Evaluation of Classification Models

Data Science Dojo

Agenda

- Evaluation of Classification Models
  - Confusion Matrix
  - Accuracy, Precision, Recall, F1 measure
- Building Robust Machine Learning Models
  - Bias/Variance Tradeoff
- Methods of Evaluation
  - Cross Validation
  - ROC Curve

The Limitations of Accuracy

- Consider a 2-class problem:
  - Number of Class 0 examples = 9990
  - Number of Class 1 examples = 10
- If the model predicts everything to be class 0, accuracy is 9990/10000 = 99.9 %
  - Accuracy is misleading!

METRICS FOR EVALUATION

Confusion Matrix

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a	b
	Class=No	c	d

a: TP (true positive)

b: FN (false negative)

c: FP (false positive)

d: TN (true negative)

Confusion Matrix

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a (TP)	b (FN)
	Class=No	c (FP)	d (TN)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{a + d}{a + b + c + d}$$

Precision

$$p = \frac{TP}{TP + FP} = \frac{a}{a + c}$$

	PREDICTED CLASS		
		Class=Yes	Class=No
ACTUAL CLASS	Class=Yes	a (TP)	b (FN)
	Class=No	c (FP)	d (TN)

Recall/Sensitivity

$$r = \frac{TP}{TP + FN} = \frac{a}{a + b}$$

	PREDICTED CLASS		
		Class=Yes	Class=No
ACTUAL CLASS	Class=Yes	a (TP)	b (FN)
	Class=No	c (FP)	d (TN)

F1-Score

$$F1 = \frac{2rp}{r+p} = \frac{2a}{2a+b+c}$$

Harmonic mean of precision and recall

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a (TP)	b (FN)
	Class=No	c (FP)	d (TN)

WILL MY MODEL BETRAY ME?

Is My Model Really Good?

- My model shows an accuracy of 90% in the **training environment**
- Would the model be 90% accurate in **production environment**?

Generalization

- A machine learning model should be able to handle any data set coming from the same distribution as the training set.
- **Generalization** refers to a models ability to handle any random variations of training data

Overfitting (Lack of generalization)

- The gravest and most common sin of machine learning
- Overfitting: learning so much from your data that you memorize it.
  - You do well on training data
  - But don't do well (or even fail miserably) on test data

Perils of Overfitting

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Perils of #overfitting @kaggle restaurant revenue prediction Pos 1 drops to 2041 in final ranking.

