



Machine Learning - Classification

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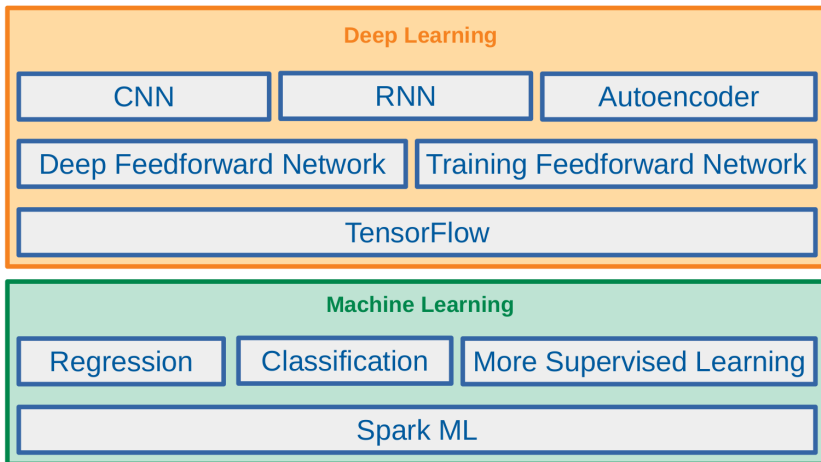




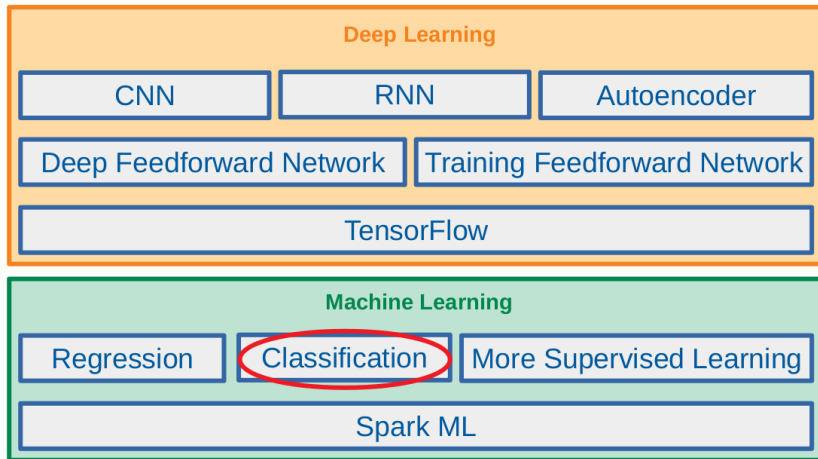
The Course Web Page

<https://id2223kth.github.io>

Where Are We?



Where Are We?



Let's Start with an Example

Example (1/4)

- Given the dataset of m cancer tests.

| Tumor size | Cancer |
|------------|----------|
| 330 | 1 |
| 120 | 0 |
| 400 | 1 |
| \vdots | \vdots |

Example (1/4)

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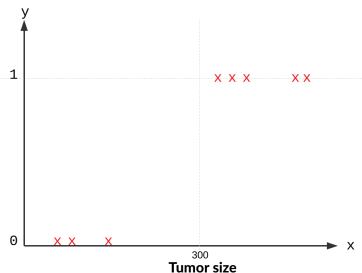
- ▶ Predict the risk of cancer, as a function of the tumor size?

$$\mathbf{x} = \begin{bmatrix} 330 \\ 120 \\ 400 \\ \vdots \\ \vdots \end{bmatrix} \quad \mathbf{y} = \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \\ \vdots \end{bmatrix}$$

Example (2/4)

| Tumor size | Cancer |
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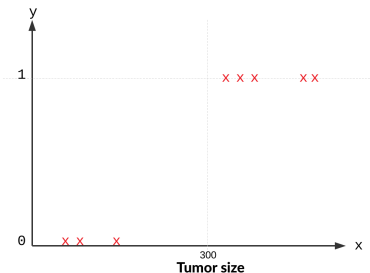


► $\mathbf{x}^{(i)} \in \mathbb{R}$: $x_1^{(i)}$ is the **tumor size** of the **i**th instance in the **training set**.

