Model Selection, Evaluation Metrics, and Learning from Imbalanced Data

Piyush Rai

Introduction to Machine Learning (CS771A)

November 1, 2018

Yet to come..

- Today: Model Selection, Evaluation, Learning from Imbalanced Data
- Reinforcement Learning
- Ensemble methods (e.g., boosting)
- Learning with time series data
- Learning with limited supervision, other practical aspects (e.g., debugging ML algorithms)

Model Selection

What is Model Selection?

Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

What is Model Selection?

Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

- Instances of same model with different complexities or hyperparams. E.g.,

What is Model Selection?

Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

- Instances of same model with different complexities or hyperparams. E.g.,
    - K-Nearest Neighbors: Different choices of K

What is Model Selection?

Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

- Instances of same model with different complexities or hyperparams. E.g.,
  - K-Nearest Neighbors: Different choices of K
  - Decision Trees: Different choices of the number of levels/leaves

What is Model Selection?

Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

- Instances of same model with different complexities or hyperparams. E.g.,
  - K-Nearest Neighbors: Different choices of K
  - Decision Trees: Different choices of the number of levels/leaves
  - Polynomial Regression: Polynomials with different degrees

What is Model Selection?

Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

- Instances of same model with different complexities or hyperparams. E.g.,
  - K-Nearest Neighbors: Different choices of K
  - Decision Trees: Different choices of the number of levels/leaves
  - Polynomial Regression: Polynomials with different degrees
  - Kernel Methods: Different choices of kernels

What is Model Selection?

Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

- Instances of same model with different complexities or hyperparams. E.g.,
  - K-Nearest Neighbors: Different choices of K
  - Decision Trees: Different choices of the number of levels/leaves
  - Polynomial Regression: Polynomials with different degrees
  - Kernel Methods: Different choices of kernels
  - Regularized Models: Different choices of the regularization hyperparameter

What is Model Selection?

Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

- Instances of same model with different complexities or hyperparams. E.g.,
  - K-Nearest Neighbors: Different choices of K
  - Decision Trees: Different choices of the number of levels/leaves
  - Polynomial Regression: Polynomials with different degrees
  - Kernel Methods: Different choices of kernels
  - Regularized Models: Different choices of the regularization hyperparameter
  - Architecture of a deep neural network (# of layers, nodes in each layer, activation function, etc)

What is Model Selection?

Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

- Instances of same model with different complexities or hyperparams. E.g.,
  - K-Nearest Neighbors: Different choices of K
  - Decision Trees: Different choices of the number of levels/leaves
  - Polynomial Regression: Polynomials with different degrees
  - Kernel Methods: Different choices of kernels
  - Regularized Models: Different choices of the regularization hyperparameter
  - Architecture of a deep neural network (# of layers, nodes in each layer, activation function, etc)
- Different types of learning models (e.g., SVM, KNN, DT, etc.)

What is Model Selection?

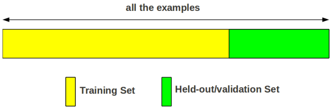
Given a set of models $\mathcal{M} = \{M_1, M_2, \ldots, M_R\}$, choose the model that is expected to do the best on the **test data**. The set $\mathcal{M}$ may consist of:

- Instances of same model with different complexities or hyperparams. E.g.,
  - K-Nearest Neighbors: Different choices of K
  - Decision Trees: Different choices of the number of levels/leaves
  - Polynomial Regression: Polynomials with different degrees
  - Kernel Methods: Different choices of kernels
  - Regularized Models: Different choices of the regularization hyperparameter
  - Architecture of a deep neural network (# of layers, nodes in each layer, activation function, etc)
- Different types of learning models (e.g., SVM, KNN, DT, etc.)

Note: Usually considered in supervised learning contexts but unsupervised learning too faces this issue (e.g., "how many clusters" when doing clustering)

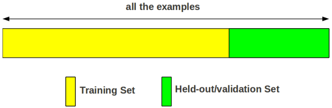
Held-out Data

- Set aside a fraction of the training data. This will be our held-out data.
    - Other names: validation/development data.



Held-out Data

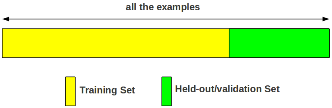
- Set aside a fraction of the training data. This will be our held-out data.
  - Other names: validation/development data.



- **Remember:** Held-out data is NOT the test data. DO NOT peek into the test data during training

Held-out Data

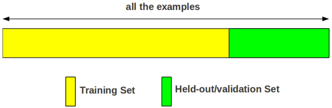
- Set aside a fraction of the training data. This will be our held-out data.
  - Other names: validation/development data.



- **Remember:** Held-out data is NOT the test data. DO NOT peek into the test data during training
- Train each model using the remaining training data

Held-out Data

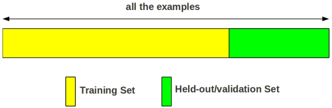
- Set aside a fraction of the training data. This will be our held-out data.
  - Other names: validation/development data.



- **Remember:** Held-out data is NOT the test data. DO NOT peek into the test data during training
- Train each model using the remaining training data
- Evaluate error on the held-out data (cross-validation)

Held-out Data

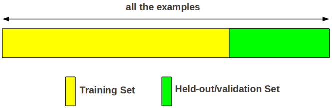
- Set aside a fraction of the training data. This will be our held-out data.
  - Other names: validation/development data.



- **Remember:** Held-out data is NOT the test data. DO NOT peek into the test data during training
- Train each model using the remaining training data
- Evaluate error on the held-out data (cross-validation)
- Choose the model with the smallest held-out error

Held-out Data

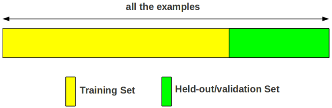
- Set aside a fraction of the training data. This will be our held-out data.
  - Other names: validation/development data.



- **Remember:** Held-out data is NOT the test data. DO NOT peek into the test data during training
- Train each model using the remaining training data
- Evaluate error on the held-out data (cross-validation)
- Choose the model with the smallest held-out error
- Problems:
  - Wastes training data. Typically used when we have plenty of training data

Held-out Data

- Set aside a fraction of the training data. This will be our held-out data.
    - Other names: validation/development data.



- **Remember:** Held-out data is NOT the test data. DO NOT peek into the test data during training
- Train each model using the remaining training data
- Evaluate error on the held-out data (cross-validation)
- Choose the model with the smallest held-out error
- Problems:
    - Wastes training data. Typically used when we have plenty of training data
    - What if there was an unfortunate train/held-out split?

