

# Machine learning primer

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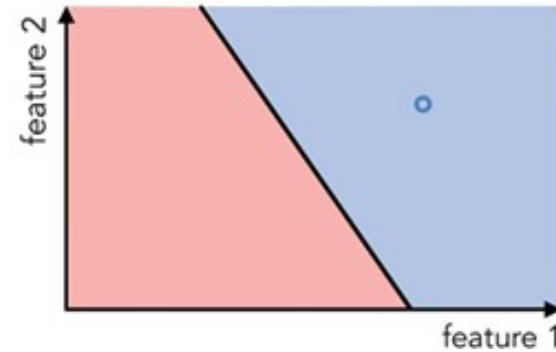
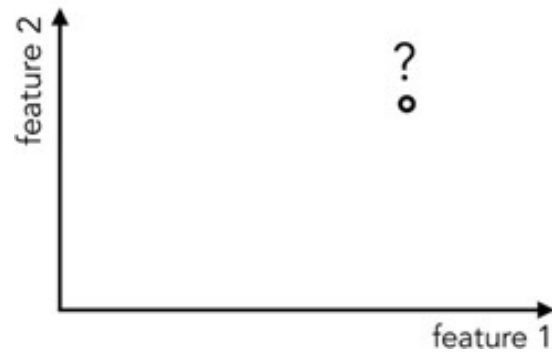
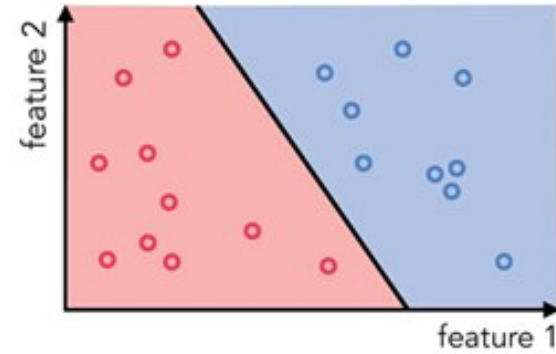
JOANNA BYSZUK & JEREMI OCHAB

DHSI 2024, “DIY COMPUTATIONAL TEXT ANALYSIS WITH R”

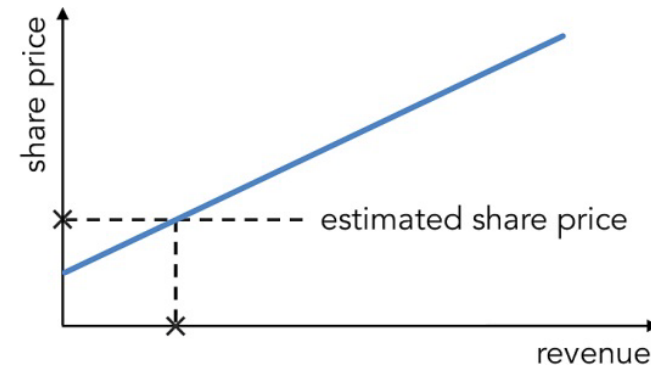
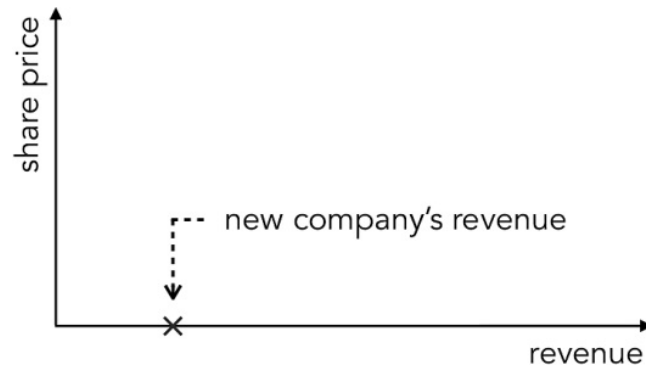
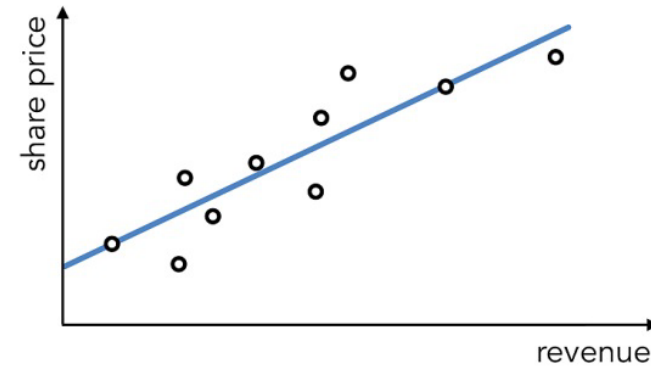
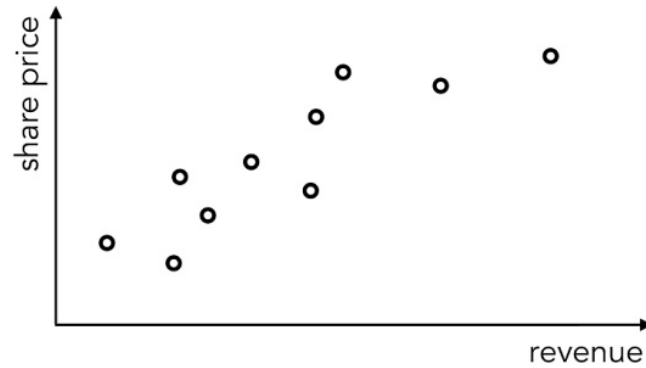


# Task examples: classification

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# Task examples: regression



# Terms and definitions

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**Example:** item, instance of the data used.

