EMBEDDED VISION DESIGN 3

ML PERFORMANCE

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CONTENTS

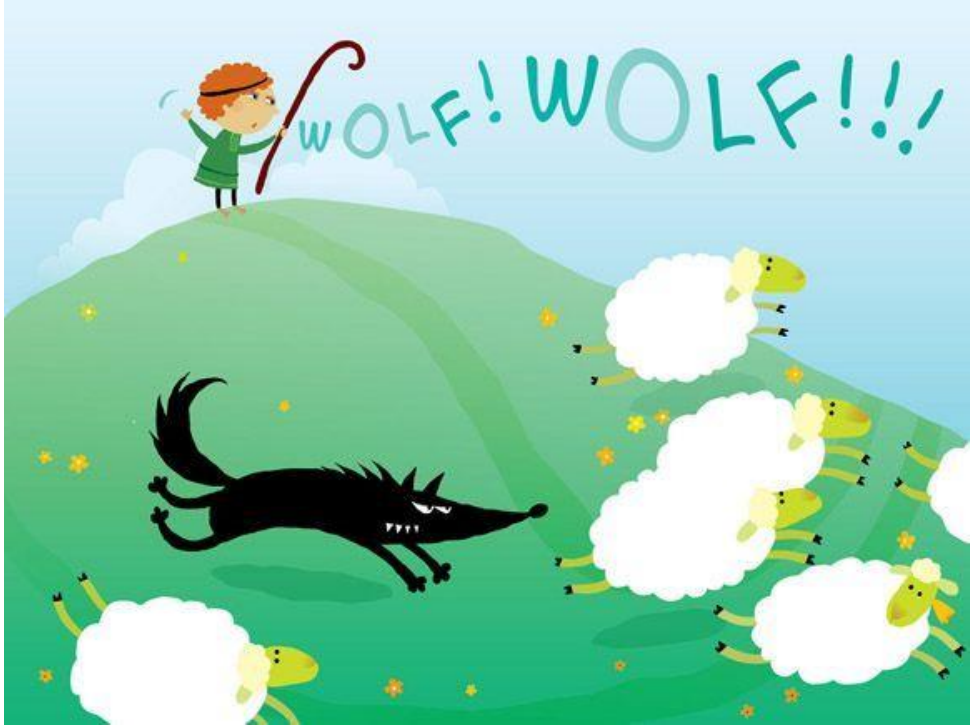
- Confusion matrix
- Evaluating classifiers
- Learning curves

THE BOY WHO CRIED WOLF

"Wolf" is a **positive class**.

"No wolf" is a **negative class**

An Aesop's Fable ~620 BCE



Source: Sam Taplin

CONFUSION MATRIX

	ACTUAL	
PREDICTED	**True Positive (TP)** Reality: A wolf threatened. Shepherd said: "Wolf." Outcome: Shepherd is a hero.	(Type I error) **False Positive (FP)** Reality: No wolf threatened. Shepherd said: "Wolf." Outcome: Villagers are angry at shepherd for waking them up.
	False Negative (FN) Reality: A wolf threatened. Shepherd said: "No wolf." Outcome: The wolf ate all the sheep. Type II error)	**True Negative (TN)** Reality: No wolf threatened. Shepherd said: "No wolf." Outcome: Everyone is fine.

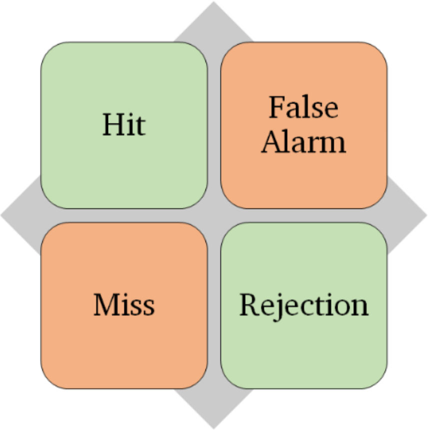
ACCURACY

- Fraction of predictions the model got right

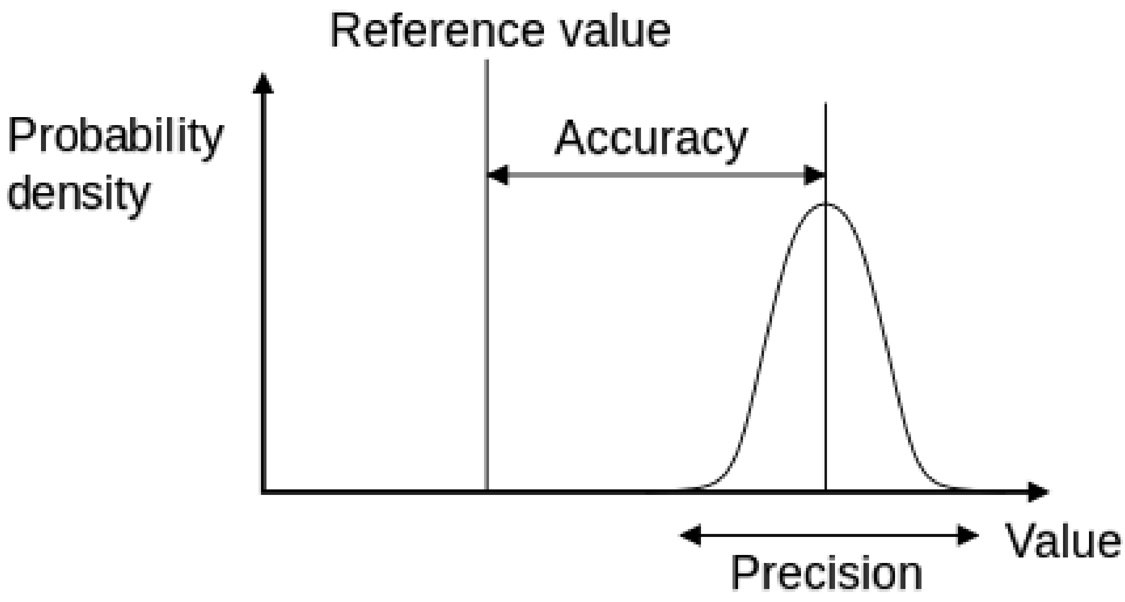
$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

- For binary classification

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$



ACCURACY VS PRECISION



accuracy is closeness of the measurements to a specific value, while **precision** is the closeness of the measurements to each other.