K-fold Cross-Validation

- Create K (e.g., 5 or 10) equal sized partitions of the training data
- Each partition has N/K examples
- Train using $K-1$ partitions, validate on the remaining partition
- Repeat this K times, each with a different validation partition

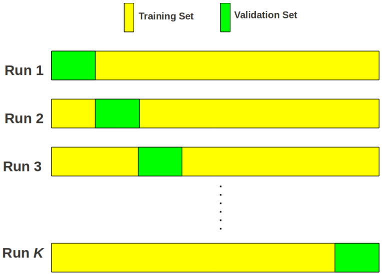
K-fold Cross-Validation

- Create K (e.g., 5 or 10) equal sized partitions of the training data
- Each partition has N/K examples
- Train using $K-1$ partitions, validate on the remaining partition
- Repeat this K times, each with a different validation partition

- Average the K validation errors

K-fold Cross-Validation

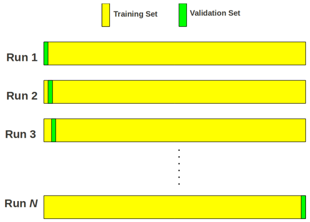
- Create K (e.g., 5 or 10) equal sized partitions of the training data
- Each partition has N/K examples
- Train using $K-1$ partitions, validate on the remaining partition
- Repeat this K times, each with a different validation partition



- Average the K validation errors
- Choose the model that gives the smallest average validation error

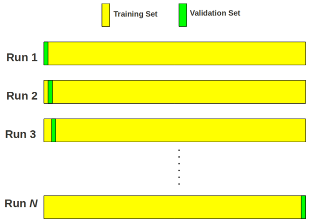
Leave-One-Out (LOO) Cross-Validation

- Special case of K-fold CV when $K = N$. Each partition is now a single example
- Train using $N - 1$ examples, validate on the remaining example
- Repeat the same N times, each with a different validation example



Leave-One-Out (LOO) Cross-Validation

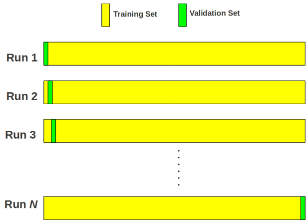
- Special case of K-fold CV when $K = N$. Each partition is now a single example
- Train using $N - 1$ examples, validate on the remaining example
- Repeat the same N times, each with a different validation example



- Average the N validation errors. Choose the model with smallest error

Leave-One-Out (LOO) Cross-Validation

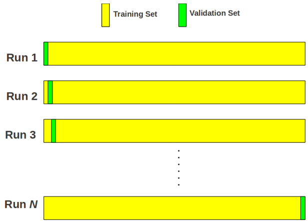
- Special case of K-fold CV when $K = N$. Each partition is now a single example
- Train using $N - 1$ examples, validate on the remaining example
- Repeat the same N times, each with a different validation example



- Average the N validation errors. Choose the model with smallest error
- Can be expensive in general, especially for large N
  - Very efficient when used for selecting K in nearest neighbor methods

Leave-One-Out (LOO) Cross-Validation

- Special case of K-fold CV when $K = N$. Each partition is now a single example
- Train using $N - 1$ examples, validate on the remaining example
- Repeat the same N times, each with a different validation example



- Average the N validation errors. Choose the model with smallest error
- Can be expensive in general, especially for large N
  - Very efficient when used for selecting K in nearest neighbor methods (NN requires no training)

Random Subsampling based Cross-Validation

- Subsample a fixed fraction αN $(0 < \alpha < 1)$ as examples as validation set

Random Subsampling based Cross-Validation

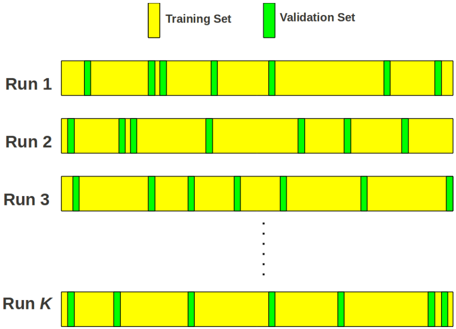
- Subsample a fixed fraction αN $(0 < \alpha < 1)$ as examples as validation set
- Train using the rest of the examples, calculate the validation error

Random Subsampling based Cross-Validation

- Subsample a fixed fraction αN $(0 < \alpha < 1)$ as examples as validation set
- Train using the rest of the examples, calculate the validation error
- Repeat K times, each with a different, randomly chosen validation set

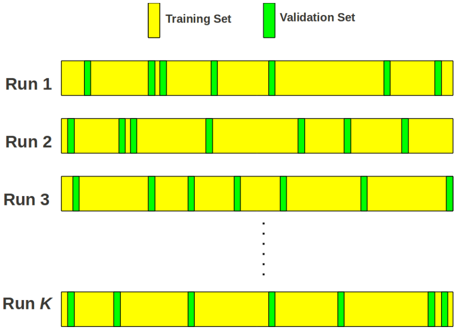
Random Subsampling based Cross-Validation

- Subsample a fixed fraction αN $(0 < \alpha < 1)$ as examples as validation set
- Train using the rest of the examples, calculate the validation error
- Repeat K times, each with a different, randomly chosen validation set



Random Subsampling based Cross-Validation

- Subsample a fixed fraction αN $(0 < \alpha < 1)$ as examples as validation set
- Train using the rest of the examples, calculate the validation error
- Repeat K times, each with a different, randomly chosen validation set



- Average the K validation errors. Choose the model with smallest error

Finding the best hyperparameters

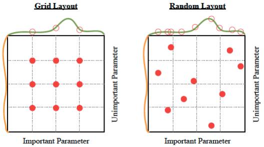
- Each setting of the hyperparameter values is a different model
- Picking the best model = Finding the best hyperparameter setting (which gives best heldout error)
- Picking the best hyperparameter(s) means cross-validation on lots of different models

Finding the best hyperparameters

- Each setting of the hyperparameter values is a different model
- Picking the best model = Finding the best hyperparameter setting (which gives best heldout error)
- Picking the best hyperparameter(s) means cross-validation on lots of different models
- Typically done using grid search. But expensive if there are lots of hyperparameters

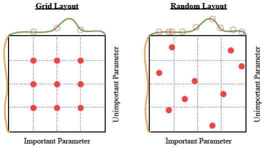
Finding the best hyperparameters

- Each setting of the hyperparameter values is a different model
- Picking the best model = Finding the best hyperparameter setting (which gives best heldout error)
- Picking the best hyperparameter(s) means cross-validation on lots of different models
- Typically done using grid search. But expensive if there are lots of hyperparameters
- The search can be "automated" using hyperparameter search techniques



Finding the best hyperparameters

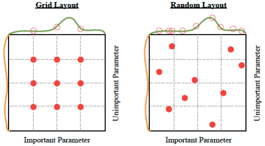
- Each setting of the hyperparameter values is a different model
- Picking the best model = Finding the best hyperparameter setting (which gives best heldout error)
- Picking the best hyperparameter(s) means cross-validation on lots of different models
- Typically done using grid search. But expensive if there are lots of hyperparameters
- The search can be "automated" using hyperparameter search techniques



- Idea: Instead of grid-search, sequentially decide which hyperparam, config. should be tried next

Finding the best hyperparameters

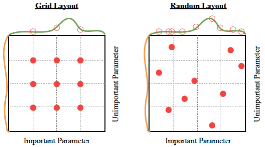
- Each setting of the hyperparameter values is a different model
- Picking the best model = Finding the best hyperparameter setting (which gives best heldout error)
- Picking the best hyperparameter(s) means cross-validation on lots of different models
- Typically done using grid search. But expensive if there are lots of hyperparameters
- The search can be "automated" using hyperparameter search techniques



- Idea: Instead of grid-search, sequentially decide which hyperparam, config. should be tried next
  - Random Search (see "Random Search for Hyper-Parameter Optimization")

Finding the best hyperparameters

- Each setting of the hyperparameter values is a different model
- Picking the best model = Finding the best hyperparameter setting (which gives best heldout error)
- Picking the best hyperparameter(s) means cross-validation on lots of different models
- Typically done using grid search. But expensive if there are lots of hyperparameters
- The search can be "automated" using hyperparameter search techniques



- Idea: Instead of grid-search, sequentially decide which hyperparam, config. should be tried next
  - Random Search (see "Random Search for Hyper-Parameter Optimization")
  - Bayesian Optimization (see "Practical Bayesian Optimization of Machine Learning Algorithms")