**Features:** attributes associated to an item, often represented as a vector (e.g., word counts).

**Labels:** category (classification) or real value (regression) associated to an item.

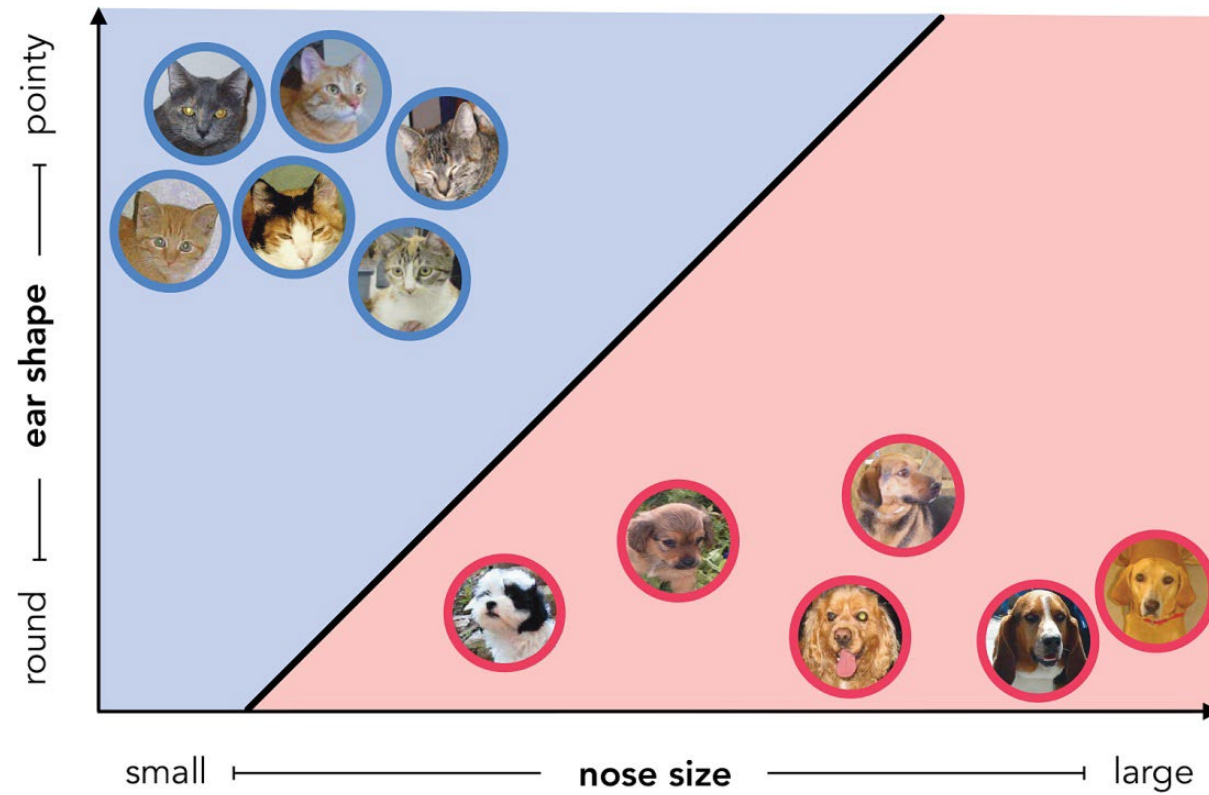
**Data:**

- ❖ training data (typically labeled).
- ❖ test data (labeled but labels not seen).
- ❖ validation data (labeled, for tuning parameters).