Example (3/4)

| Tumor size | Cancer |
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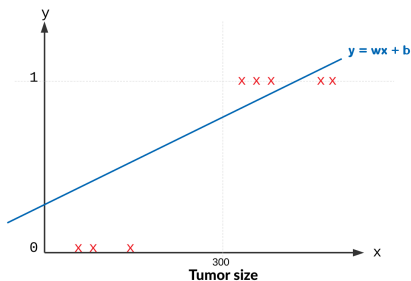


- Predict the risk of cancer \hat{y} as a function of the tumor sizes x_1 , i.e., $\hat{y} = f(x_1)$
- E.g., what is \hat{y} , if $x_1 = 500$?

Example (3/4)

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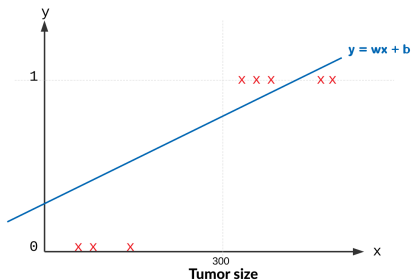


- Predict the risk of cancer \hat{y} as a function of the tumor sizes x_1 , i.e., $\hat{y} = f(x_1)$
- E.g., what is \hat{y} , if $x_1 = 500$?
- As an initial choice: $\hat{y} = f_w(\mathbf{x}) = w_0 + w_1 x_1$

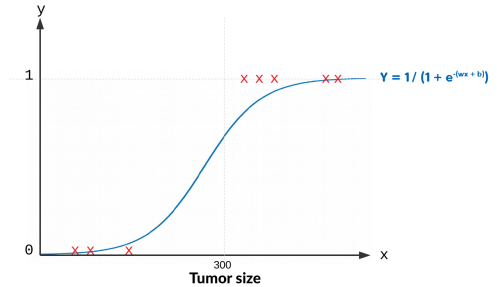
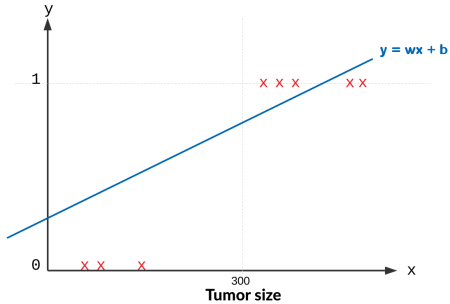
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- Predict the risk of cancer \hat{y} as a function of the tumor sizes x_1 , i.e., $\hat{y} = f(x_1)$
- E.g., what is \hat{y} , if $x_1 = 500$?
- As an initial choice: $\hat{y} = f_w(\mathbf{x}) = w_0 + w_1 x_1$
- Bad model!

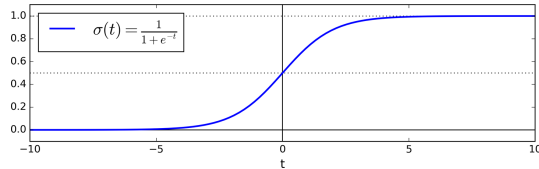


► A better model $\hat{y} = \frac{1}{1+e^{-(w_0+w_1x_1)}}$

Sigmoid Function

- ▶ The **sigmoid function**, denoted by $\sigma(\cdot)$, outputs a number **between 0 and 1**.

$$\sigma(t) = \frac{1}{1 + e^{-t}}$$

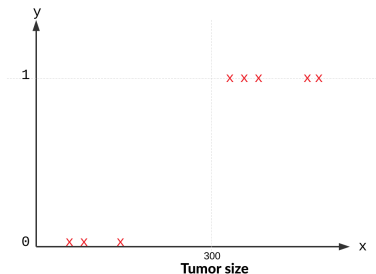


- ▶ When $t < 0$, then $\sigma(t) < 0.5$
- ▶ when $t \geq 0$, then $\sigma(t) \geq 0.5$

Binomial Logistic Regression

Binomial Logistic Regression (1/2)

- ▶ Our goal: to build a system that takes input $\mathbf{x} \in \mathbb{R}^n$ and predicts output $\hat{y} \in \{0, 1\}$.
- ▶ To specify which of 2 categories an input \mathbf{x} belongs to.