Source: https://en.wikipedia.org/wiki/Accuracy_and_precision

PRECISION AND RECALL

- Precision, fraction of correct positive predictions

  Σ True positive / Σ Predicted condition positive

$$\text{precision} = \frac{TP}{TP + FP}$$

- Recall, probability of detection

  Σ True positive / Σ Condition positive

$$\text{recall} = \frac{TP}{TP + FN}$$

precision

recall

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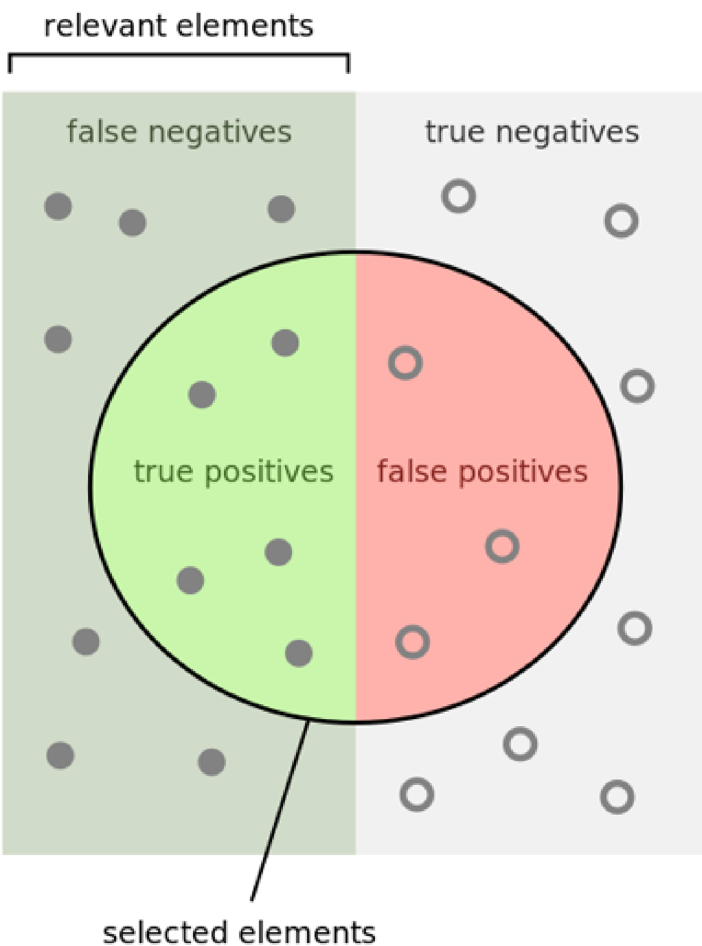
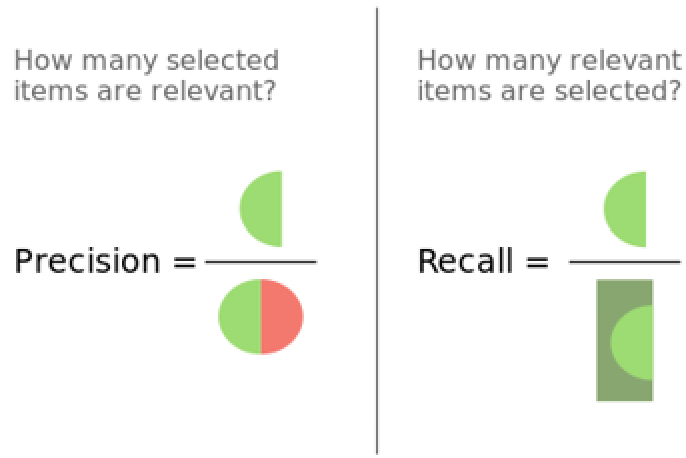
PRECISION AND RECALL

