Programming with Data Bootcamp: Lecture 5

Slides courtesy of Sam Madden / Tim Kraska (6.S079)

Key ideas:

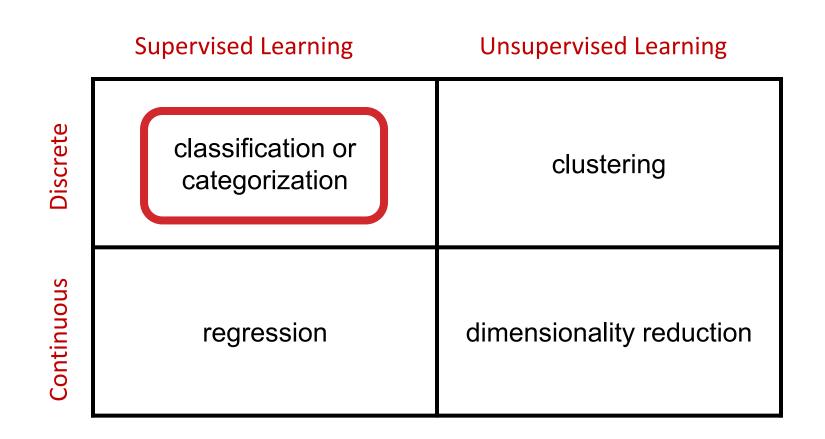
Traditional ML

- Clustering
- Dim. Reduction
- Classification
- Regression

http://dsg.csail.mit.edu/6.S079/



MACHINE LEARNING PROBLEMS



Machine Learnin



What if you model has an high error?

- Try getting more training examples
- Try smaller sets of features
- Try getting additional features
- Try creating features from existing features (kernels)
- Try decrease regularization
- Try increase regularization

What Error/Quality Metric to use?

Classification:

- Accuracy
- F-score
- F1-micro
- F1-macro
- ROC AUC (micro, macro)
- •

Regression

- Mean-Squared Error
- Root-Mean Squared Error
- Mean absolute Error
- \bullet R²
- Cohen Kappa
- ..

Precision, Recall, Accuracy

	True	False
True	tp	fp
False	fn	tn

- Precision: correctly identified positive cases
 Precision P = tp/(tp + fp)
- **Recall**: correctly identified positive cases from all the actual positive cases.

Recall
$$R = tp/(tp + fn)$$

Accuracy: measure of all the correctly identified cases
 Accuracy R = (tp+tn)/(tp + fp + fn + tn)

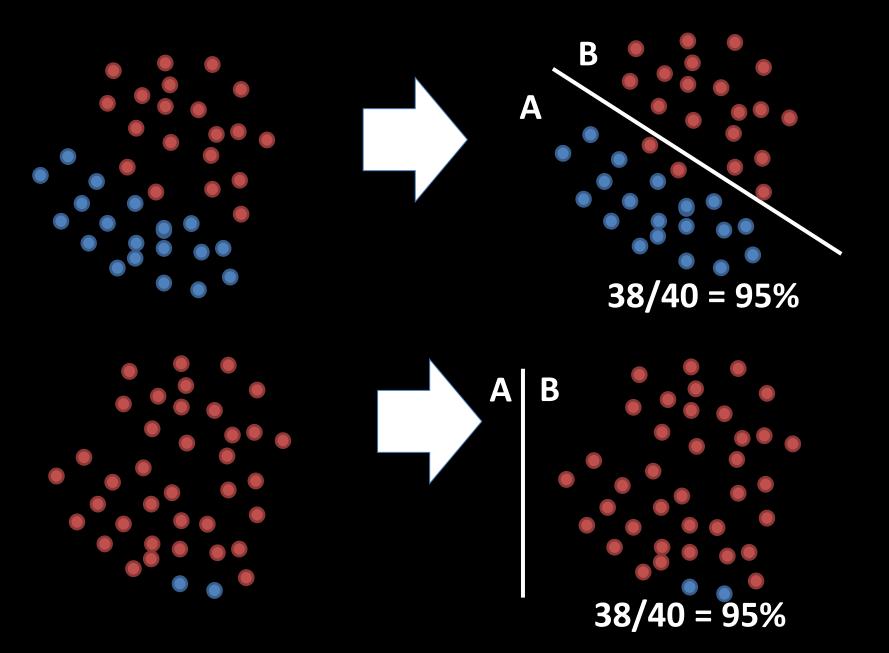
Evaluation: Accuracy isn't always enough

How do you interpret 90% accuracy?

