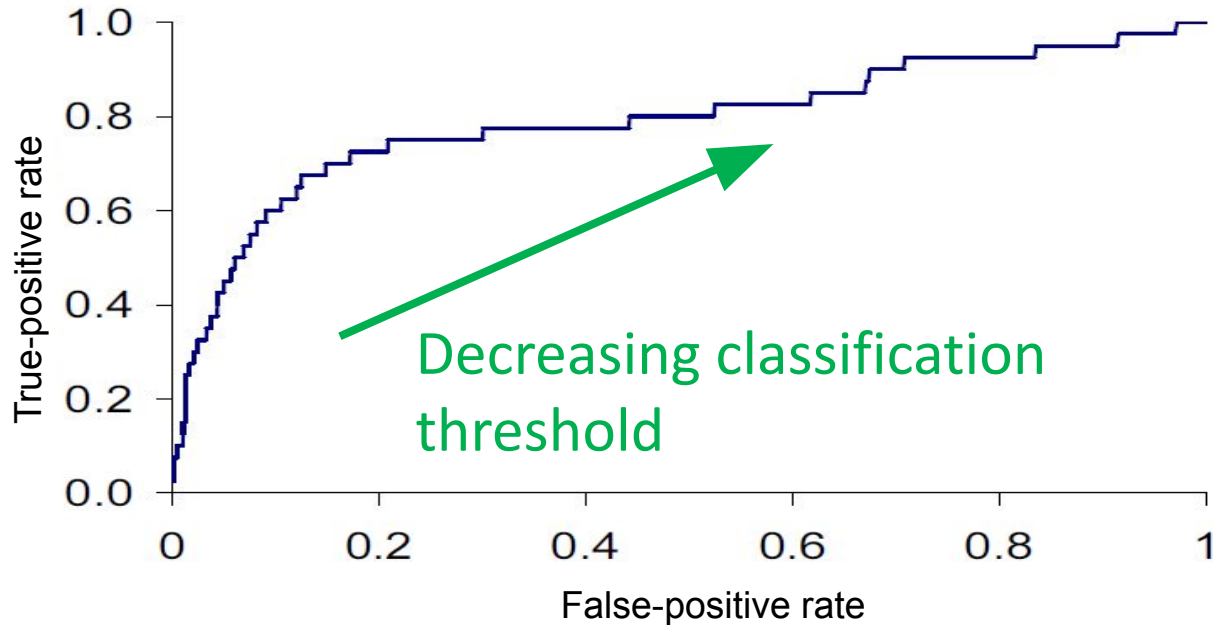
Decreasing classification threshold

ROC curve

ROC = Receiver-Operating Characteristic (WTF?!)

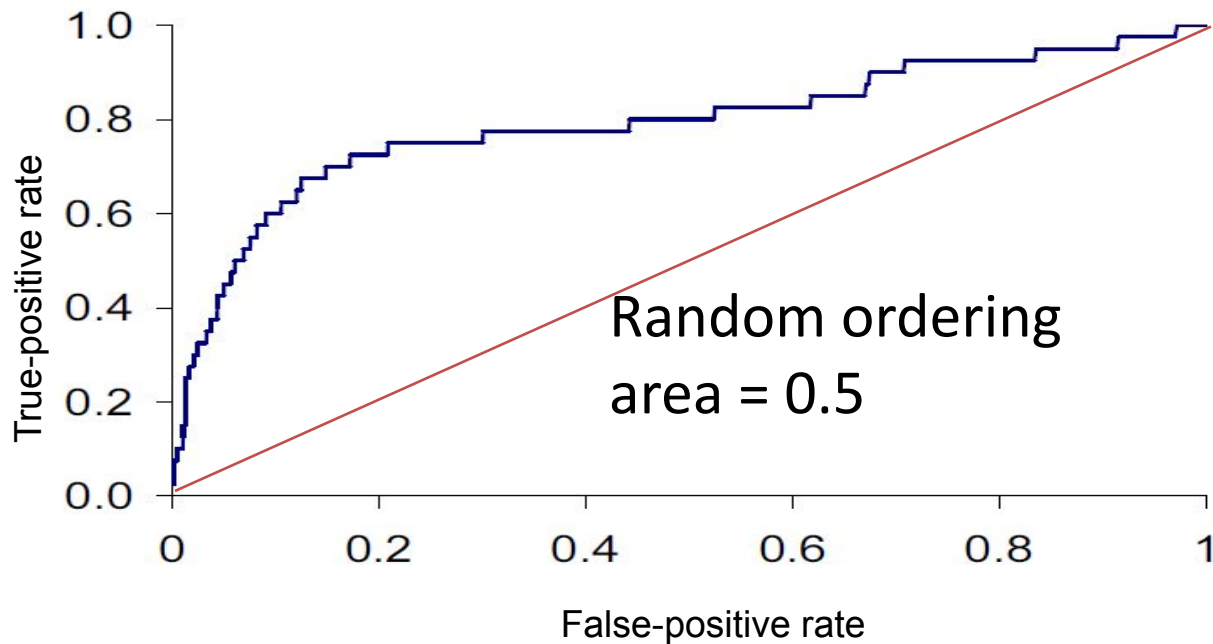
Y-axis: true-positive rate = $TP / (TP + FN)$, a.k.a. recall