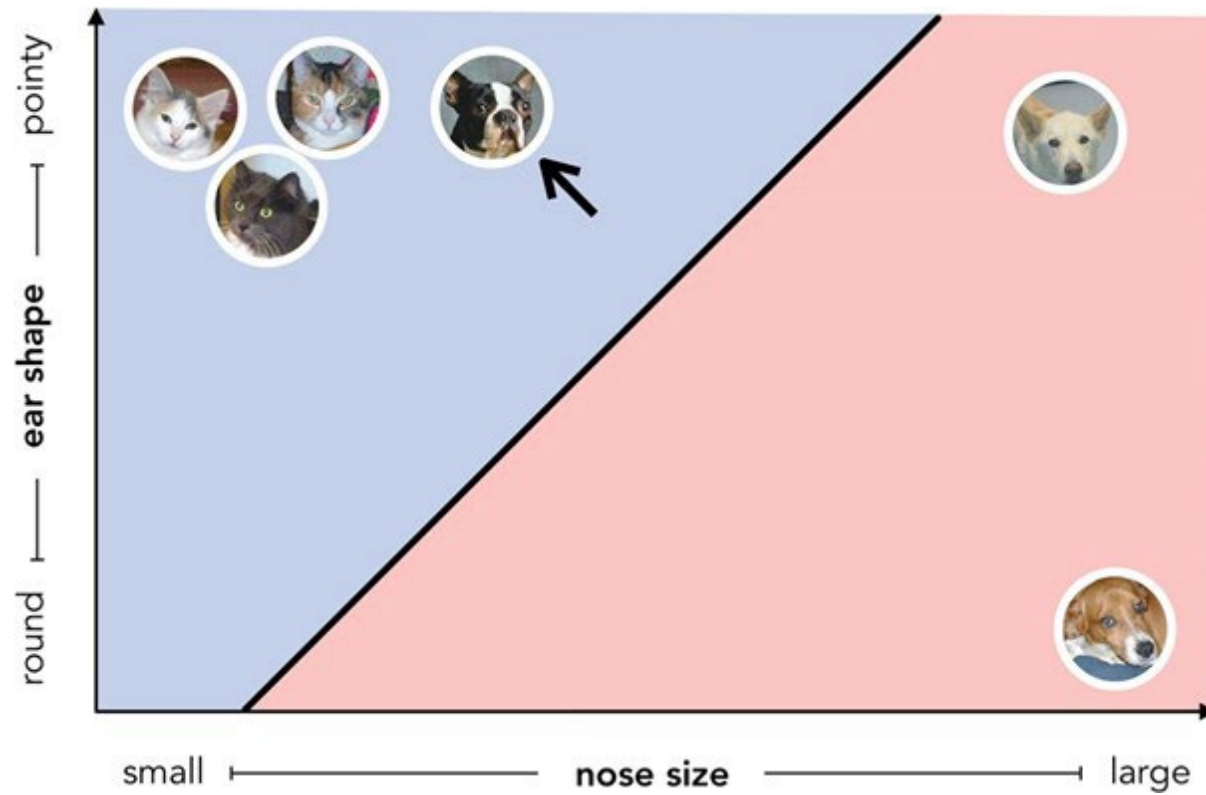
# Learning stages

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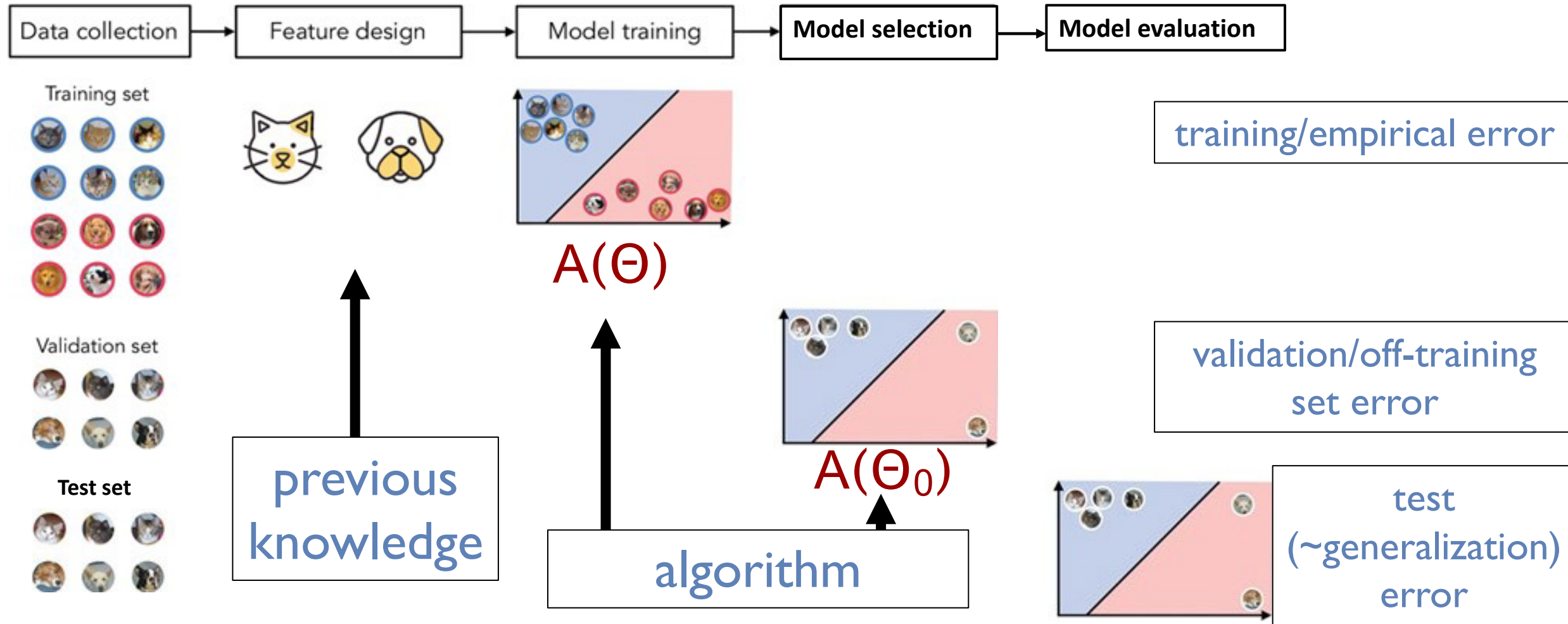
# Learning stages