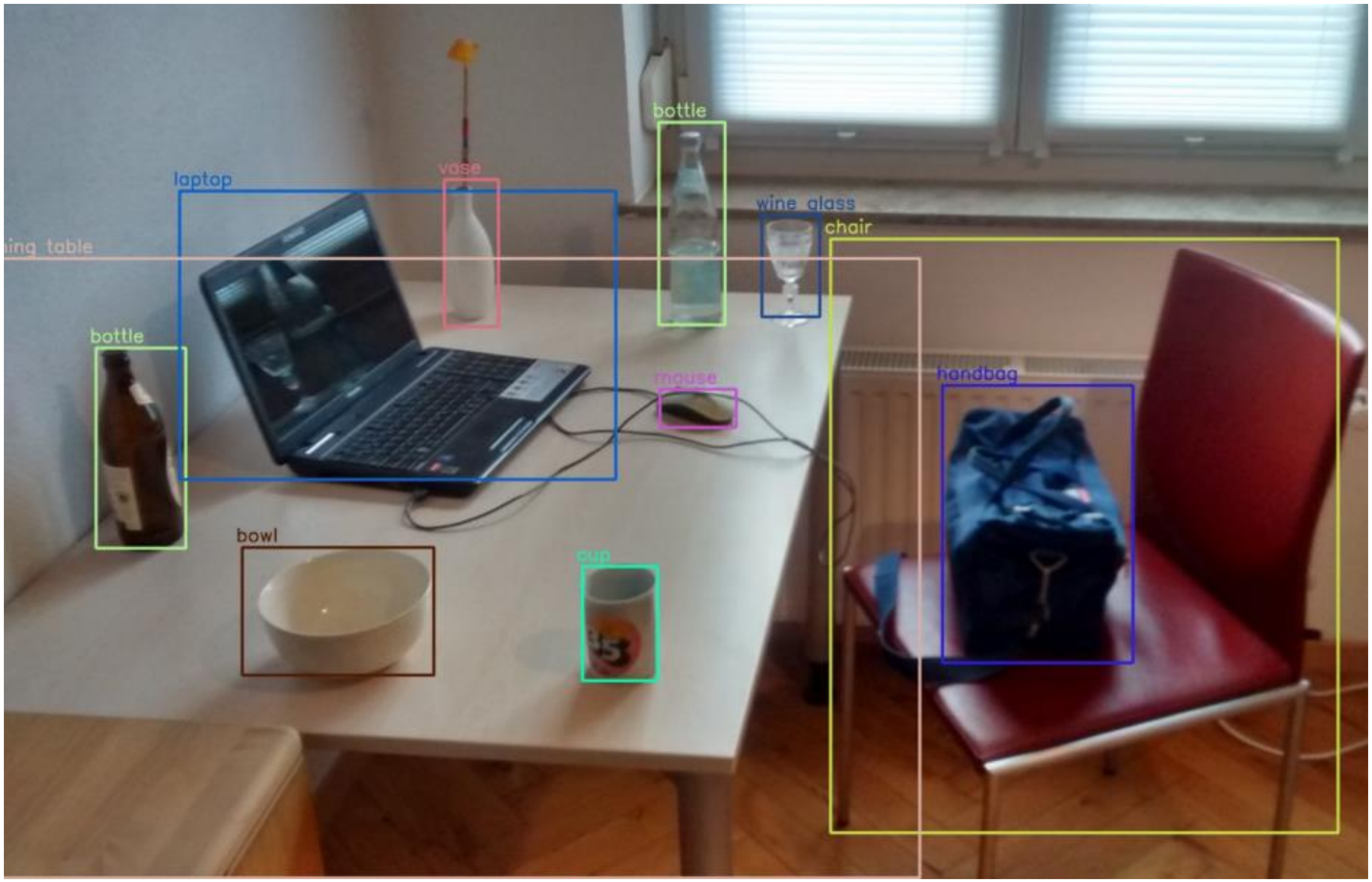


Source: https://en.wikipedia.org/wiki/Precision_and_recall



Recall = sensitivity = true positive rate (TPR)

LIMITATION OF USING SENSITIVITY AND SPECIFICITY



Source: Example of object detection. How many true negatives are there?. Wikipedia: MTheiler CC BY-SA 4.0

LET’S CHECK A VIDEO CLIP

- https://www.youtube.com/watch?v=TtIjAiSojFE

	precision	recall	f1-score
0.0	0.96	0.97	0.97
1.0	0.65	0.58	0.62

F1 SCORE

- To fully evaluate the effectiveness of a model, you must examine **both** precision and recall
- F1 score is the harmonic mean of precision and recall

$$F_1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} = \frac{TP}{TP + \frac{FN + FP}{2}}$$

MANY METRICS

veren. Alle tests van de deelnemende partijen zijn eerst beoordeeld door het RIVM. „We sturen tien monsters, vijf met SARS-CoV-2 in verschillende concentraties, drie met andere coronavirussen, en twee waar niets in zit. De labs weten niet wat waar in zit. Als hun uitslagen kloppen, is de test goed”, zegt Reusken.

De testprestaties zullen per lab wat variëren: de specificiteit (de kans dat je een niet-ziek iemand ook als niet-ziek detecteert) en de sensitiviteit (de kans dat je een ziek iemand als ziek detecteert). De E-gen test is gevoeliger dan de RdRP-gen test, maar wat minder specifiek: naar schatting 99 tot 99,5 procent. Tests op meerdere genen zijn iets specifieker. Door de variatie ligt die specificiteit landelijk minimaal op 99,5 procent, zegt Reusken.

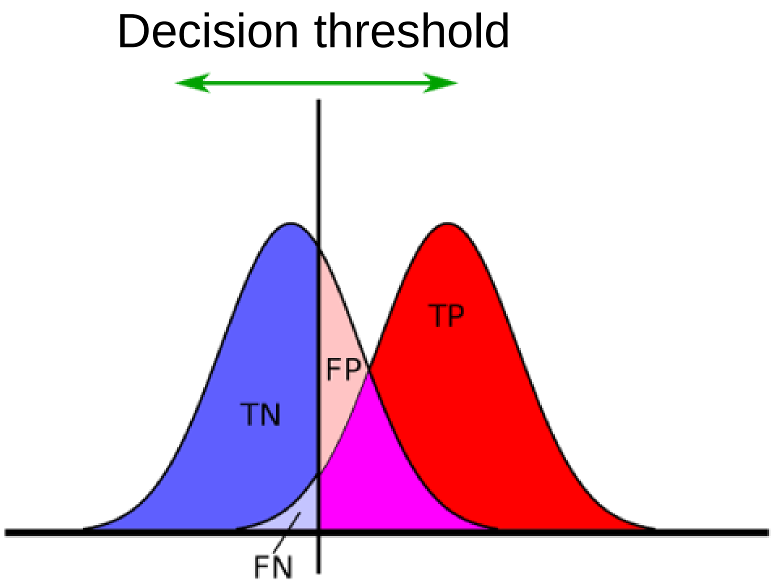
4 | Wat bepaalt hoeveel foute uitslagen een test geeft?

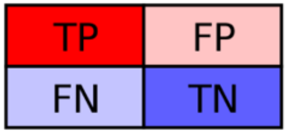
„De specificiteit hangt af van de test zelf

Source: https://en.wikipedia.org/wiki/Receiver_operating_characteristic

Predic… condit…	…egative	Prevalence $= \frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$	Accuracy (ACC) = $\frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$	
	…itive, …ror	Positive predictive value (PPV), Precision = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Predicted condition positive}}$	False discovery rate (FDR) = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Predicted condition positive}}$	
	…itive	False omission rate (FOR) = $\frac{\Sigma \text{ False negative}}{\Sigma \text{ Predicted condition negative}}$	Negative predictive value (NPV) = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Predicted condition negative}}$	
	…e rate …-out, …lse alarm …ositive / …negative	Positive likelihood ratio (LR+) $= \frac{TPR}{FPR}$	Diagnostic odds ratio (DOR) $= \frac{LR+}{LR-}$	F_1 score = $2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$
	…SPC), True …(TNR) …gative / …negative	Negative likelihood ratio (LR−) $= \frac{FNR}{TNR}$		