X-axis: false-positive rate = $FP / (FP + TN)$

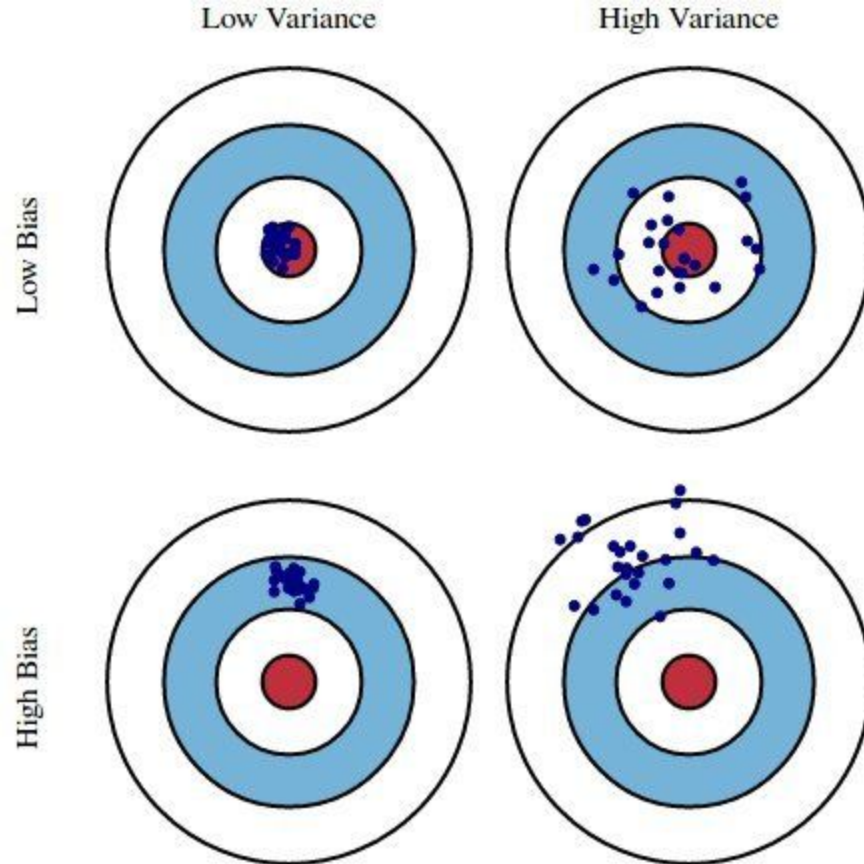


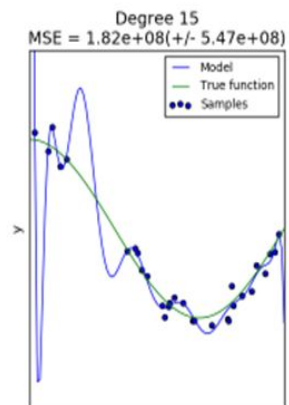
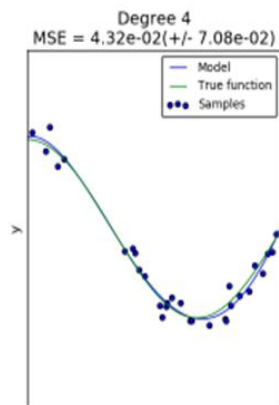
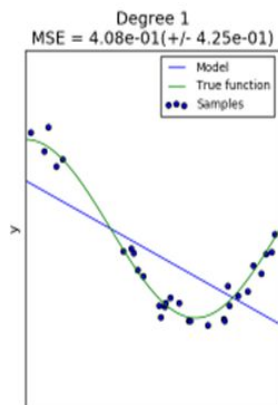
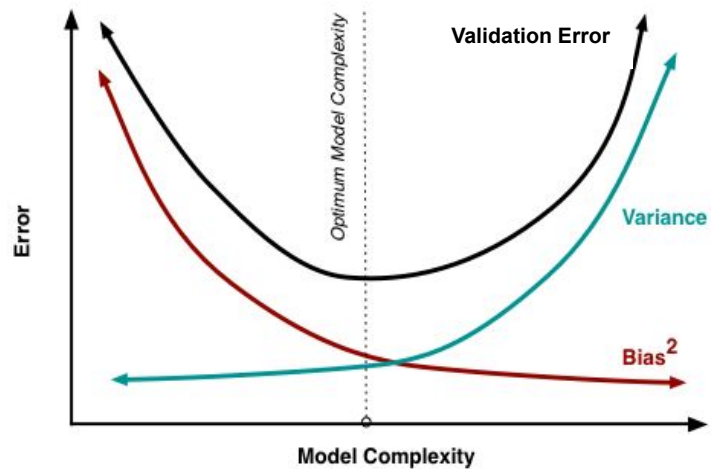
ROC AUC

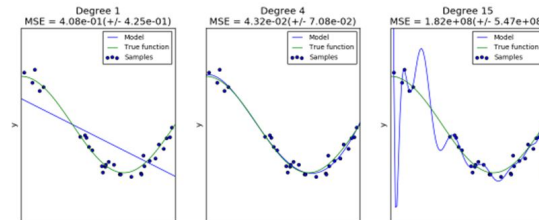
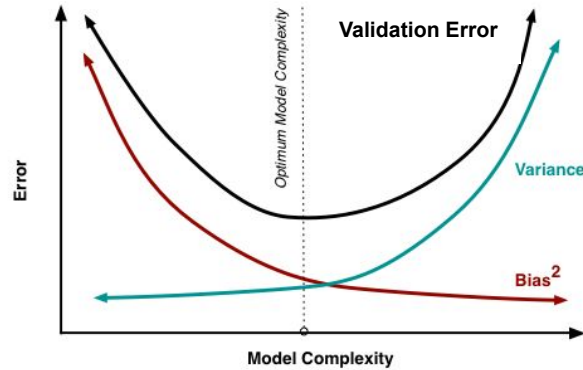