# Learning stages



# Learning stages



J. Watt, R. Borhani, A.K. Katsaggelos. *Machine Learning Refined*. © Cambridge University Press 2020



# Bias-variance tradeoff

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# Bias-variance tradeoff

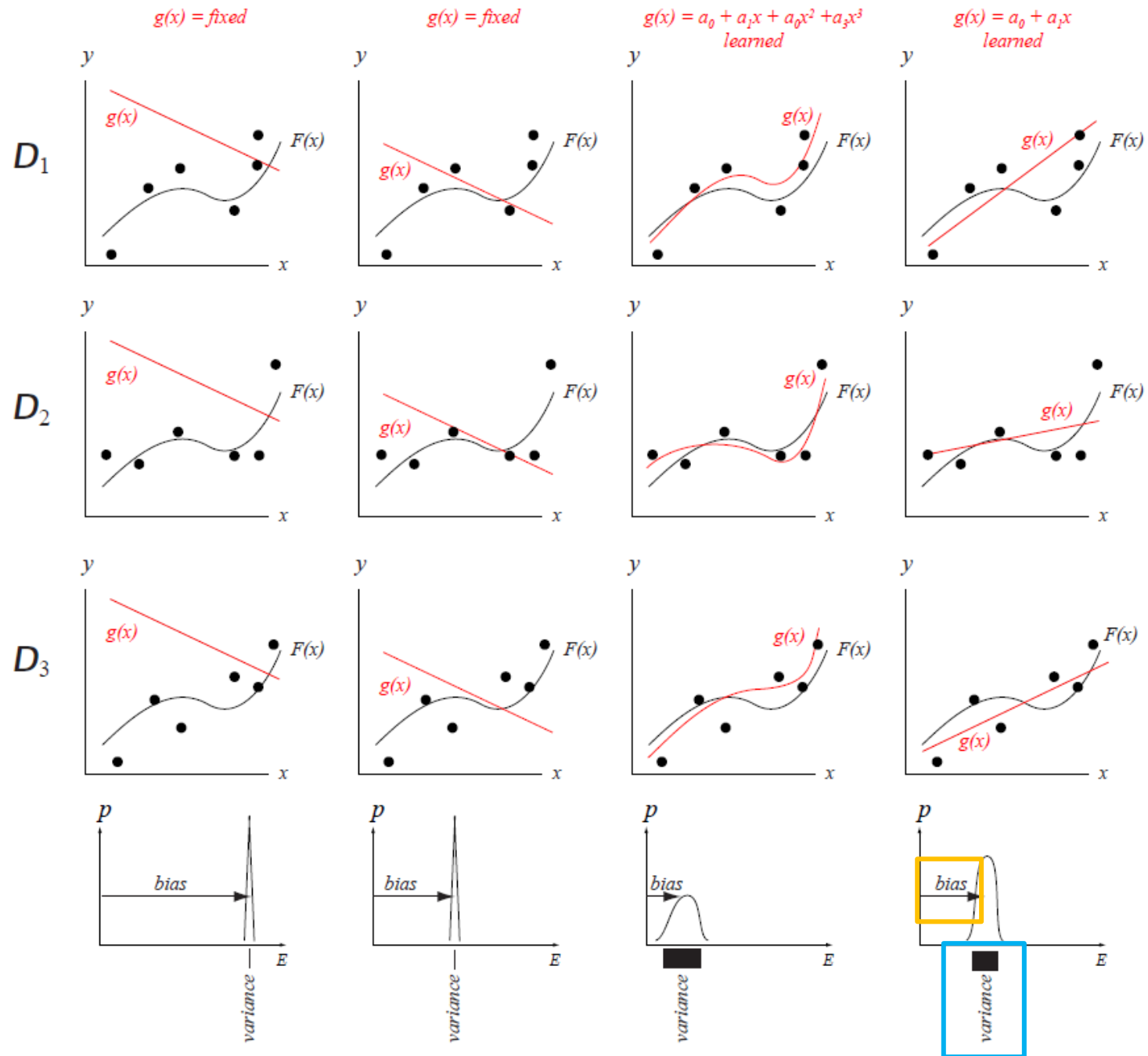
Najłatwiej na przykładzie dopasowania krzywej regresji:

- $F(\mathbf{x})$  – a true (but unknown) function with continuous valued output with noise
- $D$  – set of  $n$  training samples generated by  $F(\mathbf{x})$
- $g(\mathbf{x}; D)$  – the estimated regressions function  $F$  (depends on the set  $D$ !)
- Estimator effectiveness: average (over all sets  $D$  of size  $n$ ) mean-square deviation:

$$= \underbrace{\mathcal{E}_D [(g(\mathbf{x}; D) - F(\mathbf{x}))^2]}_{\text{bias}^2} + \underbrace{\mathcal{E}_D [(g(\mathbf{x}; D) - \mathcal{E}_D[g(\mathbf{x}; D)])^2]}_{\text{variance}}.$$

◦ bias – the difference between the true (but unknown) value and our expectations  
[=estimation accuracy]

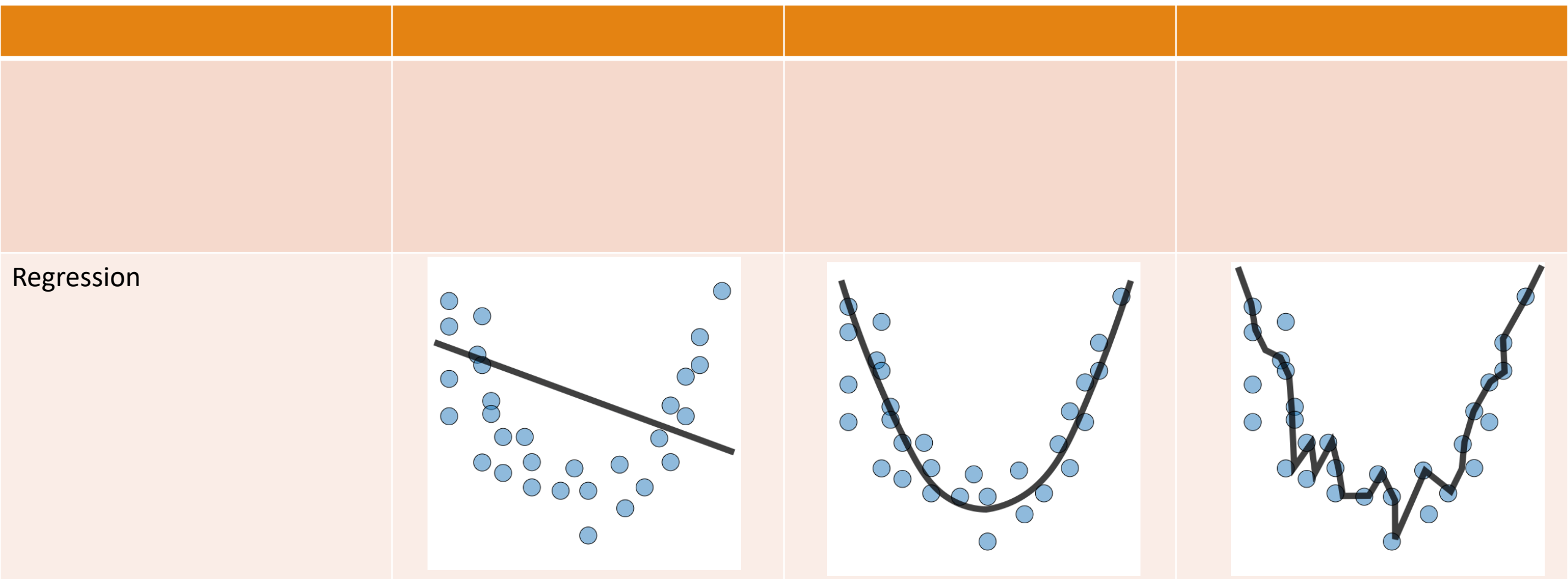
◦ variance – the instability of the estimate due to the variability of the training set