2041	↑7	Cheng Jiang
2042	↓2041	BAYZ, M.D.
2043	↓81	Alberto

Train/Test partition is not enough

Labelled Data

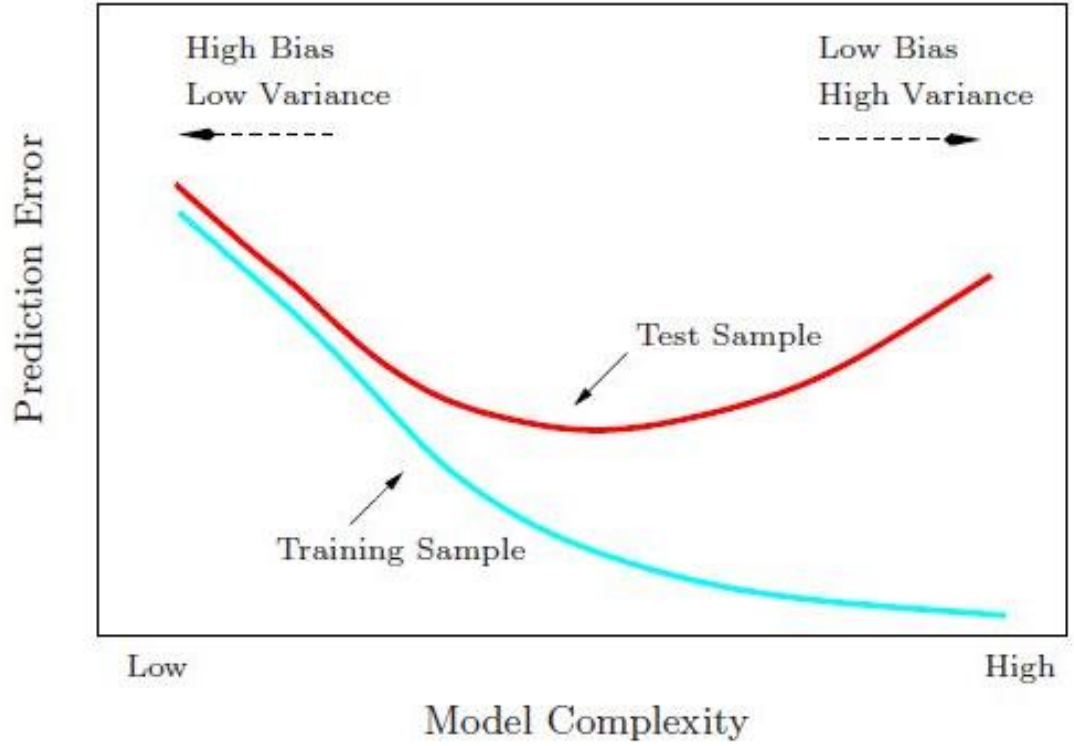
Training Data	Blind Holdout Data

70%	30%

Blind Holdout Dataset

- The person building the model has no access to the blind holdout data set
  - Why do we need to lock it away?
- Even in presence of a 70/30 split, you may end up with a model that is not **generalized**

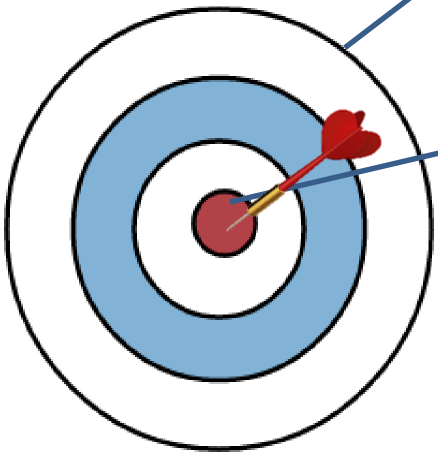
Bias/Variance Tradeoff



You can beat your data to confession

The generation of random numbers is too important to be left to chance.

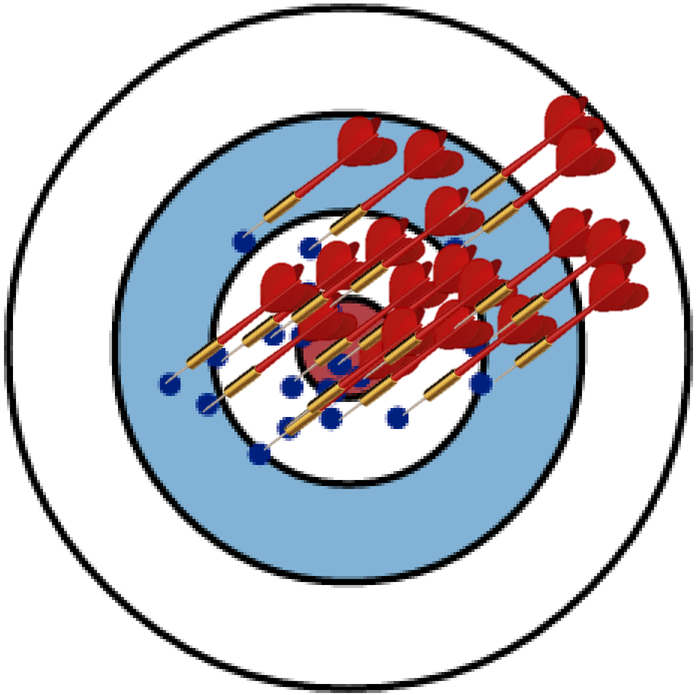
Bias/Variance Trade-off



Each dartboard represents a model

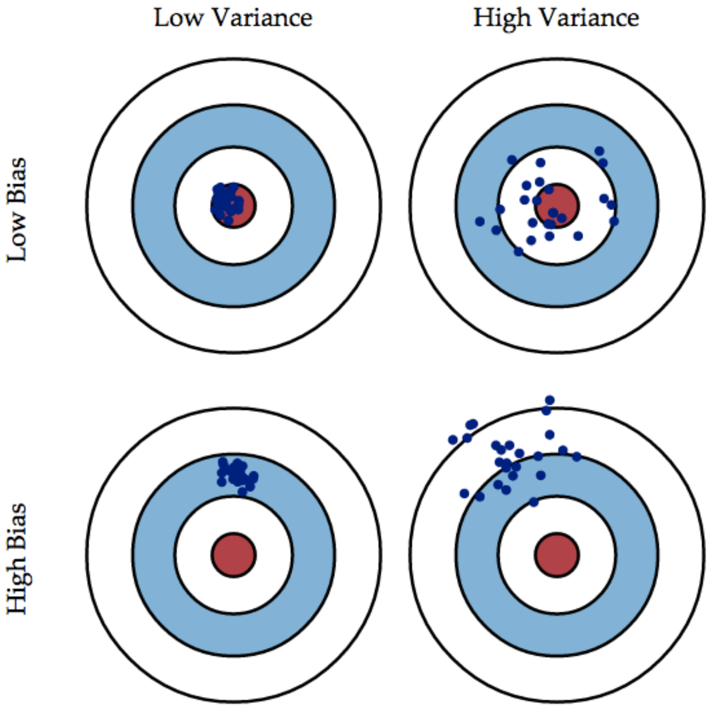
Bullseye is the theoretical best performance (accuracy, precision, recall or something else)