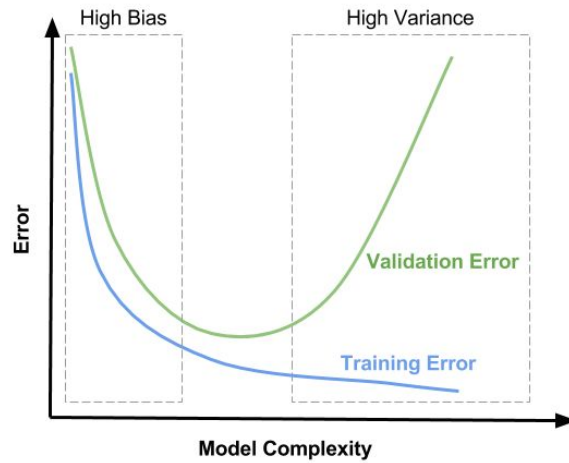
ROC AUC is the “area under the curve” – a single number that captures the overall quality of the classifier. It should be between 0.5 (random classifier) and 1.0 (perfect).



Bias and variance







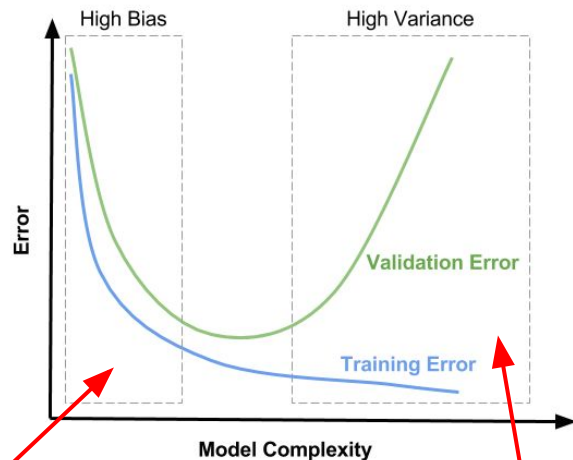
How to know where on the x-axis you are (without fiddling with model complexity)?