Evaluation: Accuracy isn't always enough

- How do you interpret 90% accuracy?
 - You can't; it depends on the problem
- Need a baseline:
 - Base Rate
 - Accuracy of trivially predicting the most-frequent class
 - Random Rate
 - Accuracy of making a random class assignment
 - Might apply prior knowledge to assign random distribution
 - Naïve Rate
 - Accuracy of some simple default or pre-existing model
 - Ex: "All females survived"

Why Optimize? Pitfalls



What Error/Quality Metric to use?

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Precision, Recall, Accuracy

		True Label	
		True	False
Predicted Label	True	tp	fp
	False	fn	tn

- Precision: correctly identified positive cases
 Precision P = tp/(tp + fp)
- Recall: correctly identified positive cases from all the actual positive cases.

Recall
$$R = tp/(tp + fn)$$

F-Score: is the harmonic mean of precision and recall

$$F = \frac{2}{\frac{1}{R} + \frac{1}{P}} = \frac{tp}{tp + \frac{1}{2}(fp + fn)}$$

F1 Micro

		True Label		
		L1	L2	L3
Predicted Label	L1	7	1	4
	L2	0	1	12
	L3	1	6	6

Precision micro: true positives for all the classes divided by the all positive predictions $\frac{1}{2}$ Precision Score Micro = $\frac{1}{2}$ (TP + FP)

$$TP = (7 + 1 + 6)$$

 $FP = 1 + 4 + 0 + 12 + 1 + 6$

Recall micro: Sum of true positives for all the classes divided by the actual positives.

Recall Score Micro: TP / (TP + FN)

F1 Score:
$$\frac{tp}{tp + \frac{1}{2}(fp + fn)}$$

F1 Macro

		True Label		
		L1	L2	L3
Predicted Label	L1	7	1	4
	L2	0	1	12
	L3	1	6	6

Precision micro: arithmetic mean of all the precision scores of different classes Precision Score Macro = ((7/8) + (1/8) + (6/22))/3

Recall micro: arithmetic mean of all the recall scores.

When to use F1 Micro and when to use F1 Macro?

F1 Macro

		True Label		
		L1	L2	L3
Predicted Label	L1	7	1	4
	L2	0	1	12
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Precision micro: arithmetic mean of all the precision scores of different classes Precision Score Macro = ((7/8) + (1/8) + (6/22))/3

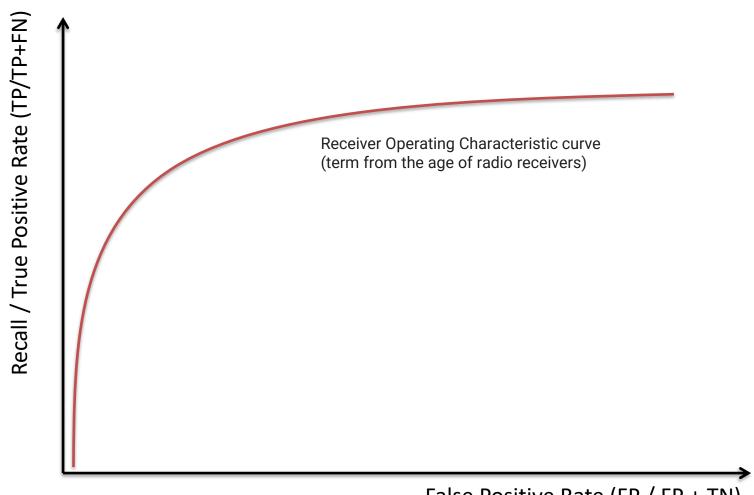
Recall micro: arithmetic mean of all the recall scores.

When to use F1 Micro and when to use F1 Macro?