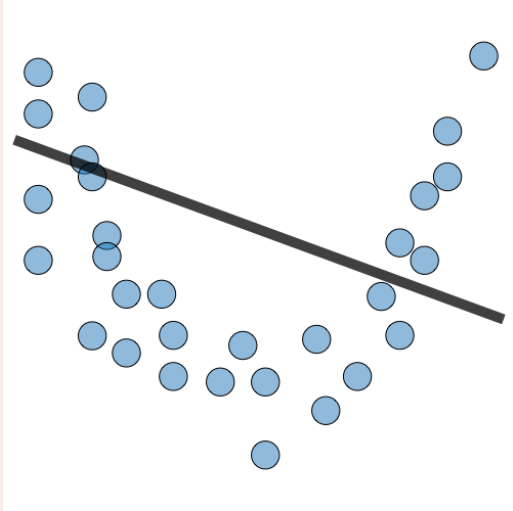
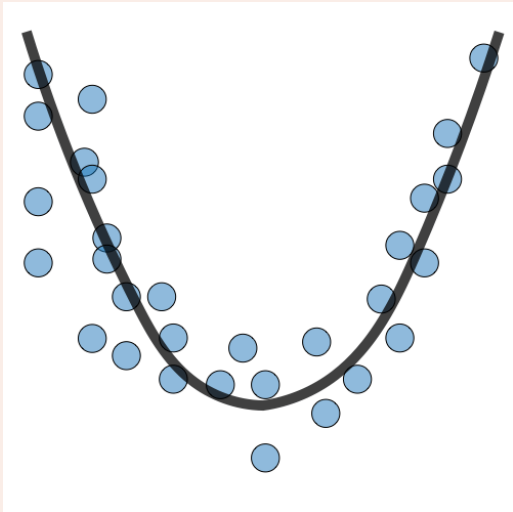
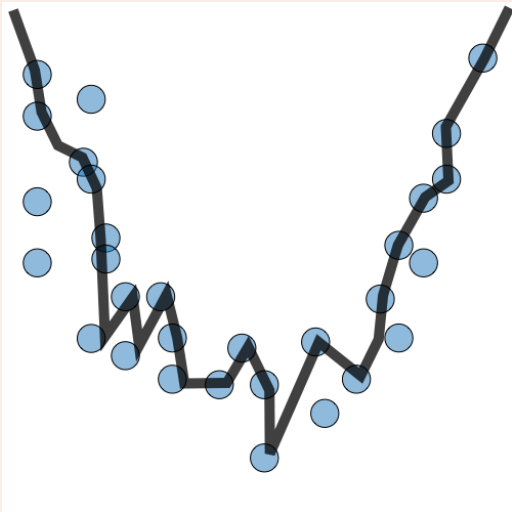
$E$  – mean squared error

$p$  – probability that we will randomly get  $D$  with the error  $E$

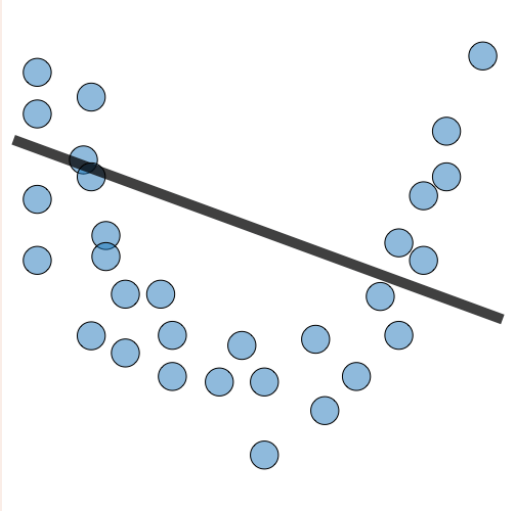
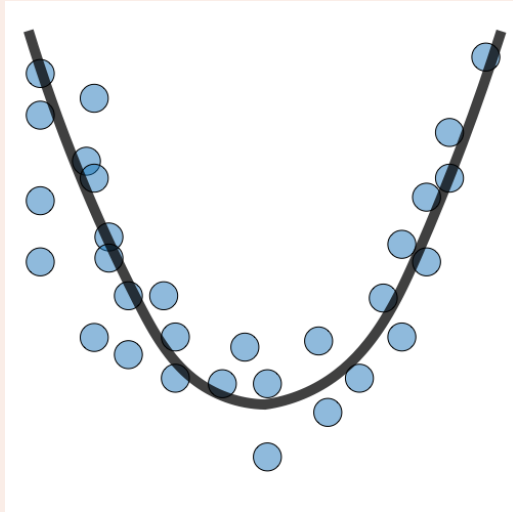
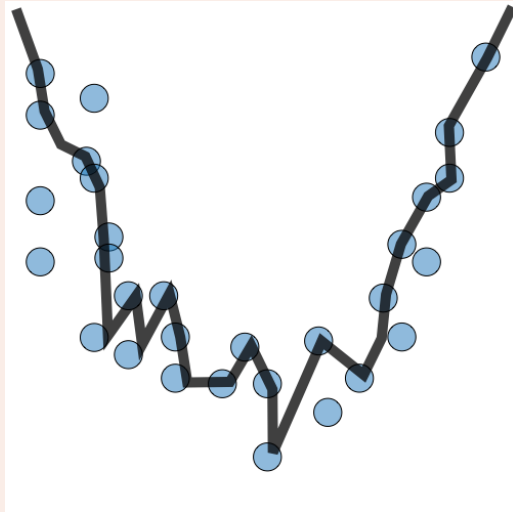
# Bias-variance tradeoff