Metrics for Evaluating ML Algorithms

Binary Classification Evaluation Metrics

- Easy to visualize via a 2×2 matrix (Confusion Matrix)
- Sum of diagonals $=$ $\#$ of correct predictions
- Sum of off-diagonals $=$ $\#$ of mistakes

Actual Class \ Predicted Class	+	-
+	# True Positives **TP**	# False Negatives **FN** **(Type-II error)**
-	# False Positives **FP** **(Type-I error)**	# True Negatives **TN**

Binary Classification Evaluation Metrics

- Easy to visualize via a 2×2 matrix (Confusion Matrix)
- Sum of diagonals = # of correct predictions
- Sum of off-diagonals = # of mistakes
- Standard evaluation measure is classification accuracy

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

		Predicted Class +	Predicted Class -
Actual Class	+	# True Positives **TP**	# False Negatives **FN (Type-II error)**
	-	# False Positives **FP (Type-I error)**	# True Negatives **TN**

Binary Classification Evaluation Metrics

- Easy to visualize via a 2×2 matrix (Confusion Matrix)
- Sum of diagonals = # of correct predictions
- Sum of off-diagonals = # of mistakes
- Standard evaluation measure is classification accuracy

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

		Predicted Class +	Predicted Class -
Actual Class	+	# True Positives **TP**	# False Negatives **FN** **(Type-II error)**
	-	# False Positives **FP** **(Type-I error)**	# True Negatives **TN**

- Various other metrics are also used to evaluate classification performance

Binary Classification Evaluation Metrics

- Easy to visualize via a 2×2 matrix (Confusion Matrix)
- Sum of diagonals $=$ # of correct predictions
- Sum of off-diagonals $=$ # of mistakes
- Standard evaluation measure is classification accuracy

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

		Predicted Class	
		+	-
Actual Class	+	# True Positives **TP**	# False Negatives **FN** **(Type-II error)**
	-	# False Positives **FP** **(Type-I error)**	# True Negatives **TN**

- Various other metrics are also used to evaluate classification performance
- Precision $=$ Of all positive predictions, what fraction is actully positives

Binary Classification Evaluation Metrics

- Easy to visualize via a 2×2 matrix (Confusion Matrix)
- Sum of diagonals = # of correct predictions
- Sum of off-diagonals = # of mistakes
- Standard evaluation measure is classification accuracy

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

		Predicted Class +	Predicted Class -
Actual Class	+	# True Positives **TP**	# False Negatives **FN** **(Type-II error)**
Actual Class	-	# False Positives **FP** **(Type-I error)**	# True Negatives **TN**

- Various other metrics are also used to evaluate classification performance
- Precision = Of all positive predictions, what fraction is actully positives
- Recall = Of all actual positives, what fraction is predicted as positives

Binary Classification Evaluation Metrics

- Easy to visualize via a 2×2 matrix (Confusion Matrix)
- Sum of diagonals $=$ # of correct predictions
- Sum of off-diagonals $=$ # of mistakes
- Standard evaluation measure is classification accuracy

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

	Predicted Class +	Predicted Class -
Actual Class +	# True Positives **TP**	# False Negatives **FN** **(Type-II error)**
Actual Class -	# False Positives **FP** **(Type-I error)**	# True Negatives **TN**

- Various other metrics are also used to evaluate classification performance
- Precision $=$ Of all positive predictions, what fraction is actully positives
- Recall $=$ Of all actual positives, what fraction is predicted as positives

$$\text{Precision (P)} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Binary Classification Evaluation Metrics

- Easy to visualize via a 2×2 matrix (Confusion Matrix)
- Sum of diagonals = # of correct predictions
- Sum of off-diagonals = # of mistakes
- Standard evaluation measure is classification accuracy

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

		Predicted Class +	Predicted Class -
Actual Class	+	# True Positives **TP**	# False Negatives **FN** **(Type-II error)**
	-	# False Positives **FP** **(Type-I error)**	# True Negatives **TN**

- Various other metrics are also used to evaluate classification performance
- Precision = Of all positive predictions, what fraction is actully positives
- Recall = Of all actual positives, what fraction is predicted as positives

$$\text{Precision (P)} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \text{Recall (R)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Binary Classification Evaluation Metrics

- Easy to visualize via a 2×2 matrix (Confusion Matrix)
- Sum of diagonals $=$ # of correct predictions
- Sum of off-diagonals $=$ # of mistakes
- Standard evaluation measure is classification accuracy

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

		Predicted Class +	Predicted Class -
Actual Class	+	# True Positives **TP**	# False Negatives **FN** **(Type-II error)**
	-	# False Positives **FP** **(Type-I error)**	# True Negatives **TN**

- Various other metrics are also used to evaluate classification performance
- Precision $=$ Of all positive predictions, what fraction is actully positives
- Recall $=$ Of all actual positives, what fraction is predicted as positives

$$\text{Precision (P)} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \text{Recall (R)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad \text{F1-score} = \frac{2\text{PR}}{\text{P+R}} \ \text{(harmonic mean)}$$

Binary Classification Evaluation Metrics (Contd)

- True Positive Rate (TPR) and False Positive Rate (FPR) are also commonly used metrics
- TPR is the same as recall: Fraction of actual positives predicted as positives

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

- FPR is the fraction of actual negatives predicted as positive

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{TN} + \mathrm{FP}}$$

Binary Classification Evaluation Metrics (Contd.)

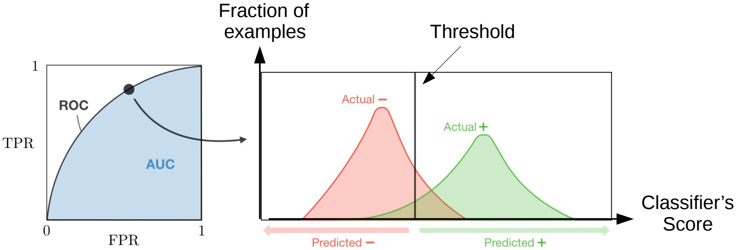
- Most classifiers predict a score (a real-valued number or a probability)

Binary Classification Evaluation Metrics (Contd.)

- Most classifiers predict a score (a real-valued number or a probability)
- Can set a threshold to decide what to call positive and what to call negative

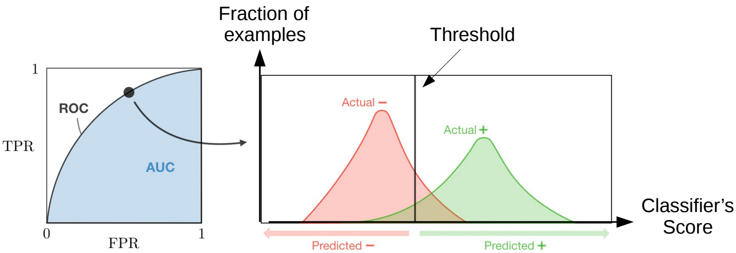
Binary Classification Evaluation Metrics (Contd.)

- Most classifiers predict a score (a real-valued number or a probability)
- Can set a threshold to decide what to call positive and what to call negative
- Can adjust the threshold to control the TPR and FPR



Binary Classification Evaluation Metrics (Contd.)

