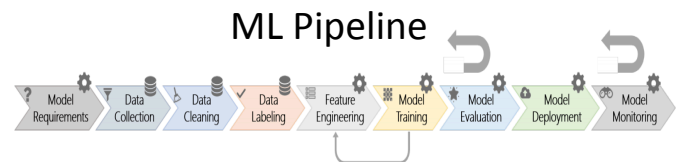


Week 3: ML Pipeline



- **Data Preparation and Feature Engineering**
 - Create new feature column with attribute combinations
 - Feature imputation
 - Process categorical feature. E.g. 1-hot encoding
 - Feature transformation. E.g. Standardization
 - Create feature process pipeline
 - Prepare training set: Stratified Sampling v.s. Random Sampling
- **Model Selection/Evaluation**
 - Cross validation
 - Hyper-parameter Tuning
 - Fine tune the model. E.g. GridSearchCV

1

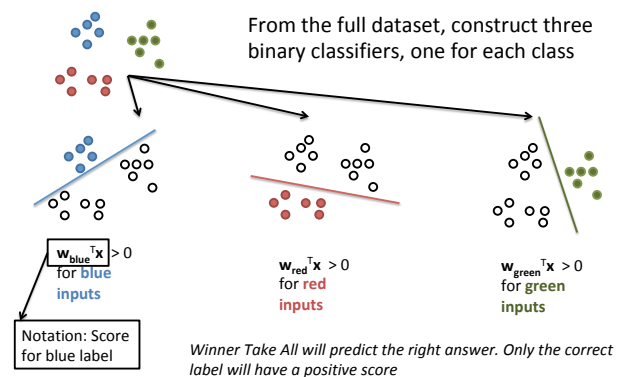
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What we have learnt so far

- **Data Preparation**
feature scaling, stratified sampling
Prepare training set and test set
- **Model Selection:**
Binary classification models: Perceptron and Adaline
Both are linear models
- **Model Evaluation:**
Accuracy score: how many the classifier got it right

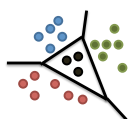
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One-Vs-Rest: Multi-class classification



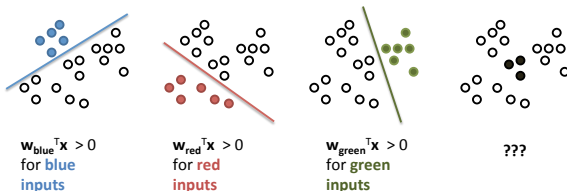
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One-Vs-Rest may not always work



Black points are not separable with a single binary classifier

The decomposition will not work for these cases!



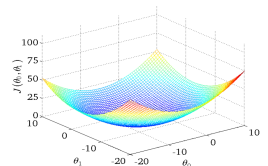
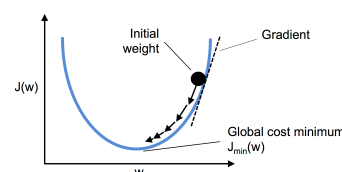
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Gradient Descent Revisit

An optimization algorithm used for finding the weights (or coefficients) of machine learning algorithms.

Cost Function for Adaline: Sum of Squared Errors

$$J(\mathbf{w}) = \frac{1}{2} \sum_i (y^{(i)} - \phi(z^{(i)}))^2$$



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Stochastic Gradient Descent

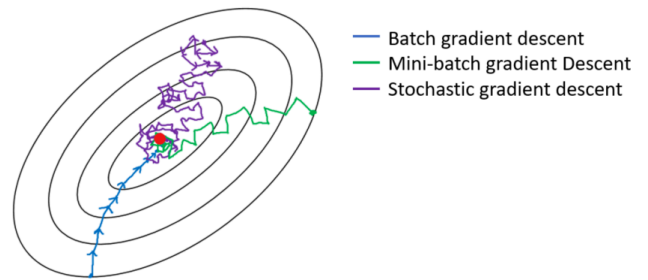
$$\Delta \mathbf{w} = \eta \sum_i \left(y^{(i)} - \phi(z^{(i)}) \right) \mathbf{x}^{(i)}$$

$$\approx \eta \left(y^{(i)} - \phi(z^{(i)}) \right) \mathbf{x}^{(i)}$$

- Enables inexpensive evaluations of the sum-function and the sum gradient (an approximation)
- Adjust weights with each sample
- Samples are selected randomly & re-shuffle the training set for every epoch.