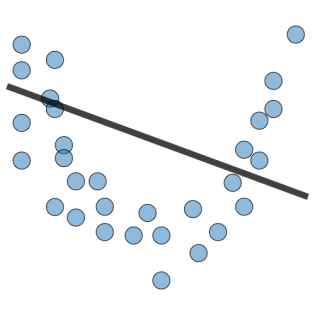
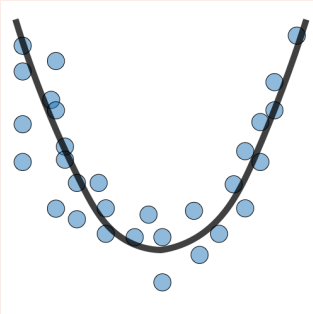
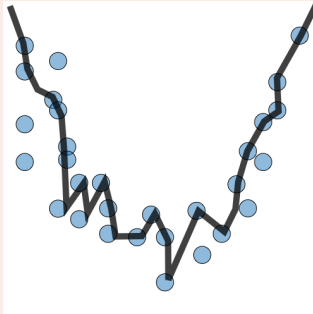
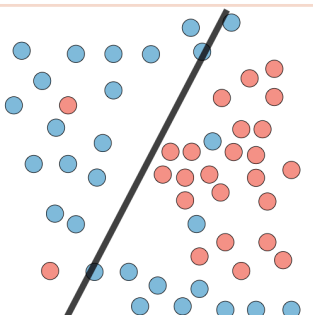
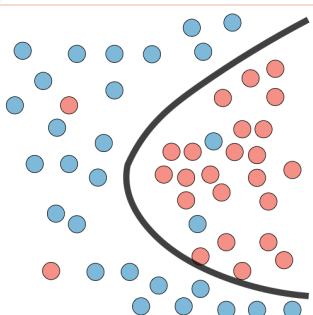
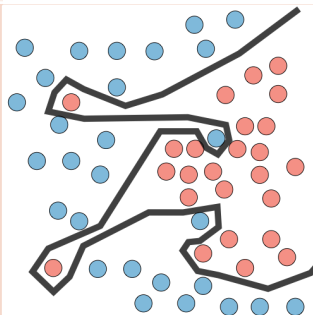
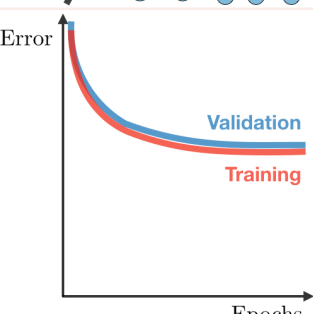
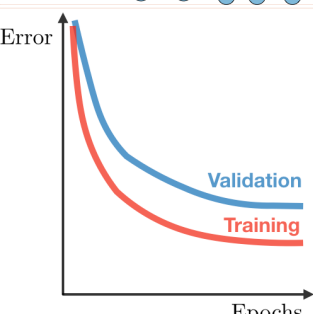
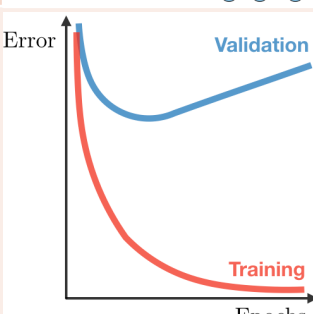


# Bias-variance tradeoff

	Underfitting	Just right	Overfitting
Regression			

# Bias-variance tradeoff

	Underfitting	Just right	Overfitting
Symptoms	<ul style="list-style-type: none"><li>▪ High training error</li><li>▪ Training error close to test error</li><li>▪ High bias</li></ul>	<ul style="list-style-type: none"><li>▪ Training error slightly lower than test error</li></ul>	<ul style="list-style-type: none"><li>▪ Low training error</li><li>▪ Training error much lower than test error</li><li>▪ High variance</li></ul>
Regression			

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Regression			
Classification			
Deep learning			
Remedies?	<ul style="list-style-type: none"> <li>complexify model</li> <li>Add more features</li> <li>Train longer</li> </ul>		<ul style="list-style-type: none"> <li>Regularise</li> <li>Get more data</li> </ul>