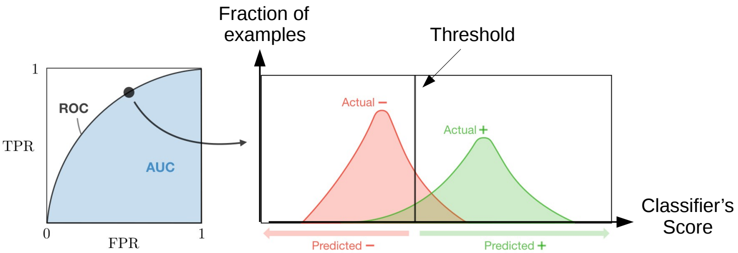
- Most classifiers predict a score (a real-valued number or a probability)
- Can set a threshold to decide what to call positive and what to call negative
- Can adjust the threshold to control the TPR and FPR



- Plot of TPR vs FPR for all possible values of the threshold is called Area Under the Receiving Operating Curve (AUCROC or AUC)

Binary Classification Evaluation Metrics (Contd.)

- Most classifiers predict a score (a real-valued number or a probability)
- Can set a threshold to decide what to call positive and what to call negative
- Can adjust the threshold to control the TPR and FPR



- Plot of TPR vs FPR for all possible values of the threshold is called Area Under the Receiving Operating Curve (AUCROC or AUC)
- The max AUC score is 1. AUC $= 0.5$ means close to random.

Multiclass Classification Evaluation Metrics

- For K classes, we will have a $K \times K$ confusion matrix

Predicted Class

Actual Class	0	1	2	3	4	5	6	7	8	9
0	852	16	0	1	14	0	24	0	69	4
1	0	1106	3	1	0	0	0	0	23	2
2	14	127	706	14	61	2	4	23	63	18
3	2	21	19	688	3	52	0	14	152	59
4	2	25	8	2	909	0	1	12	19	4
5	5	58	9	53	31	615	28	14	61	18
6	22	37	8	0	436	2	365	1	85	2
7	16	608	5	26	97	13	1	128	13	121
8	5	160	16	3	46	35	19	6	661	23
9	8	55	1	10	745	15	1	22	9	143

- Can define precision and recall w.r.t. each class

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$
- Traditional metric: Residual sum of squares: $SS_{res} = \sum_{n=1}^{N}(y_n - \hat{y}_n)^2$

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$
- Traditional metric: Residual sum of squares: $SS_{res} = \sum_{n=1}^{N}(y_n - \hat{y}_n)^2$
- Suppose the mean of true responses is $\mu = \frac{\sum_{n=1}^{N} y_n}{N}$

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$
- Traditional metric: Residual sum of squares: $SS_{res} = \sum_{n=1}^{N}(y_n - \hat{y}_n)^2$
- Suppose the mean of true responses is $\mu = \frac{\sum_{n=1}^{N} y_n}{N}$
- Define total sum of squares: $SS_{tot} = \sum_{n=1}^{N}(y_n - \mu)^2$

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$
- Traditional metric: Residual sum of squares: $SS_{res} = \sum_{n=1}^{N} (y_n - \hat{y}_n)^2$
- Suppose the mean of true responses is $\mu = \frac{\sum_{n=1}^{N} y_n}{N}$
- Define total sum of squares: $SS_{tot} = \sum_{n=1}^{N} (y_n - \mu)^2$. Prop. to original variance

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$
- Traditional metric: Residual sum of squares: $SS_{res} = \sum_{n=1}^{N}(y_n - \hat{y}_n)^2$
- Suppose the mean of true responses is $\mu = \frac{\sum_{n=1}^{N} y_n}{N}$
- Define total sum of squares: $SS_{tot} = \sum_{n=1}^{N}(y_n - \mu)^2$. Prop. to original variance
- Regression sum of squares: $SS_{reg} = \sum_{n=1}^{N}(\hat{y}_n - \mu)^2$

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$
- Traditional metric: Residual sum of squares: $SS_{res} = \sum_{n=1}^{N}(y_n - \hat{y}_n)^2$
- Suppose the mean of true responses is $\mu = \frac{\sum_{n=1}^{N} y_n}{N}$
- Define total sum of squares: $SS_{tot} = \sum_{n=1}^{N}(y_n - \mu)^2$. Prop. to original variance
- Regression sum of squares: $SS_{reg} = \sum_{n=1}^{N}(\hat{y}_n - \mu)^2$. Prop. to variance "explained" by the model

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$
- Traditional metric: Residual sum of squares: $SS_{res} = \sum_{n=1}^{N}(y_n - \hat{y}_n)^2$
- Suppose the mean of true responses is $\mu = \frac{\sum_{n=1}^{N} y_n}{N}$
- Define total sum of squares: $SS_{tot} = \sum_{n=1}^{N}(y_n - \mu)^2$. Prop. to original variance
- Regression sum of squares: $SS_{reg} = \sum_{n=1}^{N}(\hat{y}_n - \mu)^2$. Prop. to variance "explained" by the model
- The coefficient of determination metric is defined as

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_{n=1}^{N}(y_n - \hat{y}_n)^2}{\sum_{n=1}^{N}(y_n - \mu)^2}$$

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$
- Traditional metric: Residual sum of squares: $SS_{res} = \sum_{n=1}^{N}(y_n - \hat{y}_n)^2$
- Suppose the mean of true responses is $\mu = \frac{\sum_{n=1}^{N} y_n}{N}$
- Define total sum of squares: $SS_{tot} = \sum_{n=1}^{N}(y_n - \mu)^2$. Prop. to original variance
- Regression sum of squares: $SS_{reg} = \sum_{n=1}^{N}(\hat{y}_n - \mu)^2$. Prop. to variance "explained" by the model
- The coefficient of determination metric is defined as

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_{n=1}^{N}(y_n - \hat{y}_n)^2}{\sum_{n=1}^{N}(y_n - \mu)^2}$$

- A close to perfect model will have R^2 close to 1

Regression Evaluation Metrics

- Assume true responses $\boldsymbol{y} = [y_1, \ldots, y_N]$, predicted responses $\hat{\boldsymbol{y}} = [\hat{y}_1, \ldots, \hat{y}_N]$
- Traditional metric: Residual sum of squares: $SS_{res} = \sum_{n=1}^{N}(y_n - \hat{y}_n)^2$
- Suppose the mean of true responses is $\mu = \frac{\sum_{n=1}^{N} y_n}{N}$
- Define total sum of squares: $SS_{tot} = \sum_{n=1}^{N}(y_n - \mu)^2$. Prop. to original variance
- Regression sum of squares: $SS_{reg} = \sum_{n=1}^{N}(\hat{y}_n - \mu)^2$. Prop. to variance "explained" by the model
- The coefficient of determination metric is defined as

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_{n=1}^{N}(y_n - \hat{y}_n)^2}{\sum_{n=1}^{N}(y_n - \mu)^2}$$

- A close to perfect model will have R^2 close to 1
- For linear regression, $SS_{tot} = SS_{reg} + SS_{res} \Rightarrow R^2 = \frac{SS_{reg}}{SS_{tot}}$ (fraction of explained variance)

Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
    - Accuracy, normalized mutual information (NMI), rand index, purity, etc.

Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
    - Accuracy, normalized mutual information (NMI), rand index, purity, etc.
    - But need to account for cluster label permutations

Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
  - Accuracy, normalized mutual information (NMI), rand index, purity, etc.
  - But need to account for cluster label permutations

Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
  - Accuracy, normalized mutual information (NMI), rand index, purity, etc.
  - But need to account for cluster label permutations
- Metrics if no ground truth is known

Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
  - Accuracy, normalized mutual information (NMI), rand index, purity, etc.
  - But need to account for cluster label permutations
- Metrics if no ground truth is known
  - Distortion: Sum of squared errors from the closest clusters (need to penalize the number of clusters)

Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
  - Accuracy, normalized mutual information (NMI), rand index, purity, etc.
  - But need to account for cluster label permutations
- Metrics if no ground truth is known
  - Distortion: Sum of squared errors from the closest clusters (need to penalize the number of clusters)
  - Distortion on a "held-out data" (not used to learn the clusters)

Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
  - Accuracy, normalized mutual information (NMI), rand index, purity, etc.
  - But need to account for cluster label permutations
- Metrics if no ground truth is known
  - Distortion: Sum of squared errors from the closest clusters (need to penalize the number of clusters)
  - Distortion on a "held-out data" (not used to learn the clusters)
  - For probabilistic models, can look at the negative log-likelihood (penalized by number of clusters)

Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
  - Accuracy, normalized mutual information (NMI), rand index, purity, etc.
  - But need to account for cluster label permutations
- Metrics if no ground truth is known
  - Distortion: Sum of squared errors from the closest clusters (need to penalize the number of clusters)
  - Distortion on a "held-out data" (not used to learn the clusters)
  - For probabilistic models, can look at the negative log-likelihood (penalized by number of clusters)
- Distortion/reconstruction error can also be used for evaluating dimensionality reduction methods

Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
  - Accuracy, normalized mutual information (NMI), rand index, purity, etc.
  - But need to account for cluster label permutations
- Metrics if no ground truth is known
  - Distortion: Sum of squared errors from the closest clusters (need to penalize the number of clusters)
  - Distortion on a "held-out data" (not used to learn the clusters)
  - For probabilistic models, can look at the negative log-likelihood (penalized by number of clusters)
- Distortion/reconstruction error can also be used for evaluating dimensionality reduction methods
- External evaluation is often preferred when evaluating unsupervised learning models

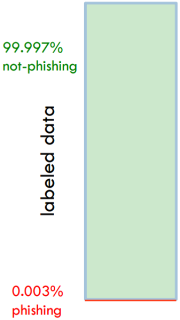
Evaluation Metrics for Unsupervised Learning

- Some clustering metrics exist if the ground truth clusters are known (rarely the case)
  - Accuracy, normalized mutual information (NMI), rand index, purity, etc.
  - But need to account for cluster label permutations
- Metrics if no ground truth is known
  - Distortion: Sum of squared errors from the closest clusters (need to penalize the number of clusters)
  - Distortion on a "held-out data" (not used to learn the clusters)
  - For probabilistic models, can look at the negative log-likelihood (penalized by number of clusters)
- Distortion/reconstruction error can also be used for evaluating dimensionality reduction methods
- External evaluation is often preferred when evaluating unsupervised learning models
  - Use the new representation to train a supervised learning model

Learning from Imbalanced Data

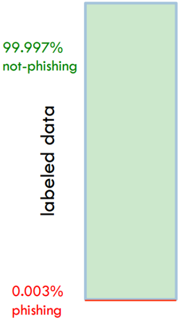
Learning from Imbalanced Data

- Consider binary classification
- Often the classes are highly imbalanced



Learning from Imbalanced Data

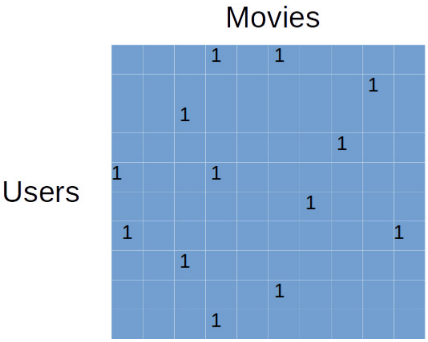
- Consider binary classification
- Often the classes are highly imbalanced



- Should I feel happy if my classifier gets 99.997% classification accuracy on test data ?

Learning from Imbalanced Data

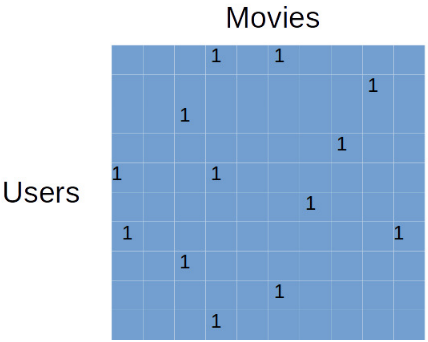
- Other problems can also exhibit imbalance (e.g., binary matrix completion)



Binary Matrix Completion
0.001 % 1s in the matrix

Learning from Imbalanced Data

- Other problems can also exhibit imbalance (e.g., binary matrix completion)



Binary Matrix Completion
0.001 % 1s in the matrix

- Should I feel happy if my matrix completion model gets 99.999% matrix completion accuracy on the test entries?

True Definition of Imbalance Data?

- Debatable..
- Scenario 1: 100,000 negative and 1000 positive examples
- Scenario 2: 10,000 negative and 10 negative examples
- Scenario 3: 1000 negative and 1 negative example

True Definition of Imbalance Data?

- Debatable..
- Scenario 1: 100,000 negative and 1000 positive examples
- Scenario 2: 10,000 negative and 10 negative examples
- Scenario 3: 1000 negative and 1 negative example
- Usually, imbalance is characterized by absolute rather than relative rarity
  - Finding needles in a haystack..

Minimizing Loss

- Any model to minimize the loss, e.g.,

$$\text{Classification:} \quad \hat{\boldsymbol{w}} = \arg\min_{\boldsymbol{w}} \sum_{n=1}^{N} \ell(y_n, \boldsymbol{w}^\top \boldsymbol{x}_n)$$

$$\text{Matrix Completion:} \quad (\hat{\mathbf{U}}, \hat{\mathbf{V}}) = \arg\min_{\mathbf{U},\mathbf{V}} ||\mathbf{X} - \mathbf{U}\mathbf{V}^\top||^2$$

.. will usually get a high accuracy

Minimizing Loss

- Any model to minimize the loss, e.g.,

$$\text{Classification:} \quad \hat{\boldsymbol{w}} = \arg\min_{\boldsymbol{w}} \sum_{n=1}^{N} \ell(y_n, \boldsymbol{w}^\top \boldsymbol{x}_n)$$

$$\text{Matrix Completion:} \quad (\hat{\mathbf{U}}, \hat{\mathbf{V}}) = \arg\min_{\mathbf{U},\mathbf{V}} ||\mathbf{X} - \mathbf{U}\mathbf{V}^\top||^2$$

.. will usually get a high accuracy

- However, it will be highly biased towards predicting the majority class

Minimizing Loss

- Any model to minimize the loss, e.g.,

$$\text{Classification:} \quad \hat{\boldsymbol{w}} = \arg\min_{\boldsymbol{w}} \sum_{n=1}^{N} \ell(y_n, \boldsymbol{w}^\top \boldsymbol{x}_n)$$

$$\text{Matrix Completion:} \quad (\hat{\mathbf{U}}, \hat{\mathbf{V}}) = \arg\min_{\mathbf{U},\mathbf{V}} ||\mathbf{X} - \mathbf{U}\mathbf{V}^\top||^2$$

.. will usually get a high accuracy

- However, it will be highly biased towards predicting the majority class
  - Thus accuracy alone can't be trusted as the evaluation measure if we care more about predicting minority class (say positive) correctly

Minimizing Loss

- Any model to minimize the loss, e.g.,

$$\text{Classification:} \quad \hat{\boldsymbol{w}} = \arg\min_{\boldsymbol{w}} \sum_{n=1}^{N} \ell(y_n, \boldsymbol{w}^\top \boldsymbol{x}_n)$$

$$\text{Matrix Completion:} \quad (\hat{\mathbf{U}}, \hat{\mathbf{V}}) = \arg\min_{\mathbf{U},\mathbf{V}} ||\mathbf{X} - \mathbf{U}\mathbf{V}^\top||^2$$