Bias/Variance Trade-off



- Test your model on several variations of the dataset
- Each dot represents a random variation of the test data set

Bias/Variance Trade-off



METHODS OF EVALUATION

Cross validation

- Split data into k disjoint partitions
- Train on k-1 partitions and test on 1
- Repeat k times

Cross validation (k=10)

Holdout Set

- 70% for training, 30% for testing
- 60/40 or 50/50 also possible
- Repeated holdout: Apply 70/30, 60/40 or 50/50 many times.

Stratified Sampling

- Use when class distribution is skewed
- Ensures that all partitions have fixed ratio of classes
  - Same ratio as training set
  - If training set is 5% class 1, 95% class 2, so is each partition

ROC CURVE

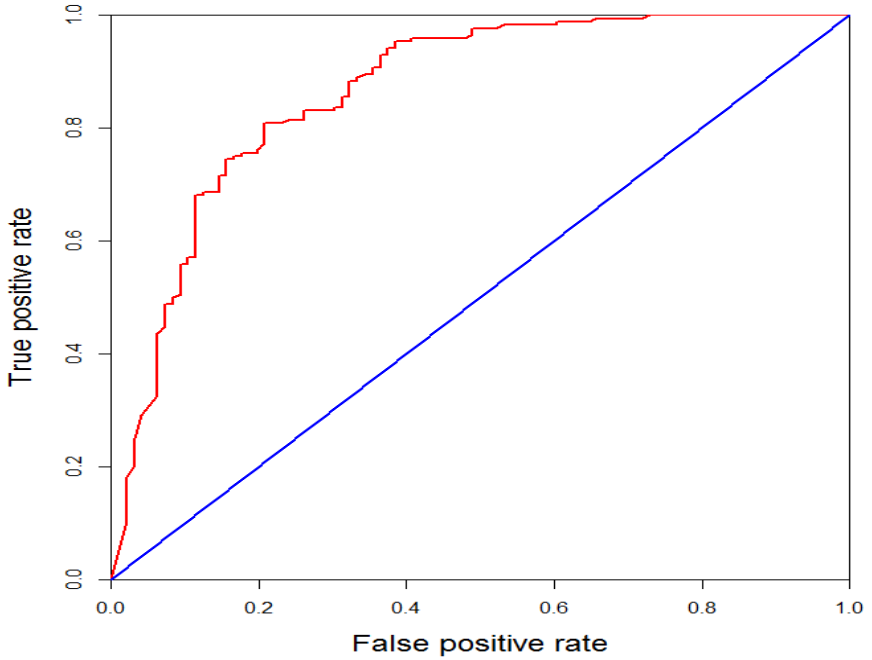
Controlling Precision and Recall

- What if probabilities are reported?
- Threshold
  - The probability value which separates positive predictions from negative predictions
  - Adjusts class label metrics

Pid	Prediction	T=0.5	T=0.25	T=0.75
2	.95	Survived	Survived	Survived
3	.86	Survived	Survived	Survived
5	.02	Dead	Dead	Dead
7	.15	Dead	Dead	Dead
13	.48	Dead	Survived	Dead
14	.35	Dead	Survived	Dead
21	.12	Dead	Dead	Dead
24	.01	Dead	Dead	Dead
34	.74	Survived	Survived	Dead
54	.63	Survived	Survived	Dead