# Generalisation

## OBSERVATIONS

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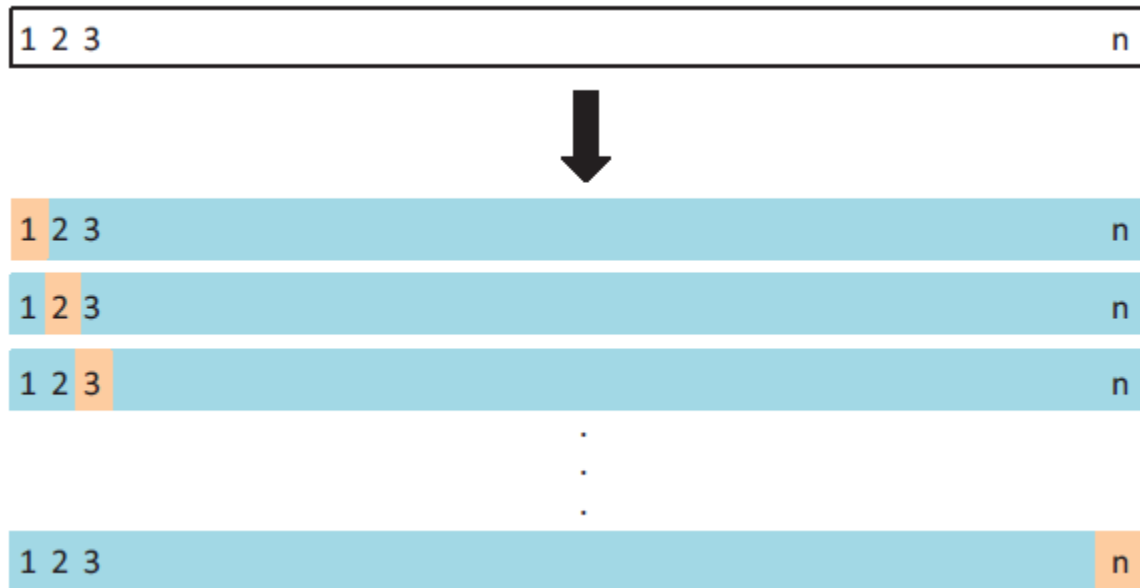
- ❖ the best hypothesis on the sample may not be the best overall.
- ❖ generalization is not memorization.
- ❖ complex rules (very complex separation surfaces) can be poor predictors.
- ❖ trade-off: complexity of hypothesis set vs sample size (underfitting/overfitting).



# Cross-validation

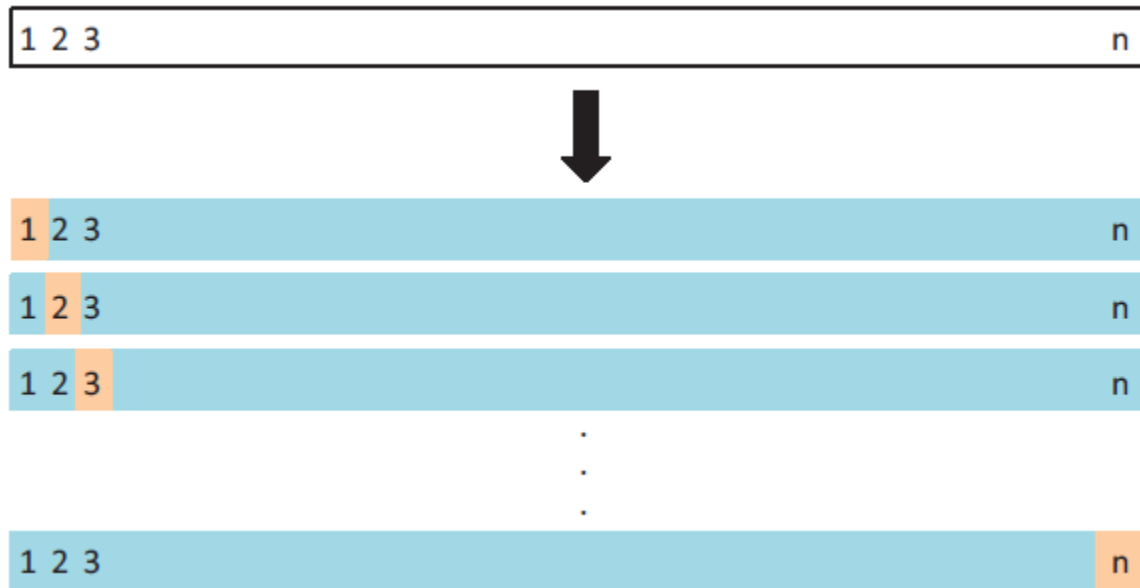
LEAVE-ONE-OUT CROSS-VALIDATION  
[JACK-KNIFE]

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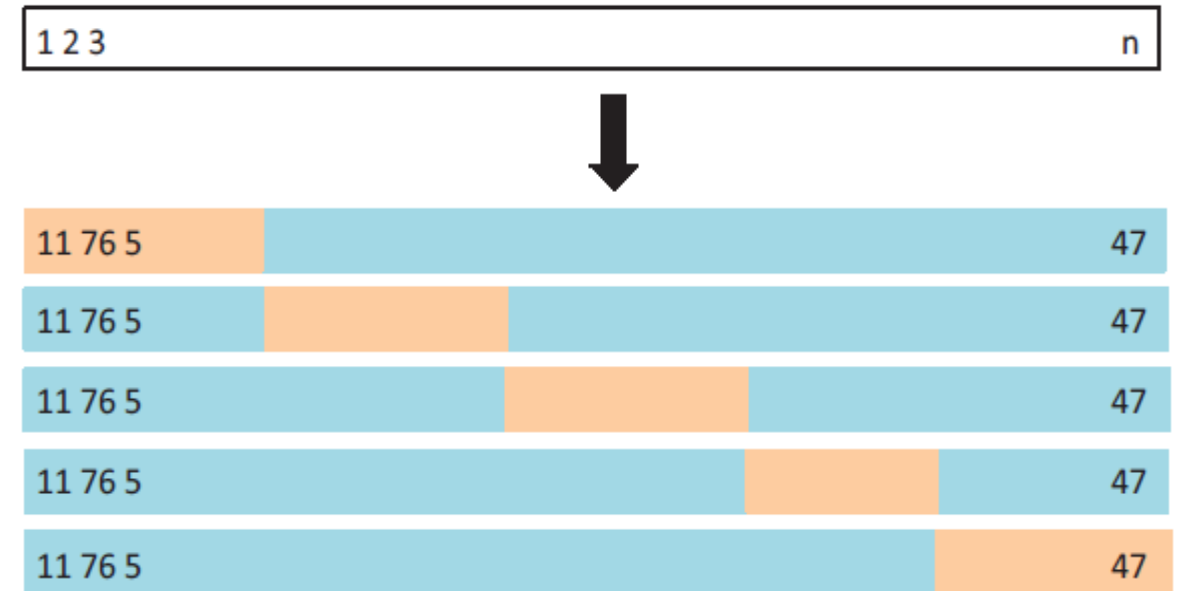