.. will usually get a high accuracy

- However, it will be highly biased towards predicting the majority class
  - Thus accuracy alone can't be trusted as the evaluation measure if we care more about predicting minority class (say positive) correctly
  - Need to use metrics such as precision, recall, F1 score, AUC, etc (that specifically care about positives)

Dealing with Class Imbalance

- Modifying the training data (the class distribution)
    - Undersampling the majority class
    - Oversampling the minority class
    - Reweighting the examples
- Modifying the learning model
    - Use loss functions customized to handle class imbalance

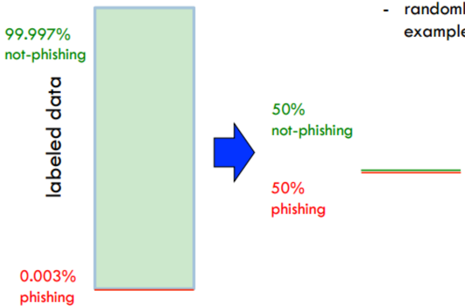
Dealing with Class Imbalance

- Modifying the training data (the class distribution)
  - Undersampling the majority class
  - Oversampling the minority class
  - Reweighting the examples
- Modifying the learning model
  - Use loss functions customized to handle class imbalance
- Reweighting can be also seen as a way to modify the loss function

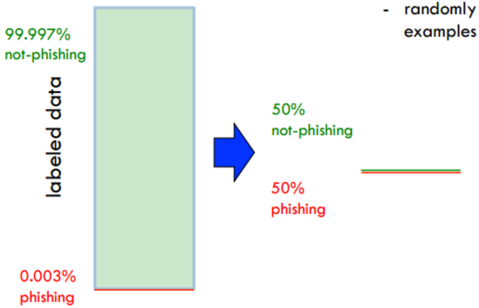
Modifying the Training Data

Undersampling

Create a new training data set by:
- including all k "positive" examples
- randomly picking k "negative" examples



Undersampling



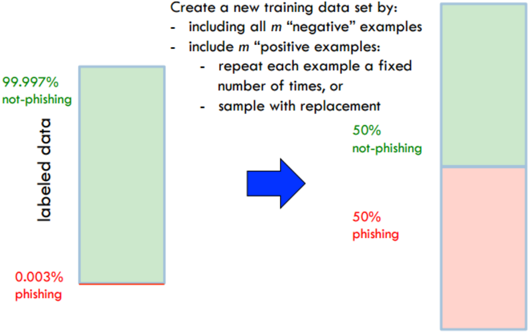
Create a new training data set by:
- including all k "positive" examples
- randomly picking k "negative" examples

- Throws away a lot of data/information. But efficient to train

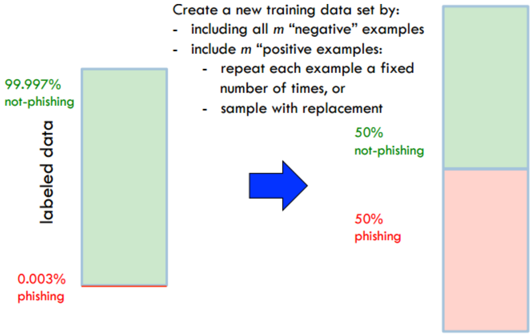
Oversampling

Create a new training data set by:

- including all m "negative" examples
- include m "positive examples:
  - repeat each example a fixed number of times, or
  - sample with replacement

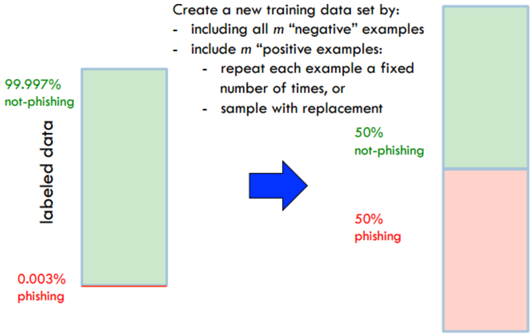


Oversampling



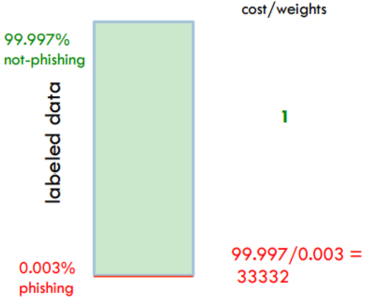
- Th repeated examples simply contribute multiple times to the loss function

Oversampling



- Th repeated examples simply contribute multiple times to the loss function
- Some oversampling methods (SMOTE) based on creating synthetic examples from minority class

Reweighting Examples



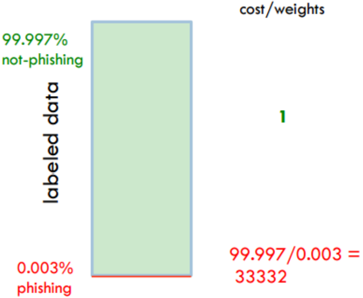
Add costs/weights to the training set

"negative" examples get weight 1

"positive" examples get a much larger weight

change learning algorithm to optimize weighted training error

Reweighting Examples



Add costs/weights to the training set

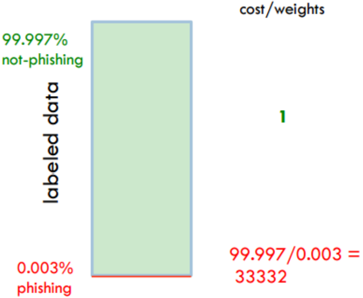
"negative" examples get weight 1

"positive" examples get a much larger weight

change learning algorithm to optimize weighted training error

- Similar effect as oversampling but is more efficient (because there is no multiplicity of examples)

Reweighting Examples



Add costs/weights to the training set

"negative" examples get weight 1

"positive" examples get a much larger weight

change learning algorithm to optimize weighted training error

- Similar effect as oversampling but is more efficient (because there is no multiplicity of examples)
- Also requires a model that can learn with weighted examples

Modifying the Loss Function

Loss Functions Customized for Imbalanced Data

- Traditional loss functions have the form: $\sum_{n=1}^{N} \ell(y_n, f(\boldsymbol{x}_n))$

Loss Functions Customized for Imbalanced Data

- Traditional loss functions have the form: $\sum_{n=1}^{N} \ell(y_n, f(\boldsymbol{x}_n))$
- Such loss functions look at positive and negative examples individually, so the majority class tends to overwhelm the minority class

Loss Functions Customized for Imbalanced Data

- Traditional loss functions have the form: $\sum_{n=1}^{N} \ell(y_n, f(\boldsymbol{x}_n))$
- Such loss functions look at positive and negative examples individually, so the majority class tends to overwhelm the minority class
- Reweighting the loss function differently for different classes can be one way to handle class imbalance, e.g., $\sum_{n=1}^{N} C_{y_n} \ell(y_n, f(\boldsymbol{x}_n))$

Loss Functions Customized for Imbalanced Data

- Traditional loss functions have the form: $\sum_{n=1}^{N} \ell(y_n, f(\boldsymbol{x}_n))$
- Such loss functions look at positive and negative examples individually, so the majority class tends to overwhelm the minority class
- Reweighting the loss function differently for different classes can be one way to handle class imbalance, e.g., $\sum_{n=1}^{N} C_{y_n} \ell(y_n, f(\boldsymbol{x}_n))$
- Alternatively, we can use loss functions that look at pairs of examples (a positive example $\boldsymbol{x}_n^+$ and a negative example $\boldsymbol{x}_m^-$).