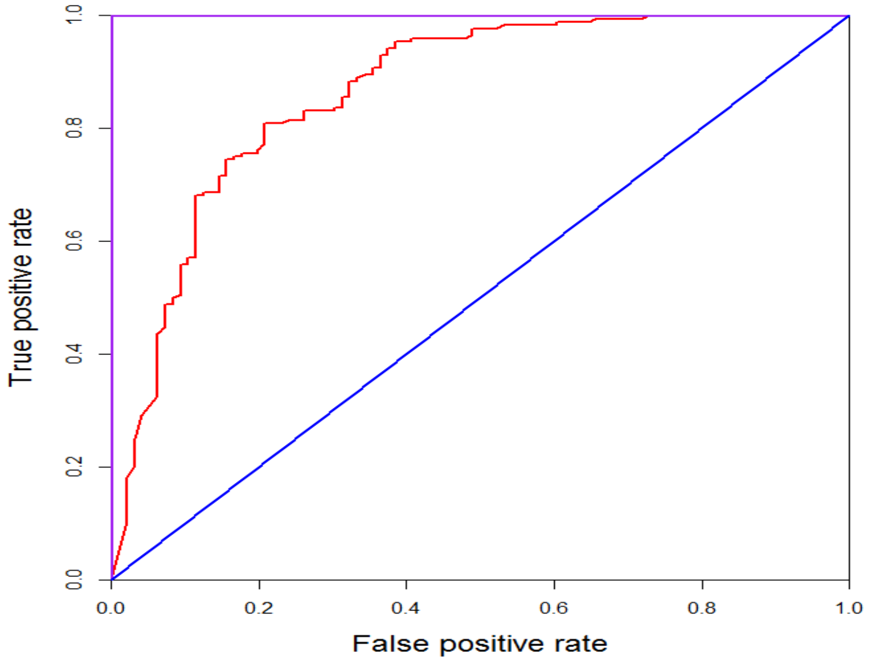
ROC(Receiver Operating Characteristic)

- Developed to analyze noisy signals
- TP on the y-axis vs FP on the x-axis
- Plot points for different threshold values
- Curve represents quality of model *independent* of threshold



ROC Curve

- Ideal curve (purple)
  - 100% True Positives
  - 0% False Positives
- Random chance (blue)
  - Worst case
- Below diagonal line?
  - Prediction is opposite of the true class



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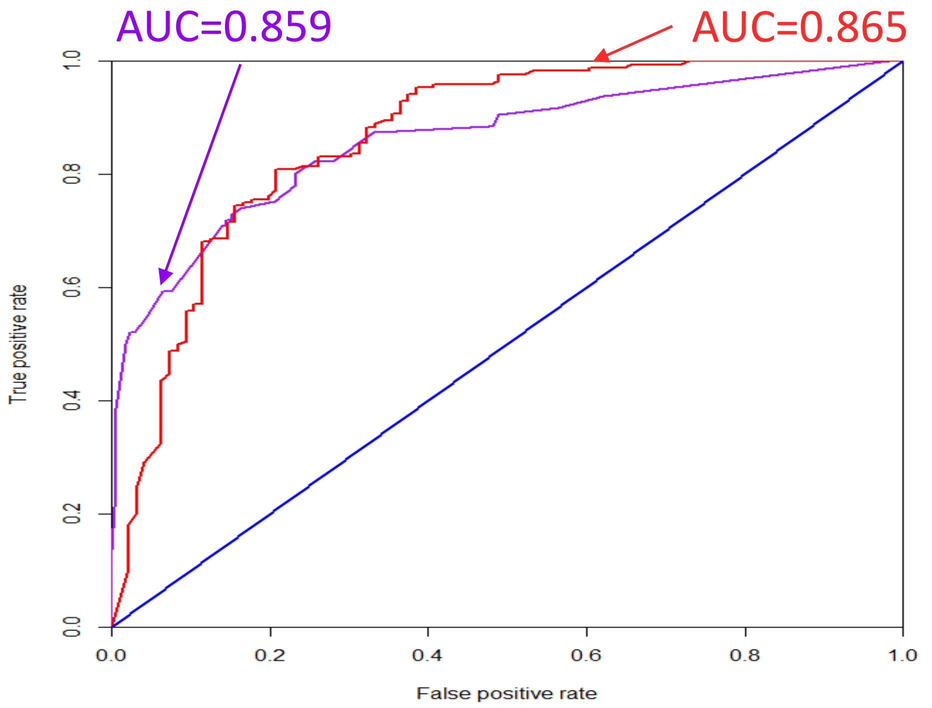
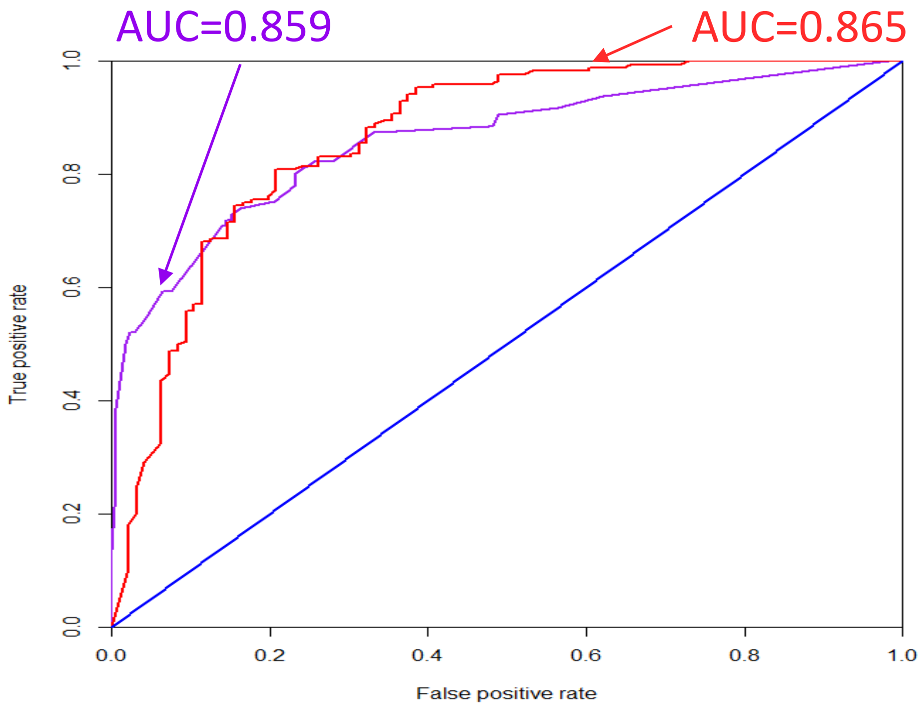
Using ROC for Model Comparison