PRECISION/RECALL TRADE-OFF





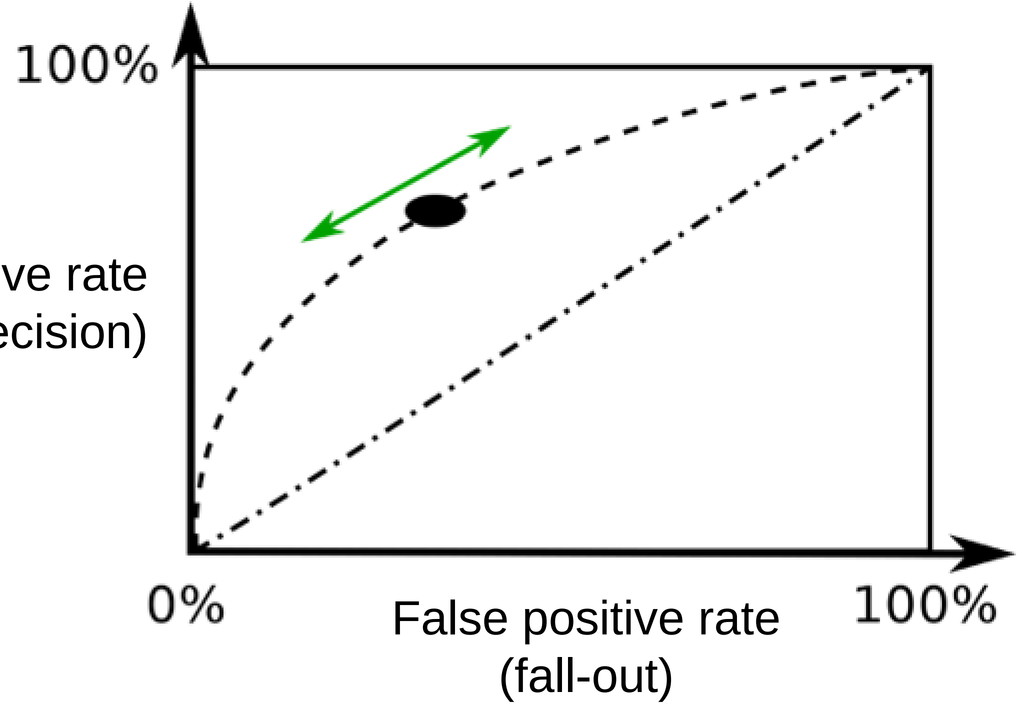
$$\text{precision} = \frac{TP}{TP + FP} \qquad \text{recall} = \frac{TP}{TP + FN}$$

Source: https://en.wikipedia.org/wiki/Tug_of_war#/media/File:Touwtrekken.jpg

Source: https://en.wikipedia.org/wiki/Receiver_operating_characteristic#/media/File:ROC_curves.svg

ROC CURVE

- *probability of detection* vs *probability of false alarm* at different decision thresholds.



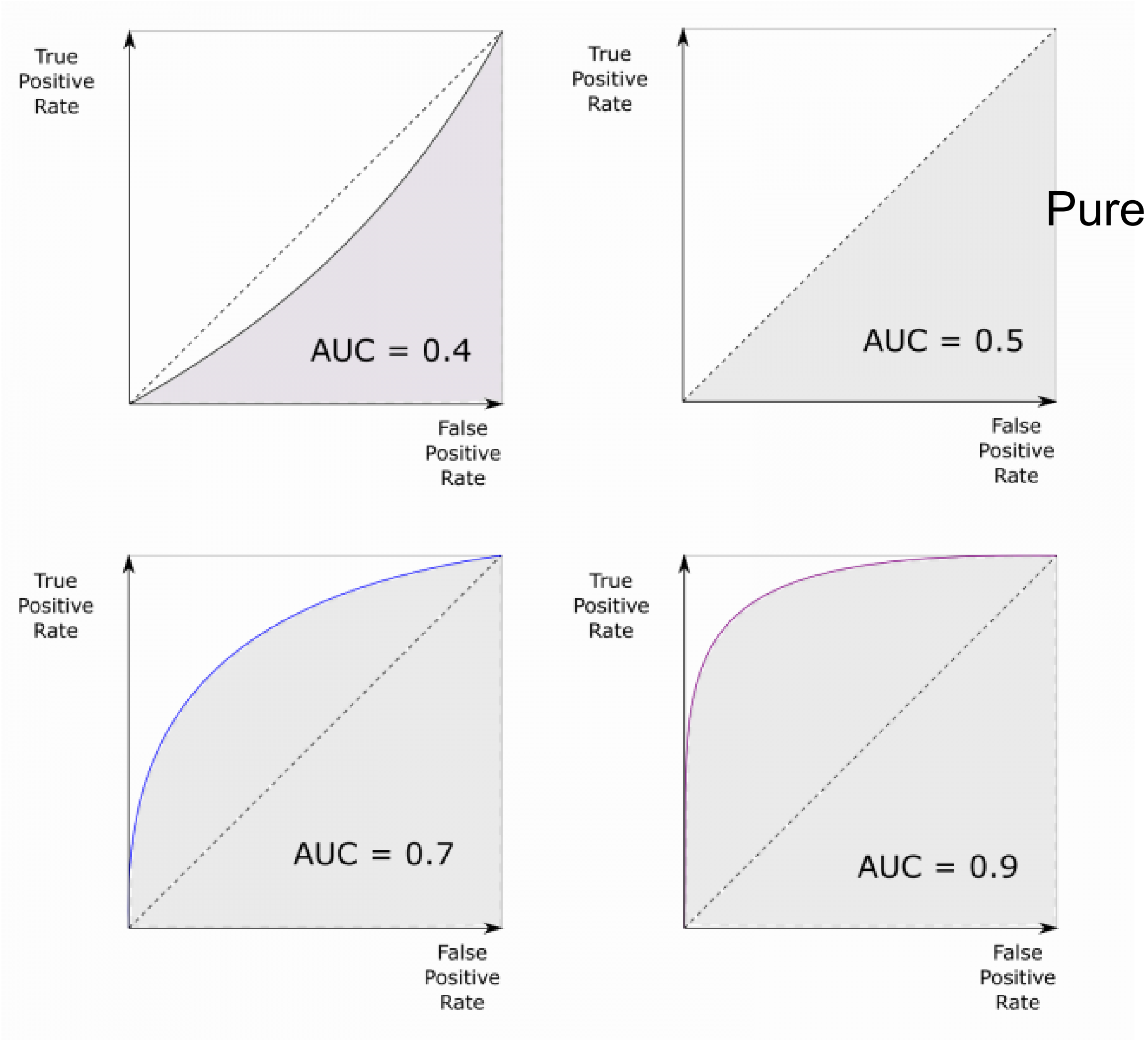
Source: https://en.wikipedia.org/wiki/Receiver_operating_characteristic#/media/File:ROC_curves.svg

COST OF CLASSIFICATION

- Sometimes false negatives don’t hurt as much as false positives
  Think of a poisonous mushroom detector….