- Micro weights each instance or prediction equally.
- Macro weights each class equally (better for imbalance of labels)
- Use weighted macro-averaging score in case of class imbalances (different number of instances related to different class labels).

ROC AUC

(usually used for models with a threshold)

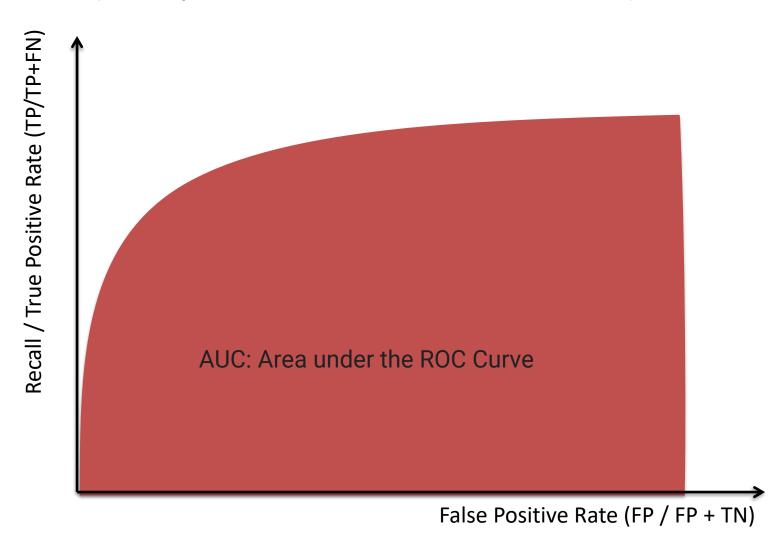


False Positive Rate (FP / FP + TN)

What would be the ideal ROC curve? How would a random guess look like

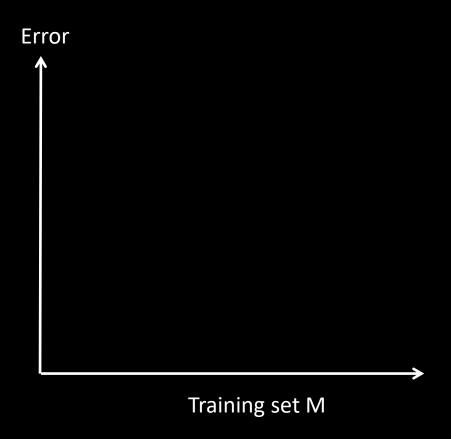
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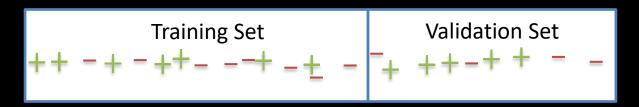


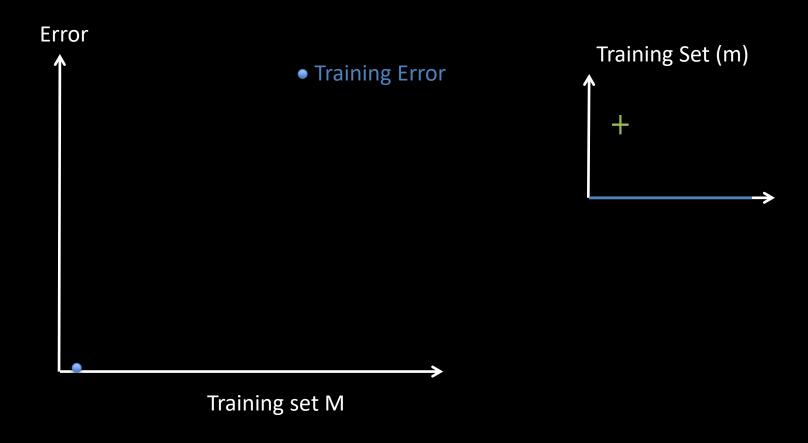
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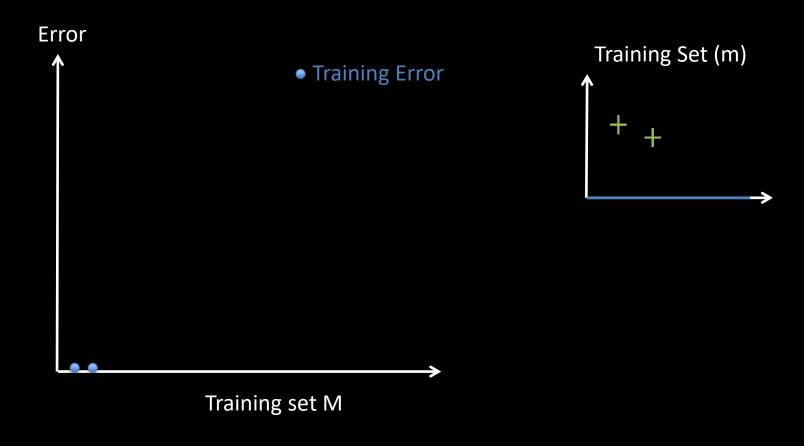