Binomial Logistic Regression (2/2)

- ▶ **Linear regression**: the model computes the **weighted sum of the input features** (plus a bias term).

$$\hat{y} = w_0x_0 + w_1x_1 + w_2x_2 + \cdots + w_nx_n = \mathbf{w}^T \mathbf{x}$$

Binomial Logistic Regression (2/2)

- ▶ **Linear regression**: the model computes the **weighted sum of the input features** (plus a bias term).

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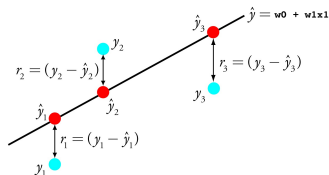
- ▶ **Binomial logistic regression**: the model computes a **weighted sum of the input features** (plus a bias term), but it **outputs the logistic of this result**.

$$z = w_0x_0 + w_1x_1 + w_2x_2 + \cdots + w_nx_n = \mathbf{w}^T \mathbf{x}$$

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}} = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}}}$$

How to Learn Model Parameters \mathbf{w} ?

Linear Regression - Cost Function



- ▶ One reasonable model should make \hat{y} close to y , at least for the training dataset.
- ▶ Cost function $J(\mathbf{w})$: the mean squared error (MSE)

$$\text{cost}(\hat{y}^{(i)}, y^{(i)}) = (\hat{y}^{(i)} - y^{(i)})^2$$

$$J(\mathbf{w}) = \frac{1}{m} \sum_i^m \text{cost}(\hat{y}^{(i)}, y^{(i)}) = \frac{1}{m} \sum_i^m (\hat{y}^{(i)} - y^{(i)})^2$$

Binomial Logistic Regression - Cost Function (1/5)

- Naive idea: minimizing the Mean Squared Error (MSE)

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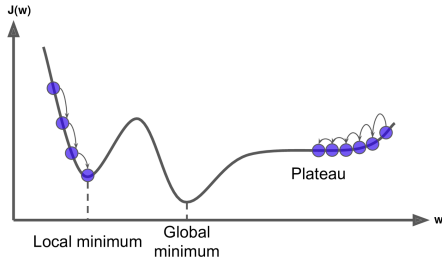
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- This cost function is a non-convex function for parameter optimization.

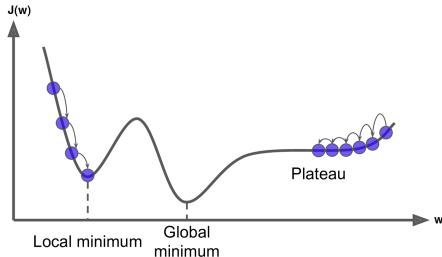
Binomial Logistic Regression - Cost Function (2/5)

- ▶ What do we mean by **non-convex**?
- ▶ If a line joining two points on the curve, **crosses the curve**.
- ▶ The algorithm may converge to a **local minimum**.



Binomial Logistic Regression - Cost Function (2/5)

- ▶ What do we mean by **non-convex**?
- ▶ If a line joining two points on the curve, **crosses the curve**.
- ▶ The algorithm may converge to a **local minimum**.
- ▶ We want a **convex** logistic regression **cost function** $J(\mathbf{w})$.





Binomial Logistic Regression - Cost Function (3/5)

- ▶ The predicted value $\hat{y} = \sigma(\mathbf{w}^T \mathbf{x}) = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}}}$
- ▶ $\text{cost}(\hat{y}^{(i)}, y^{(i)}) = ?$

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- ▶ $\text{cost}(\hat{y}^{(i)}, y^{(i)}) = ?$
- ▶ The $\text{cost}(\hat{y}^{(i)}, y^{(i)})$ should be
 - Close to 0, if the predicted value \hat{y} will be close to true value y .
 - Large, if the predicted value \hat{y} will be far from the true value y .