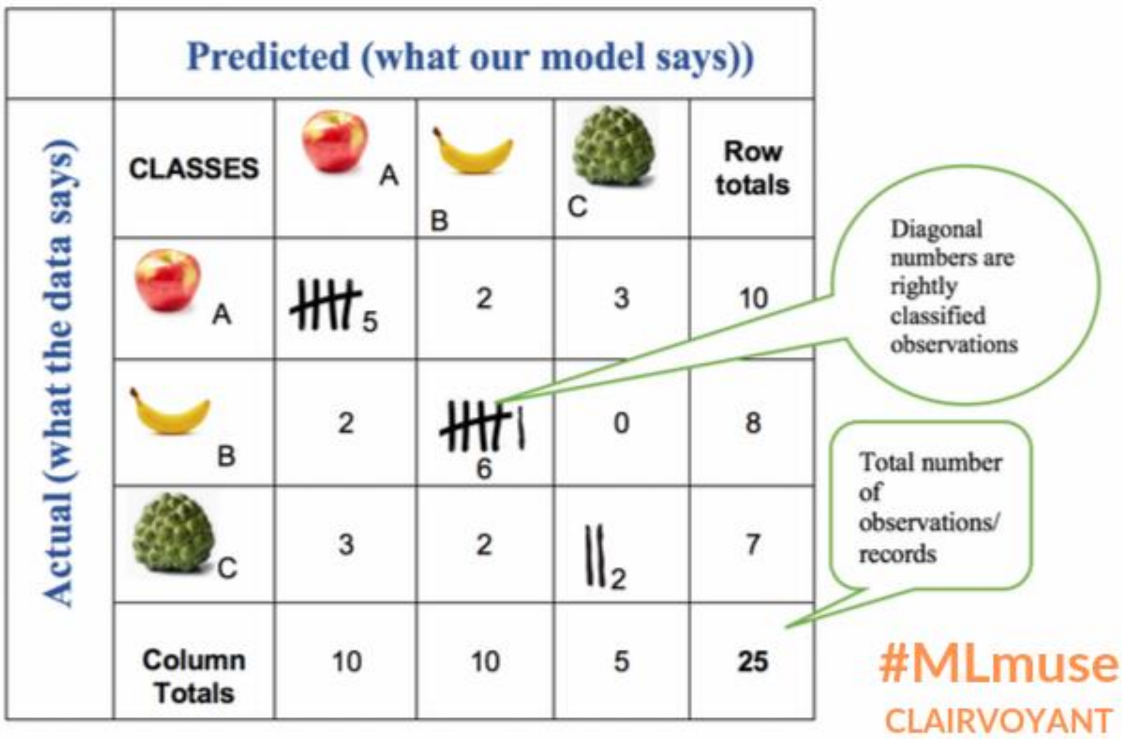
- Use the ROC curve (receiver operating characteristics) to help balance the cost of classification

ROC AREA UNDER THE CURVE (AUC)



Purely random…

MULTICLASS CONFUSION MATRIX



	Predicted (what our model says))				
Actual (what the data says)	CLASSES	A	B	C	Row totals
	A	5	2	3	10
	B	2	6	0	8
	C	3	2	2	7
	Column Totals	10	10	5	25

Source: https://miro.medium.com/max/1400/1*jtoE1zEJaG0JvGlX3jOTFQ.png

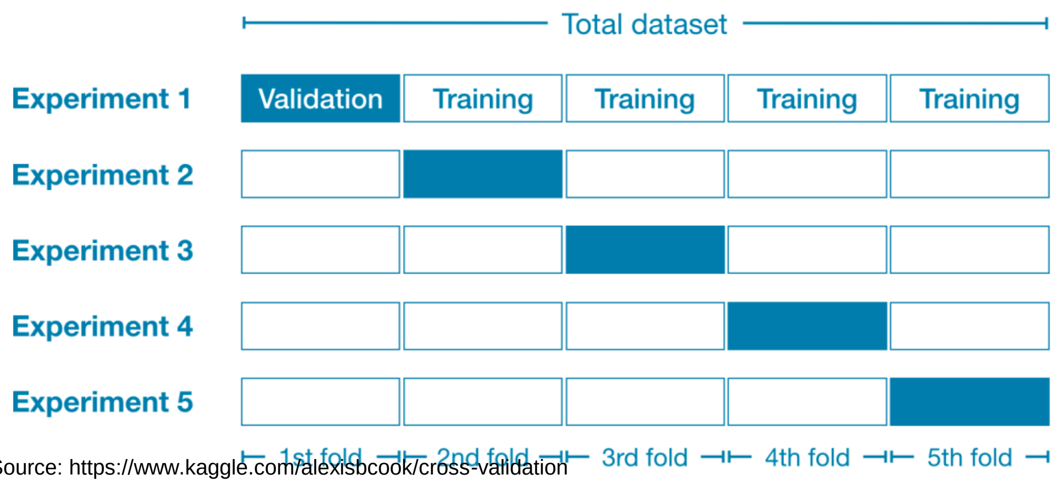
SPLITTING DATA

- Slice data into three subsets: Training, validation and test data

- Make sure that your subsets meet the following conditions:
  - Large enough to yield statistically meaningful results.
  - Representative of the data set as a whole.
    E.g. don't pick a test set with different characteristics than the training set.

CROSS-VALIDATION

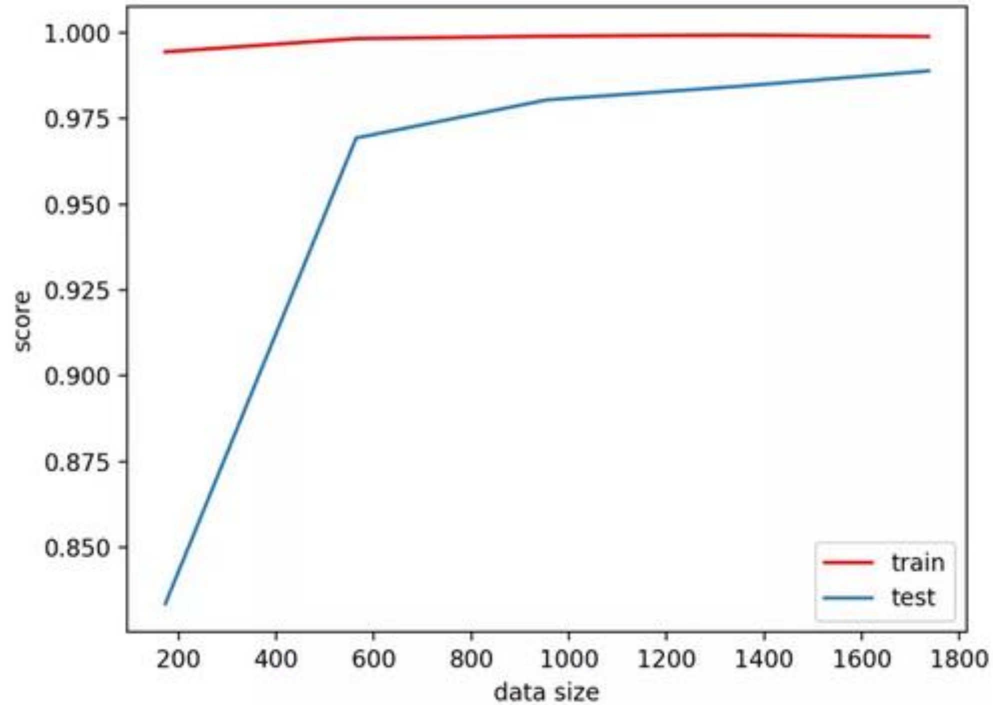
- Estimate of a model's generalization performance
- Break the data into folds



Source: https://www.kaggle.com/alexisbcook/cross-validation

- For small datasets, where extra computational burden isn't a big deal, you should run cross-validation.