Loss Functions Customized for Imbalanced Data

- Traditional loss functions have the form: $\sum_{n=1}^{N} \ell(y_n, f(\boldsymbol{x}_n))$
- Such loss functions look at positive and negative examples individually, so the majority class tends to overwhelm the minority class
- Reweighting the loss function differently for different classes can be one way to handle class imbalance, e.g., $\sum_{n=1}^{N} C_{y_n} \ell(y_n, f(\boldsymbol{x}_n))$
- Alternatively, we can use loss functions that look at pairs of examples (a positive example $\boldsymbol{x}_n^+$ and a negative example $\boldsymbol{x}_m^-$). For example:

$$\ell(f(\boldsymbol{x}_n^+), f(\boldsymbol{x}_m^-)) = \begin{cases} \end{cases}$$

Loss Functions Customized for Imbalanced Data

- Traditional loss functions have the form: $\sum_{n=1}^{N} \ell(y_n, f(\boldsymbol{x}_n))$
- Such loss functions look at positive and negative examples individually, so the majority class tends to overwhelm the minority class
- Reweighting the loss function differently for different classes can be one way to handle class imbalance, e.g., $\sum_{n=1}^{N} C_{y_n} \ell(y_n, f(\boldsymbol{x}_n))$
- Alternatively, we can use loss functions that look at pairs of examples (a positive example $\boldsymbol{x}_n^+$ and a negative example $\boldsymbol{x}_m^-$). For example:

$$\ell(f(\boldsymbol{x}_n^+), f(\boldsymbol{x}_m^-)) = \begin{cases} 0, & \text{if } f(\boldsymbol{x}_n^+) > f(\boldsymbol{x}_m^-) \\ & \end{cases}$$

Loss Functions Customized for Imbalanced Data

- Traditional loss functions have the form: $\sum_{n=1}^{N} \ell(y_n, f(\boldsymbol{x}_n))$
- Such loss functions look at positive and negative examples individually, so the majority class tends to overwhelm the minority class
- Reweighting the loss function differently for different classes can be one way to handle class imbalance, e.g., $\sum_{n=1}^{N} C_{y_n} \ell(y_n, f(\boldsymbol{x}_n))$
- Alternatively, we can use loss functions that look at pairs of examples (a positive example $\boldsymbol{x}_n^+$ and a negative example $\boldsymbol{x}_m^-$). For example:

$$\ell(f(\boldsymbol{x}_n^+), f(\boldsymbol{x}_m^-)) = \begin{cases} 0, & \text{if } f(\boldsymbol{x}_n^+) > f(\boldsymbol{x}_m^-) \\ 1, & \text{otherwise} \end{cases}$$

Loss Functions Customized for Imbalanced Data

- Traditional loss functions have the form: $\sum_{n=1}^{N} \ell(y_n, f(\boldsymbol{x}_n))$
- Such loss functions look at positive and negative examples individually, so the majority class tends to overwhelm the minority class
- Reweighting the loss function differently for different classes can be one way to handle class imbalance, e.g., $\sum_{n=1}^{N} C_{y_n} \ell(y_n, f(\boldsymbol{x}_n))$
- Alternatively, we can use loss functions that look at pairs of examples (a positive example $\boldsymbol{x}_n^+$ and a negative example $\boldsymbol{x}_m^-$). For example:

$$\ell(f(\boldsymbol{x}_n^+), f(\boldsymbol{x}_m^-)) = \begin{cases} 0, & \text{if } f(\boldsymbol{x}_n^+) > f(\boldsymbol{x}_m^-) \\ 1, & \text{otherwise} \end{cases}$$

- These are called "pairwise" loss functions

Loss Functions Customized for Imbalanced Data

- Traditional loss functions have the form: $\sum_{n=1}^{N} \ell(y_n, f(\boldsymbol{x}_n))$
- Such loss functions look at positive and negative examples individually, so the majority class tends to overwhelm the minority class
- Reweighting the loss function differently for different classes can be one way to handle class imbalance, e.g., $\sum_{n=1}^{N} C_{y_n} \ell(y_n, f(\boldsymbol{x}_n))$
- Alternatively, we can use loss functions that look at pairs of examples (a positive example $\boldsymbol{x}_n^+$ and a negative example $\boldsymbol{x}_m^-$). For example:

$$\ell(f(\boldsymbol{x}_n^+), f(\boldsymbol{x}_m^-)) = \begin{cases} 0, & \text{if } f(\boldsymbol{x}_n^+) > f(\boldsymbol{x}_m^-) \\ 1, & \text{otherwise} \end{cases}$$

- These are called "pairwise" loss functions
- Why is it a good loss function for imbalanced data?

Pairwise Loss Functions

- Using pairs with one +ve and one -ve doesn't let one class overwhelm other

$$\sum_{n=1}^{N_+}\sum_{m=1}^{N_-}\ell(f(\boldsymbol{x}_n^+), f(\boldsymbol{x}_m^-)) + \lambda R(f)$$

Pairwise Loss Functions

- Using pairs with one +ve and one -ve doesn't let one class overwhelm other

$$\sum_{n=1}^{N_+}\sum_{m=1}^{N_-}\ell(f(\boldsymbol{x}_n^+), f(\boldsymbol{x}_m^-)) + \lambda R(f)$$

- The pairwise loss function only cares about the difference between scores of a pair of positive and negative examples

Pairwise Loss Functions

- Using pairs with one +ve and one -ve doesn't let one class overwhelm other

$$\sum_{n=1}^{N_+} \sum_{m=1}^{N_-} \ell(f(\mathbf{x}_n^+), f(\mathbf{x}_m^-)) + \lambda R(f)$$

- The pairwise loss function only cares about the difference between scores of a pair of positive and negative examples
  - Want the positive ex. to have higher score than the negative ex., which is similar in spirit to maximizing the AUC (Area Under the ROC Curve) score

Pairwise Loss Functions

- Using pairs with one +ve and one -ve doesn't let one class overwhelm other

$$\sum_{n=1}^{N_+} \sum_{m=1}^{N_-} \ell(f(\boldsymbol{x}_n^+), f(\boldsymbol{x}_m^-)) + \lambda R(f)$$

- The pairwise loss function only cares about the difference between scores of a pair of positive and negative examples
  - Want the positive ex. to have higher score than the negative ex., which is similar in spirit to maximizing the AUC (Area Under the ROC Curve) score
  - AUC (intuitively): The probability that a randomly chosen pos. example will have a higher score than a randomly chosen neg. example

Pairwise Loss Functions

- Using pairs with one +ve and one -ve doesn't let one class overwhelm other

$$\sum_{n=1}^{N_+}\sum_{m=1}^{N_-}\ell(f(\mathbf{x}_n^+), f(\mathbf{x}_m^-)) + \lambda R(f)$$

- The pairwise loss function only cares about the difference between scores of a pair of positive and negative examples
  - Want the positive ex. to have higher score than the negative ex., which is similar in spirit to maximizing the AUC (Area Under the ROC Curve) score
  - AUC (intuitively): The probability that a randomly chosen pos. example will have a higher score than a randomly chosen neg. example
  - Empirical AUC of f on a training set with N_+ and N_- pos. and neg. ex.