Bias and variance

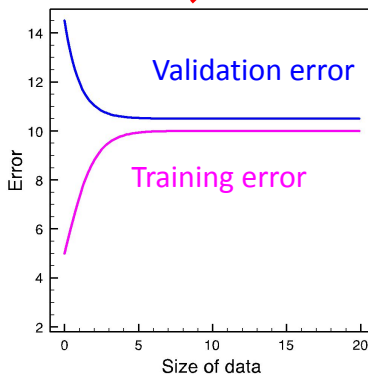
Bias and variance can be assessed by comparing the error metric on the training set and the validation set => always **plot learning curves** (training set size vs. **training/validation** errors)



When more data helps



Fixed data set size
Varying model complexity



High bias

More data doesn't help

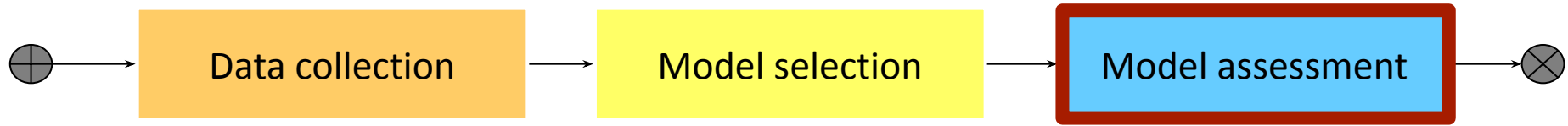


High variance

More data helps

Fixed model complexity
Varying data set size

Classification pipeline



Model assessment

- Model assessment is the goal of estimating the performance of a fixed model (i.e., the best model found during model selection)
- Ideally under real-world conditions
- Use held-out test set that you've never seen during training

Useful reads

Machine Learning that Matters

Kiri L. Wagstaff

KIRI.L.WAGSTAFF@JPL.NASA.GOV

Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Drive, Pasadena, CA 91109 USA

A Few Useful Things to Know about Machine Learning

Pedro Domingos
Department of Computer Science and Engineering
University of Washington
Seattle, WA 98195-2350, U.S.A.
pedrod@cs.washington.edu



[slides](#)

Feedback

Give us feedback on this lecture here:

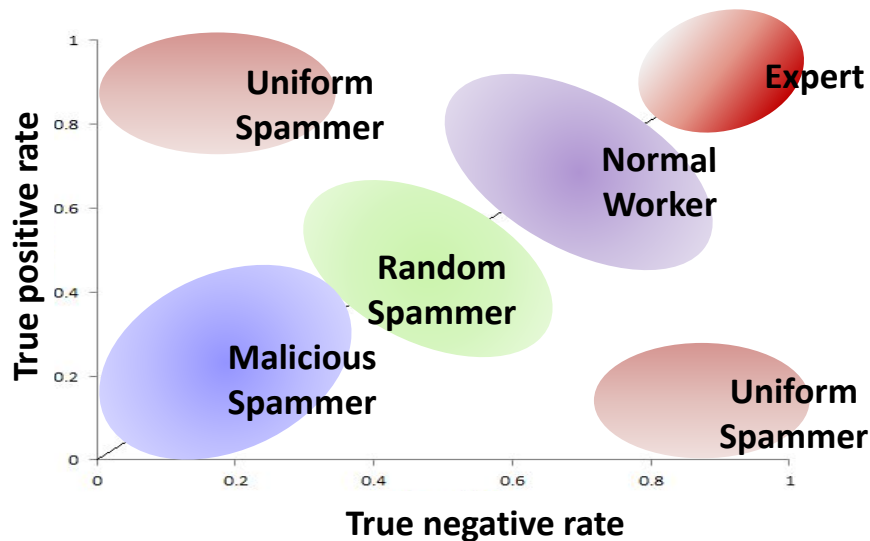
<https://go.epfl.ch/ada2025-lec8-feedback>

- What did you (not) like about this lecture?
- What was (not) well explained?
- On what would you like more (fewer) details?
- ...