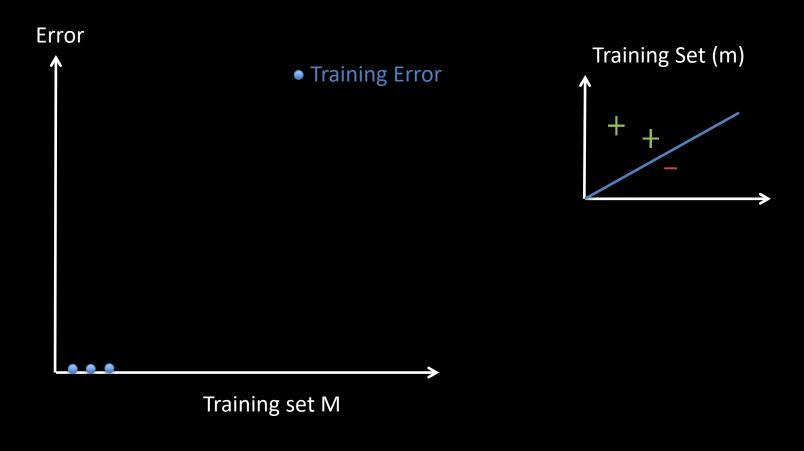


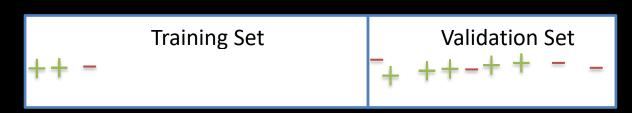






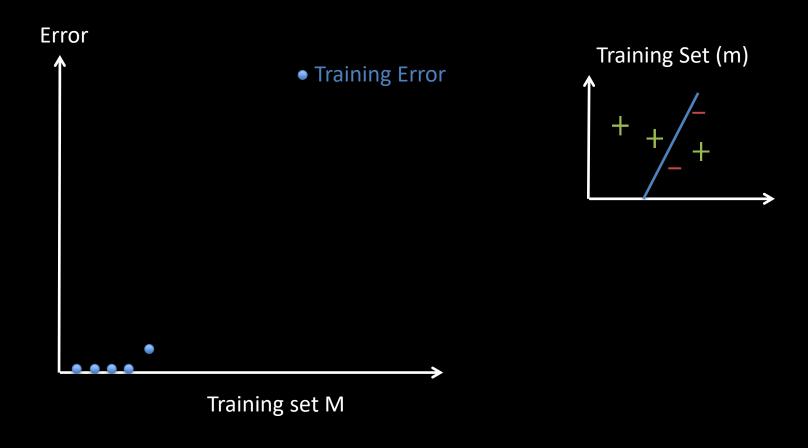










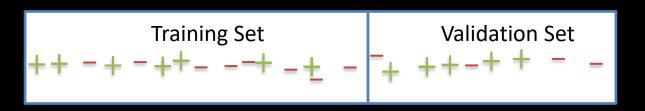












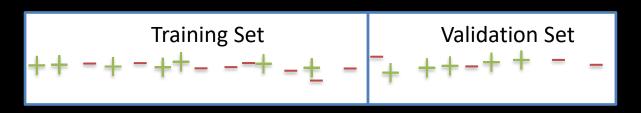




Clicker:

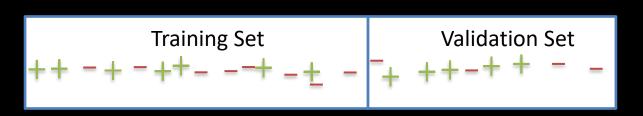
Test error

- a) decreases with M
- b) increases with M
- c) stays constant









High Bias



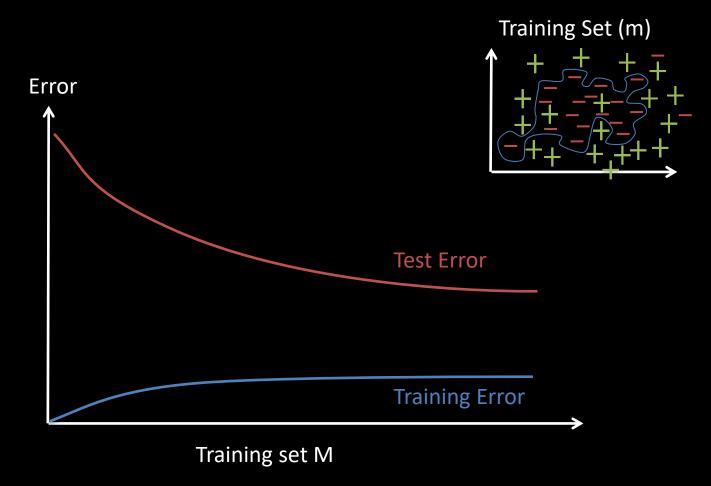
High Bias



Clicker: If you have high-bias, does more data help?

- a) No
- b) Yes

High Variance



Clicker: If you have high-variance, does more data help?

- a) No
- b) Yes

- 1. Get more training examples
- 2. Try smaller sets of features
- 3. Try getting additional features
- 4. Try adding polynomial features (kernels)
- 5. Try increase regularization
- 6. Try decrease regularization

- A. High Variance
- B. High Bias
- C. Both
- D. None

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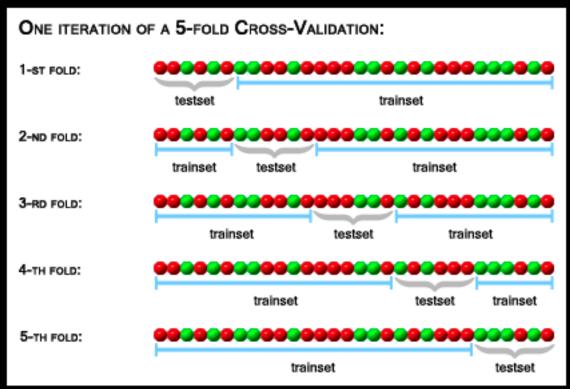
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Cross-validation

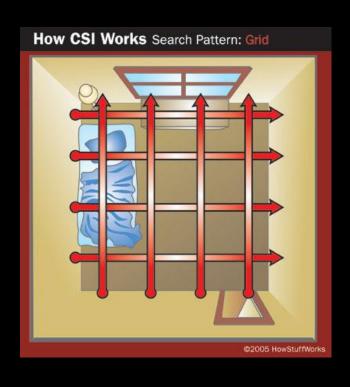
k-fold: split the data into k groups, train on every group except for one, which you test on.

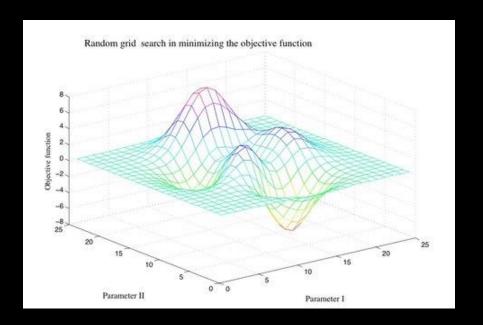
Repeat for all groups



Parameter Tuning

Grid Search





Can we use sampling?