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Mini-Batch Gradient Descent



The **batch size** is a hyper-parameter of that controls the number of training samples in each iteration of weight update

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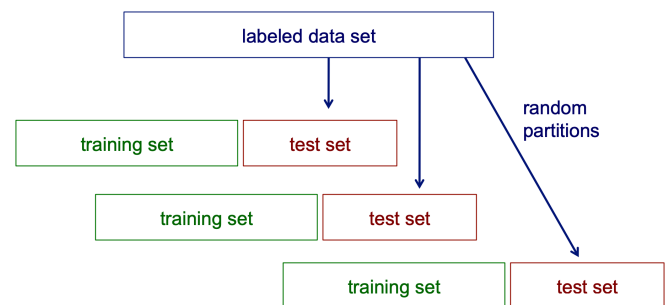
Model Evaluation

Limitation of using a single training/test partition:

- May not have enough data
- A single training set doesn't tell us how sensitive accuracy is to a particular training sample.

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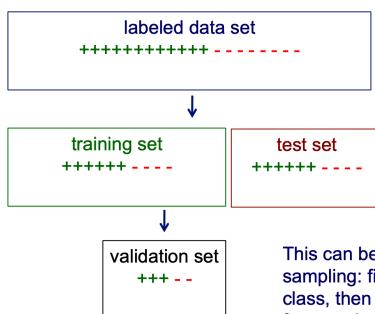
Random Partitions



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Stratified Sampling

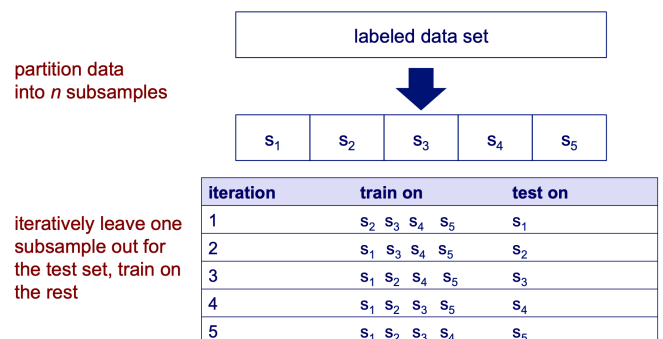
When randomly selecting training or validation sets, we may want to ensure that class proportions are maintained in each selected set



This can be done via stratified sampling: first stratify instances by class, then randomly select instances from each class proportionally.

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Cross Validation



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Performance Evaluation

- **Accuracy:** the measure as the percentage of predicted results that match the expected results.
- But...

Cross Validation - Example

Suppose we have 100 instances, and we want to estimate accuracy with cross validation

iteration	train on	test on	correct
1	s ₂ s ₃ s ₄ s ₅	s ₁	11 / 20
2	s ₁ s ₃ s ₄ s ₅	s ₂	17 / 20
3	s ₁ s ₂ s ₄ s ₅	s ₃	16 / 20
4	s ₁ s ₂ s ₃ s ₅	s ₄	13 / 20
5	s ₁ s ₂ s ₃ s ₄	s ₅	16 / 20

accuracy = 73/100 = 73%

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Confusion Matrix

		actual class	
		positive	negative
predicted class	positive	true positives (TP)	false positives (FP)
	negative	false negatives (FN)	true negatives (TN)

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

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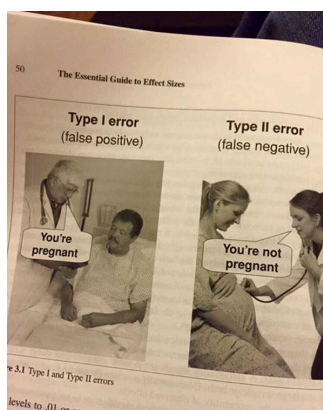
Performance Evaluation

- **Precision:** the measure of the proportion of positive predictions was actually correct.
precision = $TP / (TP + FP)$
- **Recall (Sensitivity):** the measure of the proportion of actual positives was identified correctly.
recall = $TP / (TP + FN)$

To fully evaluate the effectiveness of a model, must examine both precision and recall, but these two measure are often in tension.

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Type I & Type II Errors



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