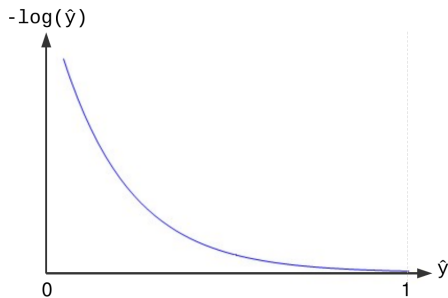
Binomial Logistic Regression - Cost Function (3/5)

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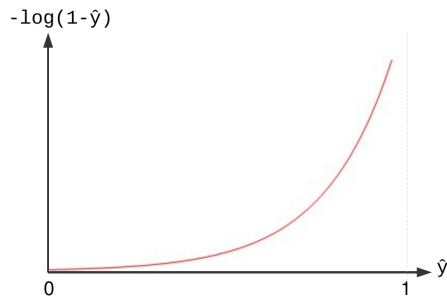
$$\text{cost}(\hat{y}^{(i)}, y^{(i)}) = \begin{cases} -\log(\hat{y}^{(i)}) & \text{if } y^{(i)} = 1 \\ -\log(1 - \hat{y}^{(i)}) & \text{if } y^{(i)} = 0 \end{cases}$$

Binomial Logistic Regression - Cost Function (4/5)

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when $y = 1$



when $y = 0$

Binomial Logistic Regression - Cost Function (5/5)

- We can define $J(\mathbf{w})$ as below

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$$J(\mathbf{w}) = \frac{1}{m} \sum_i^m \text{cost}(\hat{y}^{(i)}, y^{(i)}) = \frac{1}{m} \sum_i^m (y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}))$$



How to Learn Model Parameters \mathbf{w} ?

- ▶ We want to choose \mathbf{w} so as to minimize $J(\mathbf{w})$.
- ▶ An approach to find \mathbf{w} : gradient descent
 - Batch gradient descent
 - Stochastic gradient descent
 - Mini-batch gradient descent



Binomial Logistic Regression Gradient Descent (1/3)

► Goal: find \mathbf{w} that minimizes $J(\mathbf{w}) = \sum_i^m (y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}))$.



Binomial Logistic Regression Gradient Descent (1/3)

- ▶ **Goal:** find \mathbf{w} that **minimizes** $J(\mathbf{w}) = \sum_i^m (y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}))$.
- ▶ Start at a **random point**, and repeat the following **steps**, until the **stopping criterion** is satisfied:

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 1. Determine a **descent direction** $\frac{\partial J(\mathbf{w})}{\partial \mathbf{w}}$

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 1. Determine a **descent direction** $\frac{\partial J(\mathbf{w})}{\partial \mathbf{w}}$
 2. Choose a **step size** η
 3. **Update** the parameters: $\mathbf{w}^{(\text{next})} = \mathbf{w} - \eta \frac{\partial J(\mathbf{w})}{\partial \mathbf{w}}$ (**simultaneously** for all parameters)

Binomial Logistic Regression Gradient Descent (2/3)

- 1. Determine a **descent direction** $\frac{\partial J(\mathbf{w})}{\partial \mathbf{w}}$.

$$\hat{y} = \sigma(\mathbf{w}^T \mathbf{x}) = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}}}$$

$$J(\mathbf{w}) = \frac{1}{m} \sum_i^m \text{cost}(\hat{y}^{(i)}, y^{(i)}) = \frac{1}{m} \sum_i^m (y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}))$$

Binomial Logistic Regression Gradient Descent (2/3)

- 1. Determine a **descent direction** $\frac{\partial J(\mathbf{w})}{\partial \mathbf{w}}$.

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$$\begin{aligned} \frac{\partial J(\mathbf{w})}{\partial w_j} &= \frac{1}{m} \sum_i \left(y^{(i)} \frac{1}{\hat{y}^{(i)}} - (1 - y^{(i)}) \frac{1}{1 - \hat{y}^{(i)}} \right) \frac{\partial \hat{y}^{(i)}}{\partial w_j} \\ &= \frac{1}{m} \sum_i \left(y^{(i)} \frac{1}{\hat{y}^{(i)}} - (1 - y^{(i)}) \frac{1}{1 - \hat{y}^{(i)}} \right) \hat{y}^{(i)} (1 - \hat{y}^{(i)}) \frac{\partial \mathbf{w}^T \mathbf{x}}{\partial w_j} \\ &= \frac{1}{m} \sum_i \left(y^{(i)} (1 - \hat{y}^{(i)}) - (1 - y^{(i)}) \hat{y}^{(i)} \right) x_j \\ &= \frac{1}{m} \sum_i (\hat{y}^{(i)} - y^{(i)}) x_j \end{aligned}$$

Binomial Logistic Regression Gradient Descent (3/3)

- ▶ 2. Choose a **step size** η
- ▶ 3. **Update** the parameters: $w_j^{(\text{next})} = w_j - \eta \frac{\partial J(\mathbf{w})}{\partial w_j}$
 - $0 \leq j \leq n$, where n is the **number of features**.