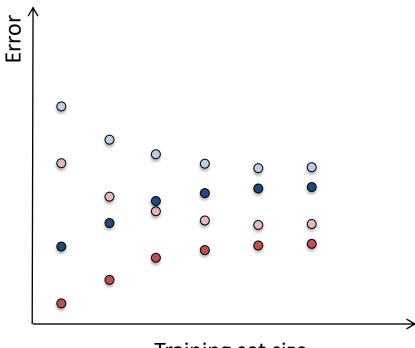
Algorithm 1:

Training

Validation

Algorithm 2:

Training



Can we use sampling?

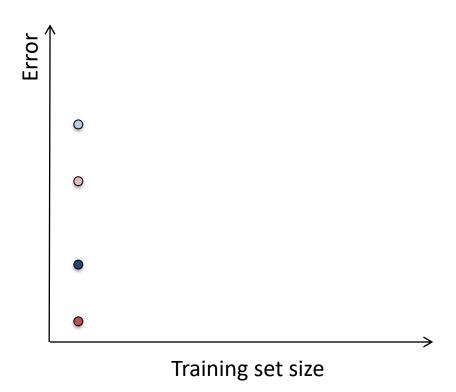
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Can we use sampling?

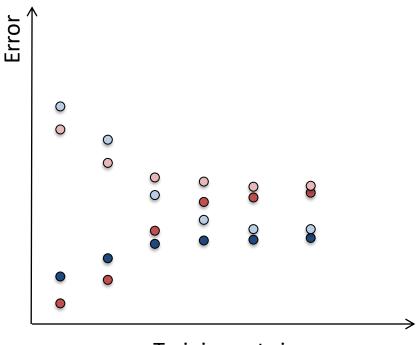
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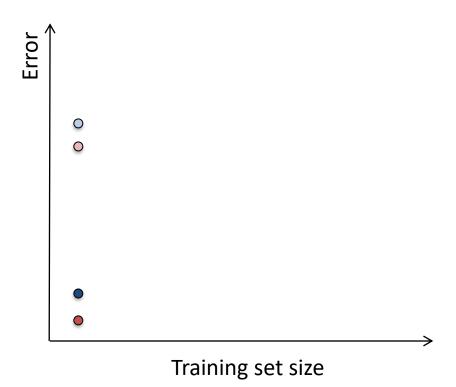
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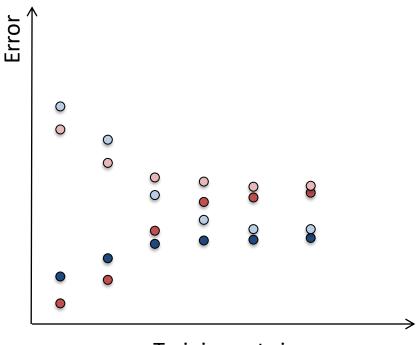
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Can we use sampling?

Algorithm 1:

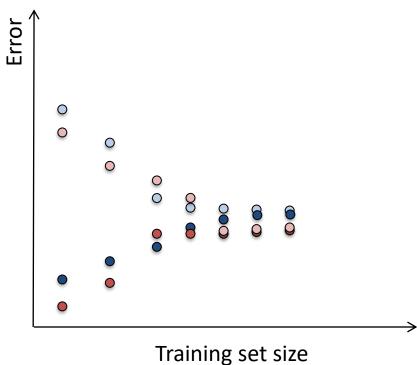
Training

Validation

Algorithm 2:

Training

Validation



Irailling set size

Can we prune now?

Can we use sampling?

Algorithm 1:

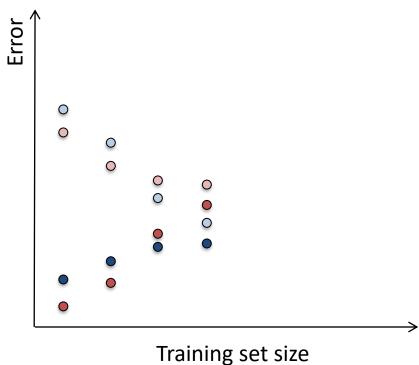
Training

Validation

Algorithm 2:

Training

Validation



Algorithm 1 training error > Algorithm 2 validation error