- No model consistently outperforms the other
  - Purple is better at low thresholds
  - Red is better at high thresholds
- Area Under ROC Curve (AUC)
  - Calculate the area under the curves
  - Compare models directly

Using ROC for Model Comparison



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TPR vs FPR

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a (TP)	b (FN)
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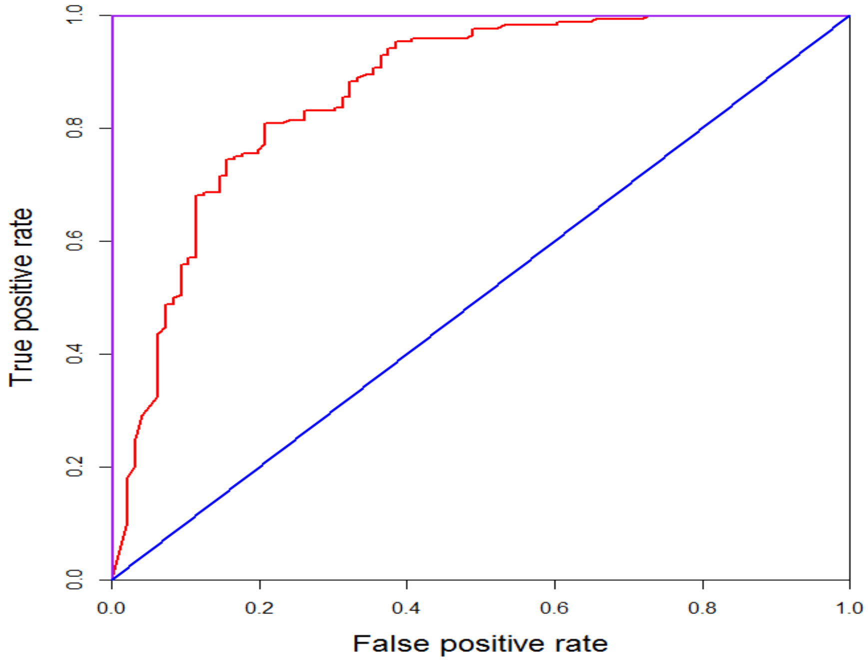
$$True\ Positive\ Rate = \frac{TP}{TP + FN}$$

$$False\ Positive\ Rate = \frac{FP}{FP + TN}$$

- Sensitivity is also called “sensitivity” or “recall”
- Specificity is also called “specificity” or “false alarm ratio”

TPR vs FPR



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$$False\ Positive\ Rate = \frac{FP}{FP + TN}$$

QUESTIONS