Binomial Logistic Regression Gradient Descent - Example (1/4)

| Tumor size | Cancer |
|------------|--------|
| 330 | 1 |
| 120 | 0 |
| 400 | 1 |

$$\mathbf{X} = \left[\begin{array}{c|c} 1 & 330 \\ 1 & 120 \\ 1 & 400 \end{array} \right] \quad \mathbf{y} = \left[\begin{array}{c} 1 \\ 0 \\ 1 \end{array} \right]$$

- Predict the risk of cancer \hat{y} as a function of the tumor sizes x_1 .
- E.g., what is \hat{y} , if $x_1 = 500$?

Binomial Logistic Regression Gradient Descent - Example (2/4)

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$$\hat{y} = \sigma(\mathbf{w}_0 + \mathbf{w}_1 \mathbf{x}_1) = \frac{1}{1 + e^{-(\mathbf{w}_0 + \mathbf{w}_1 \mathbf{x}_1)}}$$

$$J(\mathbf{w}) = \frac{1}{m} \sum_i^m (y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}))$$

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$$\begin{aligned} \frac{\partial J(\mathbf{w})}{\partial \mathbf{w}_0} &= \frac{1}{3} \sum_i^3 (\hat{y}^{(i)} - y^{(i)}) \mathbf{x}_0 \\ &= \frac{1}{3} \left[\left(\frac{1}{1 + e^{-(\mathbf{w}_0 + 330\mathbf{w}_1)}} - 1 \right) + \left(\frac{1}{1 + e^{-(\mathbf{w}_0 + 120\mathbf{w}_1)}} - 0 \right) + \left(\frac{1}{1 + e^{-(\mathbf{w}_0 + 400\mathbf{w}_1)}} - 1 \right) \right] \end{aligned}$$

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$$\begin{aligned} \frac{\partial J(\mathbf{w})}{\partial \mathbf{w}_1} &= \frac{1}{3} \sum_i (\hat{y}^{(i)} - y^{(i)}) \mathbf{x}_1 \\ &= \frac{1}{3} \left[330 \left(\frac{1}{1 + e^{-(\mathbf{w}_0 + 330\mathbf{w}_1)}} - 1 \right) + 120 \left(\frac{1}{1 + e^{-(\mathbf{w}_0 + 120\mathbf{w}_1)}} - 0 \right) + 400 \left(\frac{1}{1 + e^{-(\mathbf{w}_0 + 400\mathbf{w}_1)}} - 1 \right) \right] \end{aligned}$$

Binomial Logistic Regression Gradient Descent - Example (4/4)

$$\begin{aligned}w_0^{(\text{next})} &= w_0 - \eta \frac{\partial J(\mathbf{w})}{\partial w_0} \\w_1^{(\text{next})} &= w_1 - \eta \frac{\partial J(\mathbf{w})}{\partial w_1}\end{aligned}$$



Binomial Logistic Regression in Spark

```
case class cancer(x1: Long, y: Long)

val trainData = Seq(cancer(330, 1), cancer(120, 0), cancer(400, 1)).toDF
val testData = Seq(cancer(500, 0)).toDF
```



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import org.apache.spark.ml.feature.VectorAssembler

val va = new VectorAssembler().setInputCols(Array("x1")).setOutputCol("features")

val train = va.transform(trainData)
val test = va.transform(testData)
```


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```
import org.apache.spark.ml.classification.LogisticRegression

val lr = new LogisticRegression().setFeaturesCol("features").setLabelCol("y")
    .setMaxIter(10).setRegParam(0.3).setElasticNetParam(0.8)

val lrModel = lr.fit(train)
lrModel.transform(test).show
```

Binomial Logistic Regression

Probabilistic Interpretation



Probability and Likelihood (1/2)

- ▶ Let $X : \{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$ be a discrete random variable drawn independently from a distribution probability p depending on a parameter θ .