Crowdsourcing

Different types of workers

- Truthful
 - Expert
 - Normal
- Untruthful
 - Uniform spammer
 - Random spammer
 - Malicious spammer (a.k.a. a\$#\$*le)



Catching malicious spammers

- Insert obvious examples for which you already know the labels (“honeypot”)
 - Tell workers they won’t be paid if they don’t get those right
 - Filter out workers who don’t get them right
- Aggregate multiple answers
 - p.t.o.

Crowdsourcing

Answer aggregation problem

- Have each example labeled by several workers, aggregate:
 - e.g., majority vote (works if only a minority is malicious)
 - e.g., “peer prediction”, “[prediction markets](#)” (game theory: workers are paid more if they agree with others)



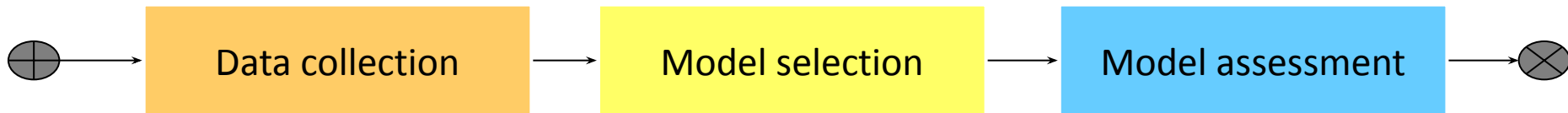
Crowd (workers)

Worker	Webpage	Credible
W_1	www.diet.com	C
W_2	www.diet.com	¬C
W_3	www.diet.com	C
...



www.diet.com	C
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Recap

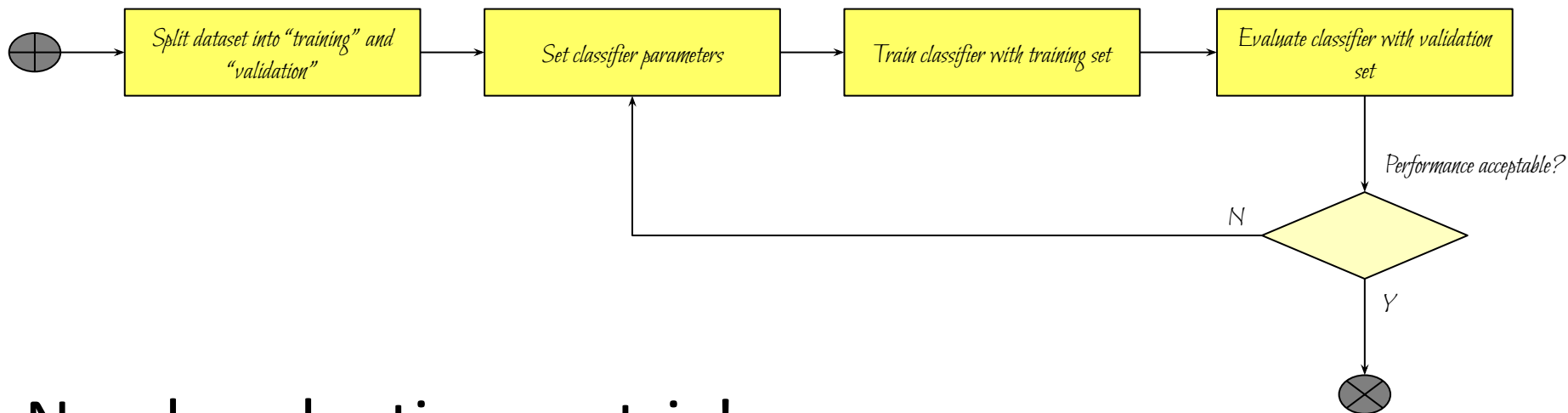


- Model selection:
 - Use training data in cross-validation
 - Need evaluation metric
 - Typically based on confusion matrix
 - e.g., accuracy, precision, recall