$$\text{AUC}(f) = \frac{1}{N_+ N_-}\sum_{n=1}^{N_+}\sum_{m=1}^{N_-}\mathbb{1}(f(\mathbf{x}_n^+) > f(\mathbf{x}_m^-))$$

Pairwise Loss Functions

- Using pairs with one +ve and one -ve doesn't let one class overwhelm other

$$\sum_{n=1}^{N_+}\sum_{m=1}^{N_-}\ell(f(\boldsymbol{x}_n^+), f(\boldsymbol{x}_m^-)) + \lambda R(f)$$

- The pairwise loss function only cares about the difference between scores of a pair of positive and negative examples
  - Want the positive ex. to have higher score than the negative ex., which is similar in spirit to maximizing the AUC (Area Under the ROC Curve) score
  - AUC (intuitively): The probability that a randomly chosen pos. example will have a higher score than a randomly chosen neg. example
  - Empirical AUC of f on a training set with N_+ and N_- pos. and neg. ex.

$$\text{AUC}(f) = \frac{1}{N_+ N_-}\sum_{n=1}^{N_+}\sum_{m=1}^{N_-}\mathbb{1}(f(\boldsymbol{x}_n^+) > f(\boldsymbol{x}_m^-))$$

- Note: Commonly used pairwise loss functions maximize a proxy of the AUC score (or closely related measures such as F1 score)

Pairwise Loss Functions

- A proxy based on hinge-loss like pairwise loss function for a linear model

$$\ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-) = \max\{0, 1 - (\boldsymbol{w}^\top \boldsymbol{x}_n^+ - \boldsymbol{w}^\top \boldsymbol{x}_m^-)\} = \max\{0, 1 - \boldsymbol{w}^\top (\boldsymbol{x}_n^+ - \boldsymbol{x}_m^-)\}$$

Pairwise Loss Functions

- A proxy based on hinge-loss like pairwise loss function for a linear model

$$\ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-) = \max\{0, 1 - (\boldsymbol{w}^\top \boldsymbol{x}_n^+ - \boldsymbol{w}^\top \boldsymbol{x}_m^-)\} = \max\{0, 1 - \boldsymbol{w}^\top (\boldsymbol{x}_n^+ - \boldsymbol{x}_m^-)\}$$

- It basically says that the difference between scorees of positive and negative examples should be at least 1 (which is like a "margin")

Pairwise Loss Functions

- A proxy based on hinge-loss like pairwise loss function for a linear model

$$\ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-) = \max\{0, 1 - (\boldsymbol{w}^\top \boldsymbol{x}_n^+ - \boldsymbol{w}^\top \boldsymbol{x}_m^-)\} = \max\{0, 1 - \boldsymbol{w}^\top (\boldsymbol{x}_n^+ - \boldsymbol{x}_m^-)\}$$

- It basically says that the difference between scorees of positive and negative examples should be at least 1 (which is like a "margin")
- The overall objective will have the form

$$\frac{||\boldsymbol{w}||^2}{2} + \sum_{n=1}^{N_+} \sum_{m=1}^{N_-} \ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-)$$

Pairwise Loss Functions

- A proxy based on hinge-loss like pairwise loss function for a linear model

$$\ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-) = \max\{0, 1 - (\boldsymbol{w}^\top \boldsymbol{x}_n^+ - \boldsymbol{w}^\top \boldsymbol{x}_m^-)\} = \max\{0, 1 - \boldsymbol{w}^\top (\boldsymbol{x}_n^+ - \boldsymbol{x}_m^-)\}$$

- It basically says that the difference between scorees of positive and negative examples should be at least 1 (which is like a "margin")
- The overall objective will have the form

$$\frac{||\boldsymbol{w}||^2}{2} + \sum_{n=1}^{N_+} \sum_{m=1}^{N_-} \ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-)$$

- Convex objective (if using the hinge loss). Can be efficiently optimized using stochastic optimization (see "Online AUC Maximization", Zhao et al, 2011)

Pairwise Loss Functions

- A proxy based on hinge-loss like pairwise loss function for a linear model

$$\ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-) = \max\{0, 1 - (\boldsymbol{w}^\top \boldsymbol{x}_n^+ - \boldsymbol{w}^\top \boldsymbol{x}_m^-)\} = \max\{0, 1 - \boldsymbol{w}^\top (\boldsymbol{x}_n^+ - \boldsymbol{x}_m^-)\}$$

- It basically says that the difference between scorees of positive and negative examples should be at least 1 (which is like a "margin")
- The overall objective will have the form

$$\frac{||\boldsymbol{w}||^2}{2} + \sum_{n=1}^{N_+} \sum_{m=1}^{N_-} \ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-)$$

- Convex objective (if using the hinge loss). Can be efficiently optimized using stochastic optimization (see "Online AUC Maximization", Zhao et al, 2011)
- Note: Similar ideas can be used for solving binary matrix factorization and matrix completion problems as well

Pairwise Loss Functions

- A proxy based on hinge-loss like pairwise loss function for a linear model

$$\ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-) = \max\{0, 1 - (\boldsymbol{w}^\top \boldsymbol{x}_n^+ - \boldsymbol{w}^\top \boldsymbol{x}_m^-)\} = \max\{0, 1 - \boldsymbol{w}^\top (\boldsymbol{x}_n^+ - \boldsymbol{x}_m^-)\}$$

- It basically says that the difference between scorees of positive and negative examples should be at least 1 (which is like a "margin")
- The overall objective will have the form

$$\frac{||\boldsymbol{w}||^2}{2} + \sum_{n=1}^{N_+} \sum_{m=1}^{N_-} \ell(\boldsymbol{w}, \boldsymbol{x}_n^+, \boldsymbol{x}_m^-)$$

- Convex objective (if using the hinge loss). Can be efficiently optimized using stochastic optimization (see "Online AUC Maximization", Zhao et al, 2011)
- Note: Similar ideas can be used for solving binary matrix factorization and matrix completion problems as well
  - E.g., if matrix entry $X_{nm} = 1$ and $X_{nm'} = -1$ then loss=0 if $\boldsymbol{u}_n^\top \boldsymbol{v}_m > \boldsymbol{u}_n^\top \boldsymbol{v}_{m'}$

Summary

- Imbalanced data needs to be handled with care

Summary

- Imbalanced data needs to be handled with care
- Classification accuracies can be very misleading for such data

Summary

- Imbalanced data needs to be handled with care
- Classification accuracies can be very misleading for such data
    - Should look at measures such as precision, recall, or other variants that are robust to class imbalance

Summary

- Imbalanced data needs to be handled with care
- Classification accuracies can be very misleading for such data
  - Should look at measures such as precision, recall, or other variants that are robust to class imbalance
- Sampling heuristics work reasonably on many data sets

Summary

- Imbalanced data needs to be handled with care
- Classification accuracies can be very misleading for such data
  - Should look at measures such as precision, recall, or other variants that are robust to class imbalance
- Sampling heuristics work reasonably on many data sets
- More principled approaches are based on modifying the loss function
  - Instead of minimizing the classication error, optimize w.r.t. other metrics such as precision, recall, F1 score, AUC, etc.

Summary

- Imbalanced data needs to be handled with care
- Classification accuracies can be very misleading for such data
  - Should look at measures such as precision, recall, or other variants that are robust to class imbalance
- Sampling heuristics work reasonably on many data sets
- More principled approaches are based on modifying the loss function
  - Instead of minimizing the classication error, optimize w.r.t. other metrics such as precision, recall, F1 score, AUC, etc.
- Another way to look at this problem could be as an anomaly detection problem (minority class is anomaly) or density estimation problem