Probability and Likelihood (1/2)

- Let $X : \{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$ be a discrete random variable drawn independently from a distribution probability p depending on a parameter θ .
- For six tosses of a coin, $X : \{h, t, t, t, h, t\}$, h : head, and t : tail.
 - Suppose you have a coin with probability θ to land heads and $(1 - \theta)$ to land tails.

Probability and Likelihood (1/2)

- ▶ Let $X : \{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$ be a discrete random variable drawn independently from a distribution probability p depending on a parameter θ .
 - For six tosses of a coin, $X : \{h, t, t, t, h, t\}$, h : head, and t : tail.
 - Suppose you have a coin with probability θ to land heads and $(1 - \theta)$ to land tails.
- ▶ $p(X \mid \theta = \frac{2}{3})$ is the probability of X given $\theta = \frac{2}{3}$.

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- ▶ $p(X \mid \theta = \frac{2}{3})$ is the **probability** of **X** given $\theta = \frac{2}{3}$.
- ▶ $p(X = h \mid \theta)$ is the **likelihood** of θ given $X = h$.

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- ▶ $p(X = h \mid \theta)$ is the **likelihood** of θ given $X = h$.
- ▶ **Likelihood (L)**: a function of the **parameters (θ)** of a probability model, given **specific observed data**, e.g., $X = h$.

$$L(\theta) = p(X \mid \theta)$$

Probability and Likelihood (2/2)

- If samples in \mathbf{X} are **independent** we have:

$$\begin{aligned} L(\theta) &= p(\mathbf{X} \mid \theta) = p(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \dots, \mathbf{x}^{(m)} \mid \theta) \\ &= p(\mathbf{x}^{(1)} \mid \theta) p(\mathbf{x}^{(2)} \mid \theta) \cdots p(\mathbf{x}^{(m)} \mid \theta) = \prod_{i=1}^m p(\mathbf{x}^{(i)} \mid \theta) \end{aligned}$$



Likelihood and Log-Likelihood

- ▶ The Likelihood product is prone to numerical underflow.

$$L(\theta) = p(X | \theta) = \prod_{i=1}^m p(x^{(i)} | \theta)$$

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 - Transforms a product into a sum.

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- ▶ Negative Log-Likelihood: $-\log L(\theta) = -\sum_{i=1}^m \log p(x^{(i)} | \theta)$

Binomial Logistic Regression and Log-Likelihood (1/2)

- Let's consider the value of $\hat{y}^{(i)}$ as the **probability**:

$$\begin{cases} p(y^{(i)} = 1 \mid \mathbf{x}^{(i)}; \mathbf{w}) = \hat{y}^{(i)} \\ p(y^{(i)} = 0 \mid \mathbf{x}^{(i)}; \mathbf{w}) = 1 - \hat{y}^{(i)} \end{cases} \Rightarrow p(y^{(i)} \mid \mathbf{x}^{(i)}; \mathbf{w}) = (\hat{y}^{(i)})^{y^{(i)}} (1 - \hat{y}^{(i)})^{(1-y^{(i)})}$$

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- ▶ So the **likelihood** is:

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- ▶ And the **negative log-likelihood**:

$$-\log(L(\mathbf{w})) = -\sum_{i=1}^m \log p(y^{(i)} \mid \mathbf{x}^{(i)}; \mathbf{w}) = -\sum_{i=1}^m y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)})$$

Binomial Logistic Regression and Log-Likelihood (2/2)

- The **negative log-likelihood**:

$$-\log(L(\mathbf{w})) = -\sum_{i=1}^m \log p(y^{(i)} | \mathbf{x}^{(i)}; \mathbf{w}) = -\sum_{i=1}^m y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)})$$

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- ▶ This equation is the same as the **logistic regression cost function**.

$$J(\mathbf{w}) = \frac{1}{m} \sum_i^m (y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}))$$

Binomial Logistic Regression and Log-Likelihood (2/2)

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$$J(\mathbf{w}) = \frac{1}{m} \sum_i^m (y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}))$$

- ▶ **Minimize the negative log-likelihood** to **minimize the cost function** $J(\mathbf{w})$.