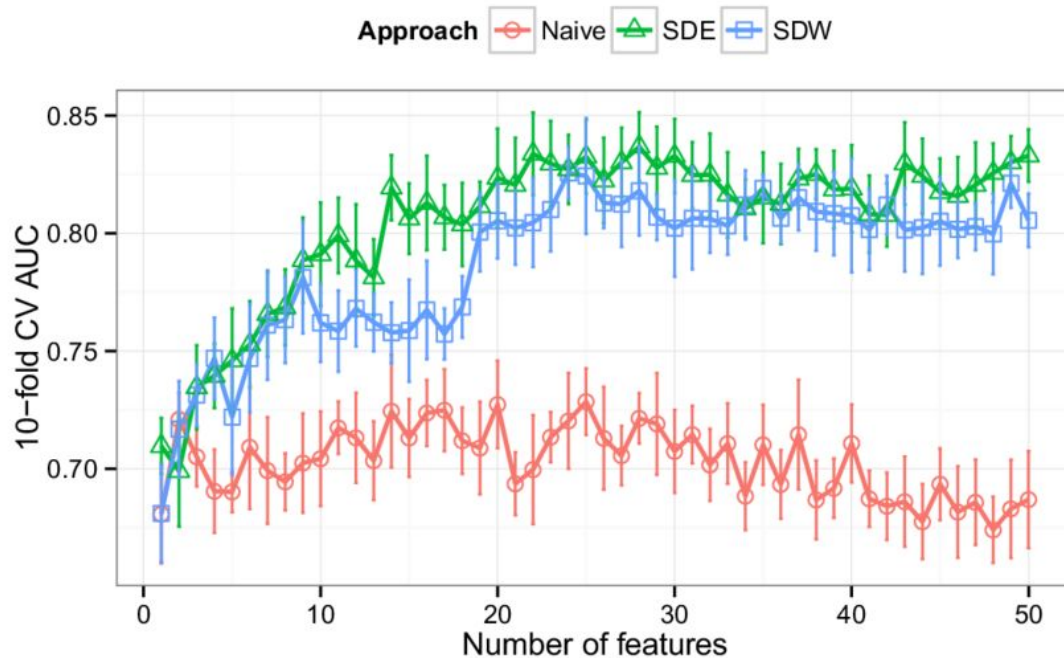
		Class	
		A	B
Classified	A	TP	FP
	B	FN	TN