# Cross-validation

LEAVE-ONE-OUT CROSS-VALIDATION  
[JACK-KNIFE]

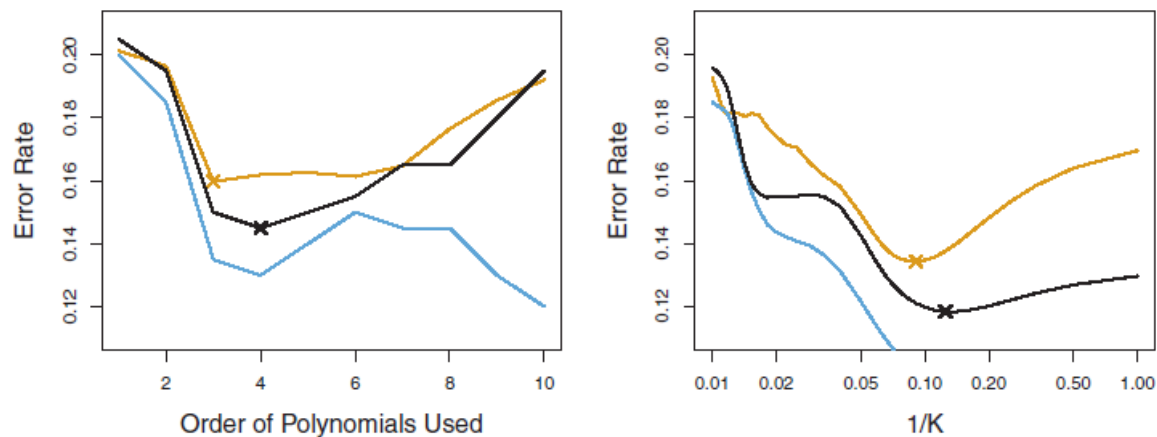


K-FOLD CROSS-VALIDATION

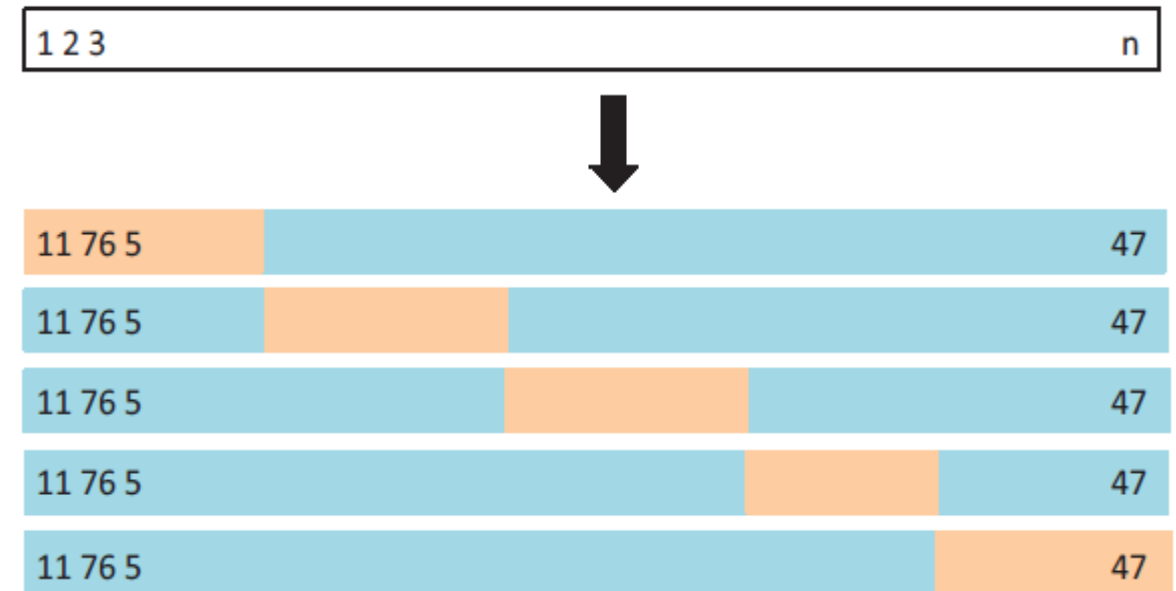


# Cross-validation

## K-FOLD CROSS-VALIDATION



**FIGURE 5.8.** Test error (brown), training error (blue), and 10-fold CV error (black) on the two-dimensional classification data displayed in Figure 5.7. Left: Logistic regression using polynomial functions of the predictors. The order of the polynomials used is displayed on the x-axis. Right: The KNN classifier with different values of  $K$ , the number of neighbors used in the KNN classifier.



# Cross-validation

## MORE TYPES

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- Stratified CV stratified
- Group CV

[https://scikit-learn.org/stable/modules/cross\\_validation.html#k-fold](https://scikit-learn.org/stable/modules/cross_validation.html#k-fold)