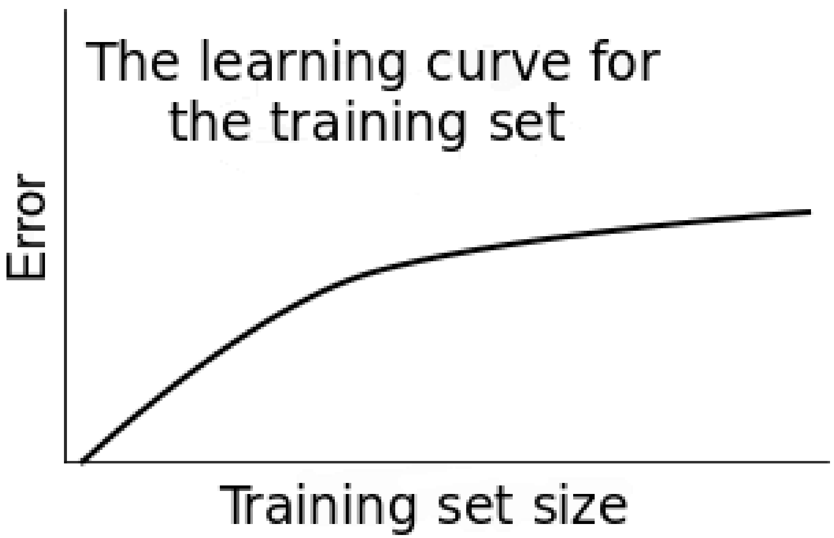
LEARNING CURVES

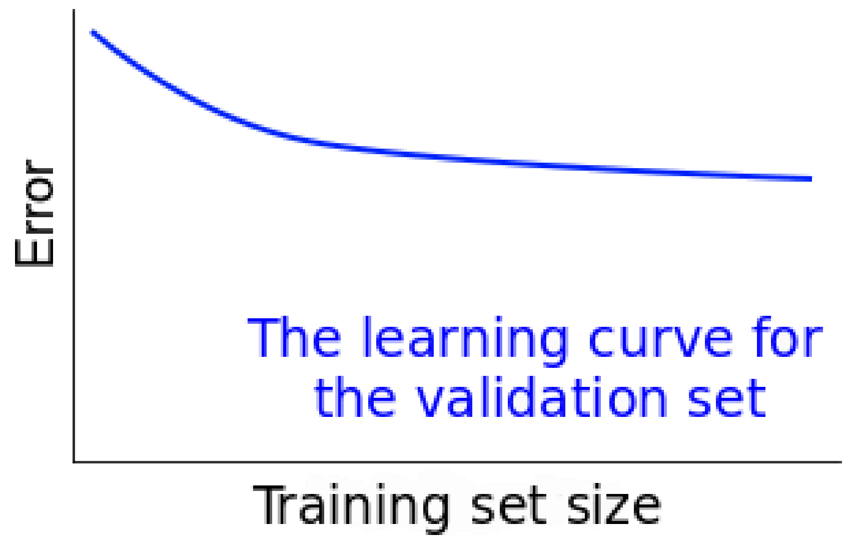



```
from sklearn.model_selection import learning_cu
from sklearn.svm import SVC
from sklearn.datasets import load_digits
from matplotlib import pyplot as plt
import numpy as np

X, y = load_digits(return_X_y=True)
estimator = SVC(gamma=0.001)

train_sizes, train_scores, test_scores, fit_times, _ = learning_curve(estimator, X, y, cv=30,return_times=True)

plt.plot(train_sizes,np.mean(train_scores,axis=1))
```

LEARNING CURVES

- Cost as a function of the training set size (or the training iteration)
- Examine evolution of train and validation learning curves