Model selection

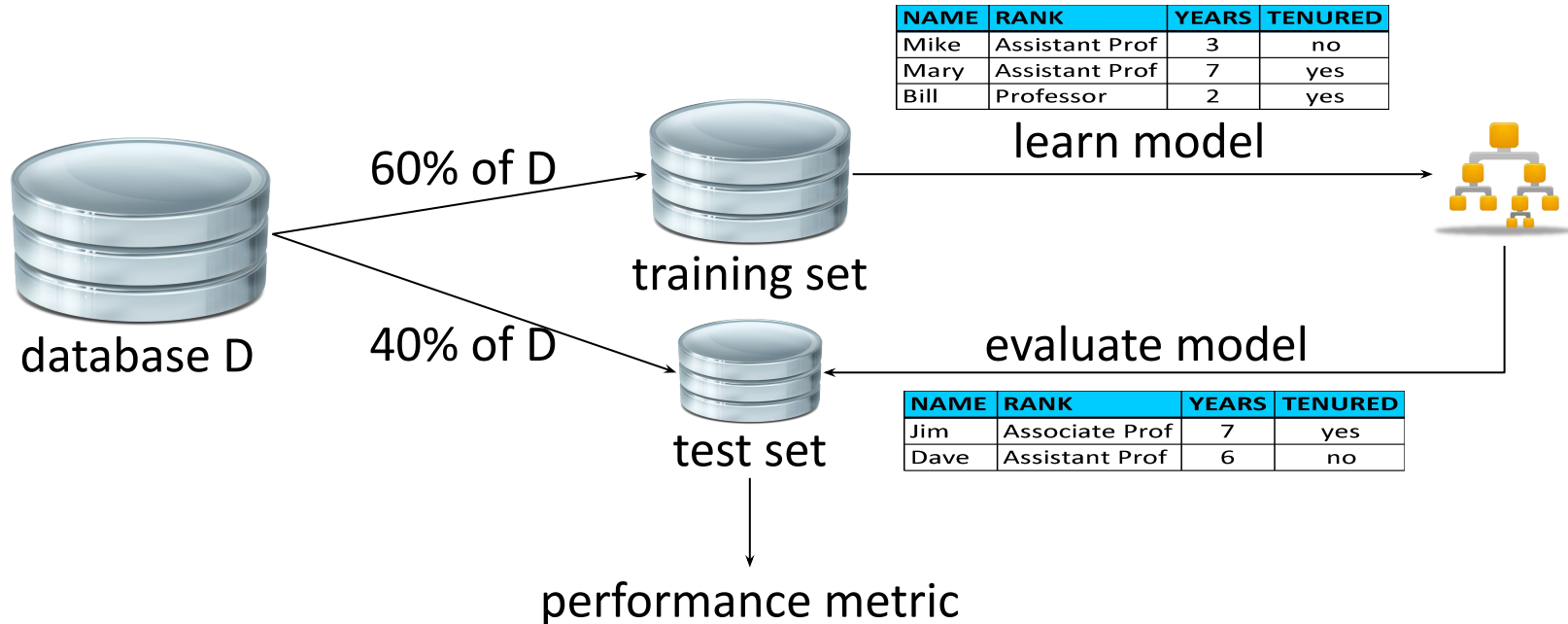


Need evaluation metric!