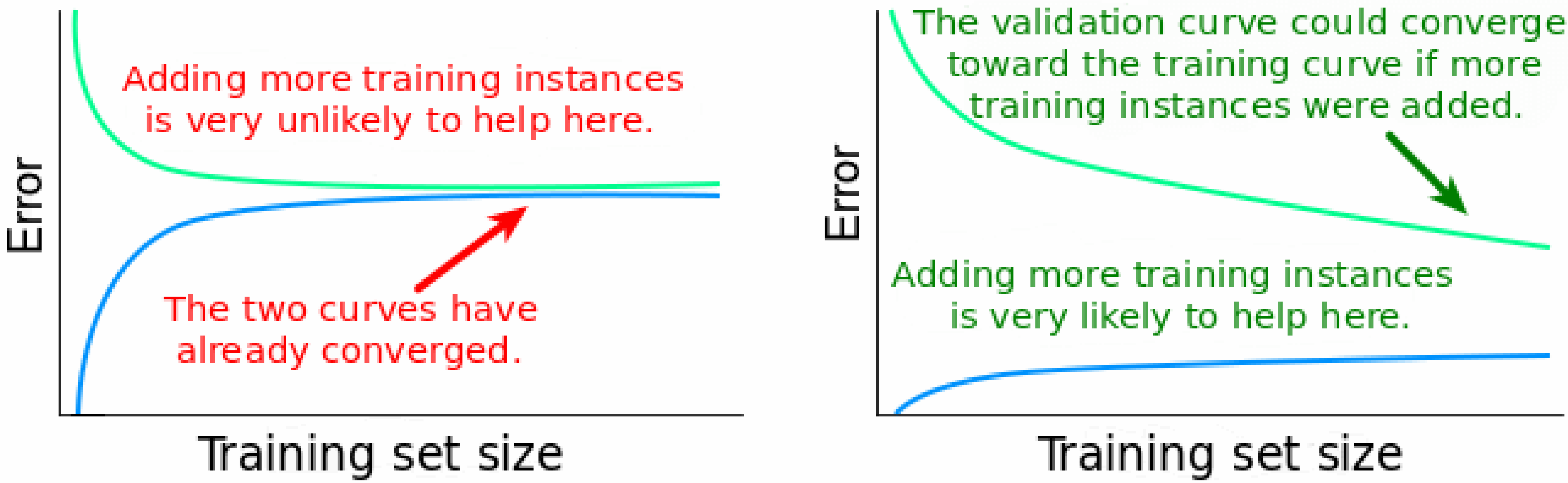




Source: https://www.dataquest.io/blog/learning-curves-machine-learning/

LEARNING CURVES

- Convergence of curves
- Diagnose generalization problems



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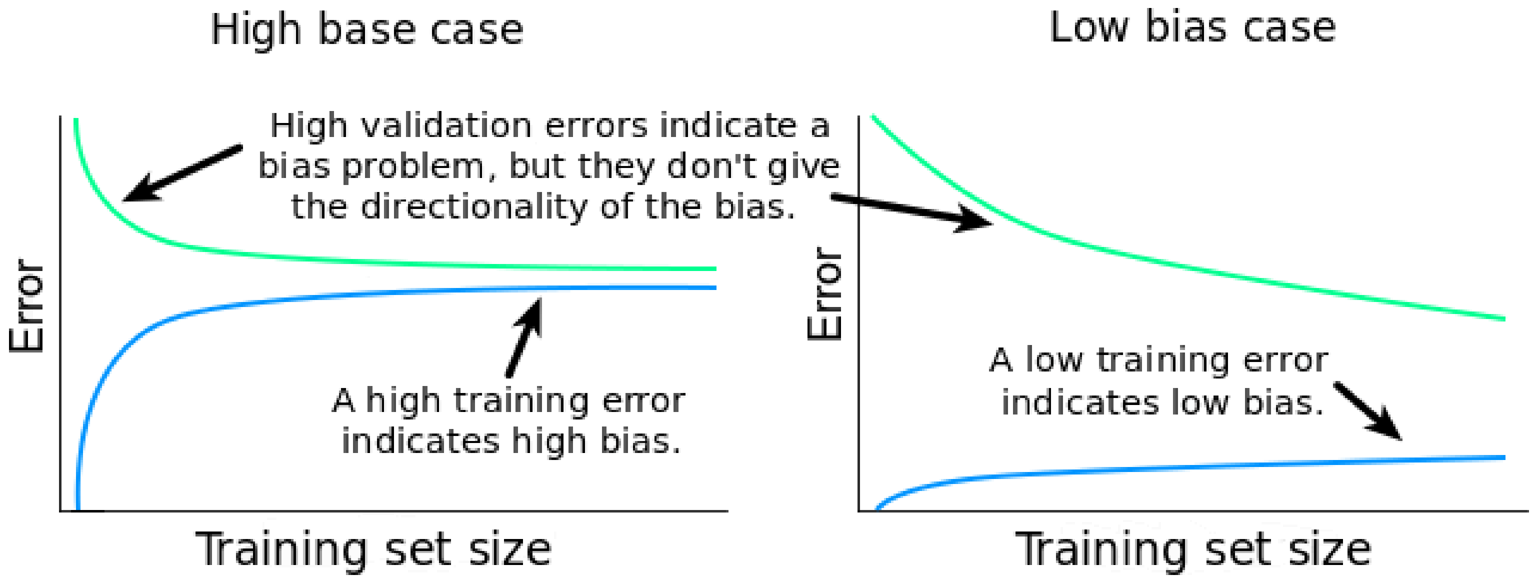
BIAS PROBLEM

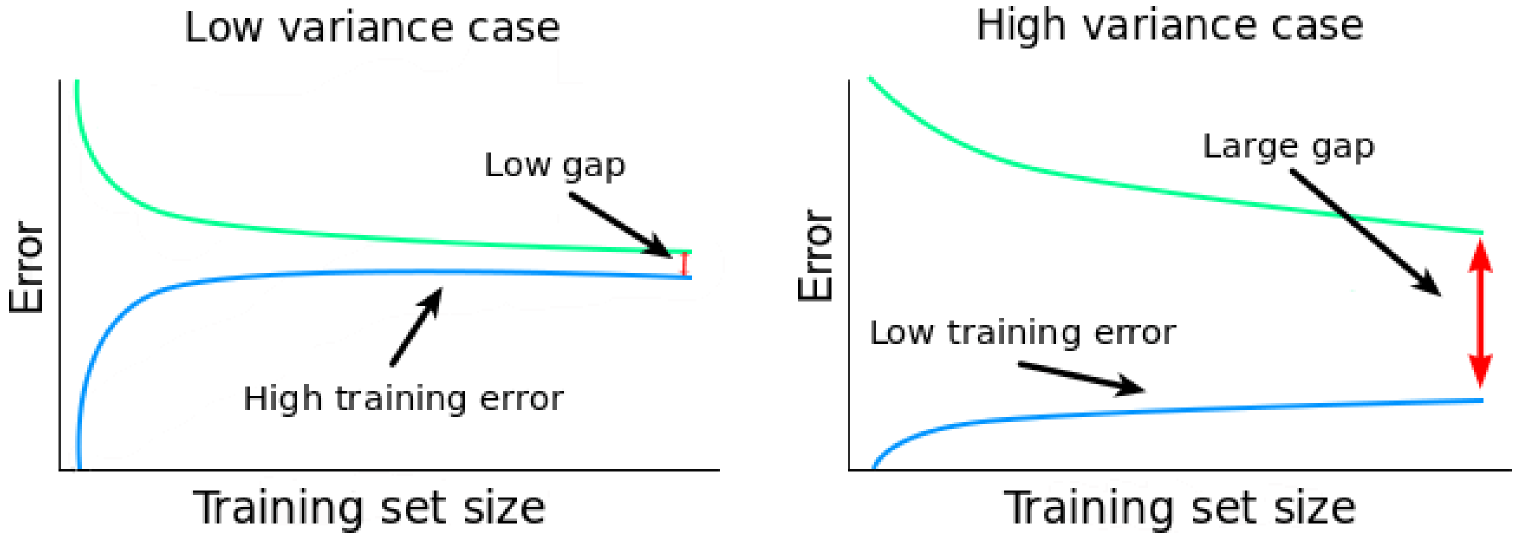
- High validation error indicates a prediction bias problem
- Underfitting usually gives high bias



Source: https://www.dataquest.io/blog/learning-curves-machine-learning/

VARIANCE PROBLEM

- Low gap indicates low prediction variance
- Overfitting usually gives high variance



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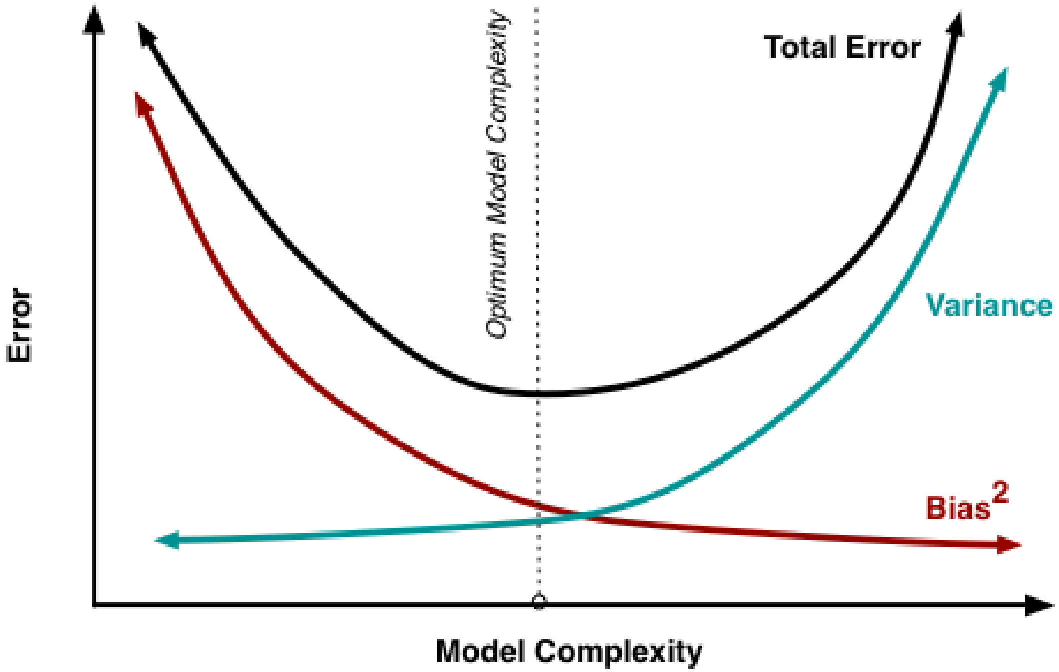
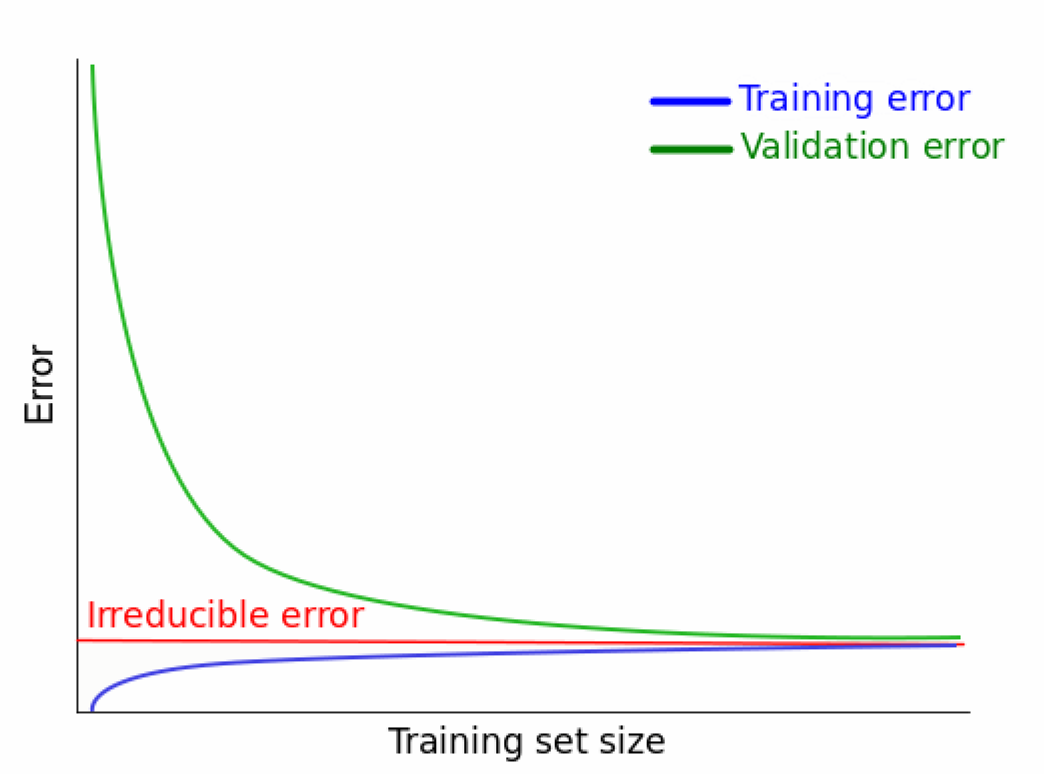
PREDICTION BIAS–VARIANCE TRADEOFF

- Central problem in supervised learning



IRREDUCIBLE ERROR

- Noise
- Cannot be predicted
- Loss cannot be reduced



Source: https://www.dataquest.io/blog/learning-curves-machine-learning/

MORE ON PREDICTION BIAS

- Average of predictions ≈ average of labels in test set
- A significant difference shows there is bias
- Possible causes:
  - Underfitting, e.g. incomplete feature set, overly strong regularization
  - Biased training samples
  - (Noisy data set)

QUESTION

- We know that on average, 1% of all emails are spam.

- My spam filter predicts that 20% of my incoming mail is spam.

What can we say about my spam filter?

COMPUTING CROSS-VALIDATED METRICS

- Predefined scoring parameters

Scoring	Function	Comment
Classification		
'accuracy'	`metrics.accuracy_score`	
'balanced_accuracy'	`metrics.balanced_accuracy_score`	
'average_precision'	`metrics.average_precision_score`	
'neg_brier_score'	`metrics.brier_score_loss`	
'f1'	`metrics.f1_score`	for binary targets
'f1_micro'	`metrics.f1_score`	micro-averaged
'f1_macro'	`metrics.f1_score`	macro-averaged
'f1_weighted'	`metrics.f1_score`	weighted average
'f1_samples'	`metrics.f1_score`	by multilabel sample
'neg_log_loss'	`metrics.log_loss`	requires `predict_proba` support
'precision' etc.	`metrics.precision_score`	suffixes apply as with 'f1'
'recall' etc.	`metrics.recall_score`	suffixes apply as with 'f1'
'jaccard' etc.	`metrics.jaccard_score`	suffixes apply as with 'f1'
'roc_auc'	`metrics.roc_auc_score`	
'roc_auc_ovr'	`metrics.roc_auc_score`	

See: https://scikit-learn.org/stable/modules/model_evaluation.html