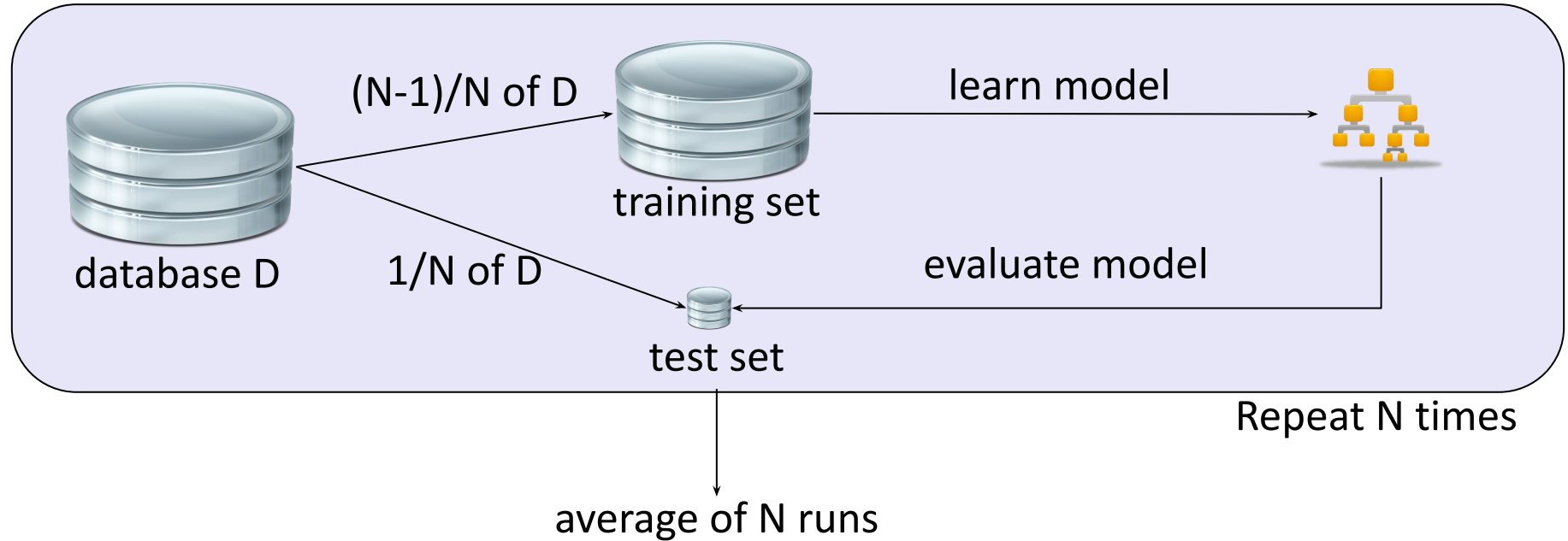
Fwd-selected features vs. performance



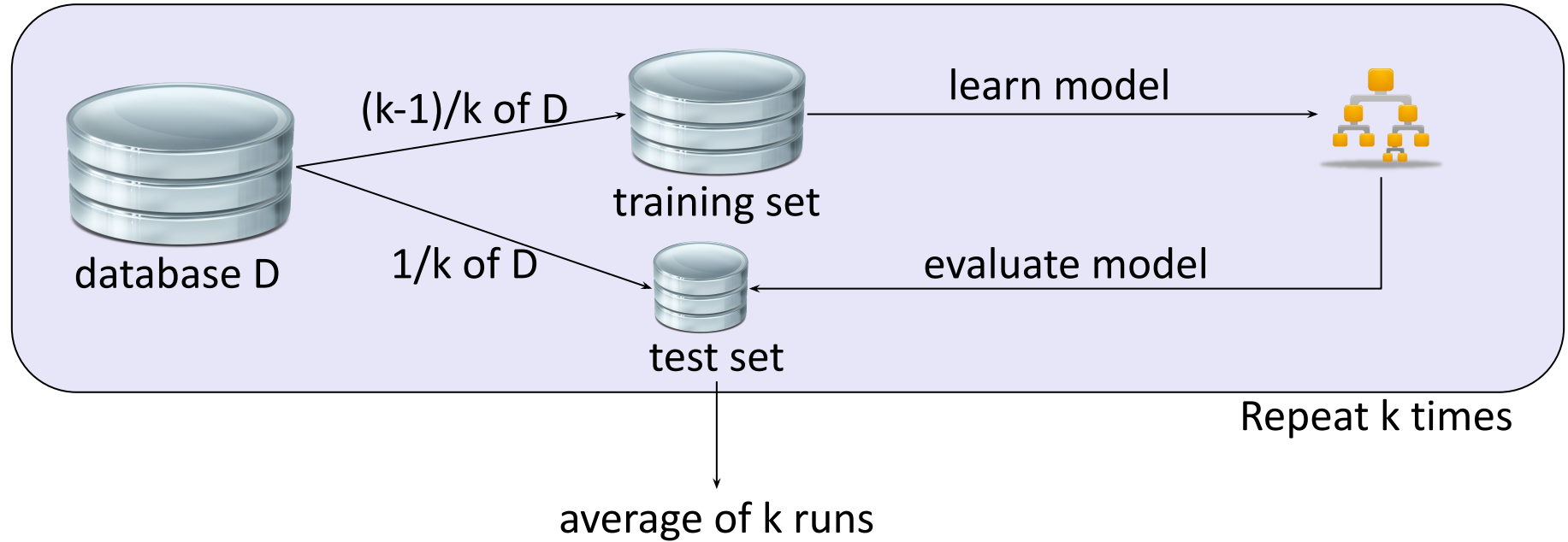
Training and testing with heaps of data



Data-efficient training and testing: Leave-one-out cross-validation



Data-efficient training and testing: k-fold cross validation



More data often beats better algorithms



EXPERT OPINION

Contact Editor: **Brian Brannon**, bbrannon@computer.org

The Unreasonable Effectiveness of Data

Alon Halevy, Peter Norvig, and Fernando Pereira, *Google*

Large Language Models in Machine Translation

Thorsten Brants Ashok C. Papat Peng Xu Franz J. Och Jeffrey Dean

Google, Inc.

1600 Amphitheatre Parkway

Mountain View, CA 94303, USA

`{brants,papat,xp,och,jeff}@google.com`

Abstract

This paper reports on the benefits of large-scale statistical language modeling in machine translation. A distributed infrastructure is proposed which we use to train on up to 2 trillion tokens, resulting in language models having up to 300 billion n -grams. It is capable of providing smoothed probabilities for fast, single-pass decoding. We introduce a new smoothing method, dubbed *Stupid Backoff*, that is inexpensive to train on large data sets and approaches the quality of Kneser-Ney Smoothing as the amount of training data increases.

How might one build a language model that allows scaling to very large amounts of training data? (2) How much does translation performance improve as the size of the language model increases? (3) Is there a point of diminishing returns in performance as a function of language model size?

This paper proposes one possible answer to the first question, explores the second by providing learning curves in the context of a particular statistical machine translation system, and hints that the third may yet be some time in answering. In particular, it proposes a *distributed* language model training and deployment infrastructure, which allows direct and efficient integration into the hypothesis-search algorithm rather than a follow-on re-scoring phase.