Binomial Logistic Regression and Cross-Entropy (1/2)

- ▶ Negative log-likelihood is also called the **cross-entropy**
- ▶ **Cross-entropy**: quantify the **difference (error)** between **two probability distributions**.
- ▶ **How close** is the **predicted distribution** to the **true distribution**?

$$H(p, q) = - \sum_j p_j \log(q_j)$$

- ▶ Where **p** is the **true distribution**, and **q** is the **predicted distribution**.



Binomial Logistic Regression and Cross-Entropy (2/2)

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Binomial Logistic Regression and Cross-Entropy (2/2)

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- ▶ $p \in \{y, 1 - y\}$ and $q \in \{\hat{y}, 1 - \hat{y}\}$
- ▶ So, the **cross-entropy** of p and q is nothing but the **logistic cost function**.

$$H(p, q) = - \sum_j p_j \log(q_j) = -(y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})) = \text{cost}(y, \hat{y})$$



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$$J(\mathbf{w}) = \frac{1}{m} \sum_i^m \text{cost}(y, \hat{y}) = \frac{1}{m} \sum_i^m H(p, q) = -\frac{1}{m} \sum_i^m (y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}))$$

- Minimize the cross-entropy to minimize the cost function $J(\mathbf{w})$.

Multinomial Logistic Regression



Multinomial Logistic Regression

- ▶ **Multinomial classifiers** can distinguish between **more than two classes**.
- ▶ Instead of $y \in \{0, 1\}$, we have $y \in \{1, 2, \dots, k\}$.

Binomial vs. Multinomial Logistic Regression (1/2)

- ▶ In a **binomial classifier**, $y \in \{0, 1\}$, the **estimator** is $\hat{y} = p(y = 1 \mid \mathbf{x}; \mathbf{w})$.
 - We find **one** set of parameters \mathbf{w} .

$$\mathbf{w}^T = [w_0, w_1, \dots, w_n]$$

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 - We find **k** set of parameters \mathbf{W} .

$$\mathbf{W} = \begin{bmatrix} [w_{0,1}, w_{1,1}, \dots, w_{n,1}] \\ [w_{0,2}, w_{1,2}, \dots, w_{n,2}] \\ \vdots \\ [w_{0,k}, w_{1,k}, \dots, w_{n,k}] \end{bmatrix} = \begin{bmatrix} \mathbf{w}_1^T \\ \mathbf{w}_2^T \\ \vdots \\ \mathbf{w}_k^T \end{bmatrix}$$

Binomial vs. Multinomial Logistic Regression (2/2)

- In a **binary class**, $y \in \{0, 1\}$, we use the **sigmoid** function.

$$\mathbf{w}^T \mathbf{x} = w_0 x_0 + w_1 x_1 + \cdots + w_n x_n$$

$$\hat{y} = p(y = 1 \mid \mathbf{x}; \mathbf{w}) = \sigma(\mathbf{w}^T \mathbf{x}) = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}}}$$

Binomial vs. Multinomial Logistic Regression (2/2)

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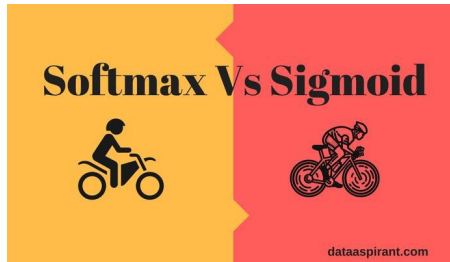
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- In **multiclass**, $y \in \{1, 2, \dots, k\}$, we use the **softmax** function.

$$\mathbf{w}_j^T \mathbf{x} = w_{0,j} x_0 + w_{1,j} x_1 + \cdots + w_{n,j} x_n, 1 \leq j \leq k$$
$$\hat{y}_j = p(y = j \mid \mathbf{x}; \mathbf{w}_j) = \sigma(\mathbf{w}_j^T \mathbf{x}) = \frac{e^{\mathbf{w}_j^T \mathbf{x}}}{\sum_{i=1}^k e^{\mathbf{w}_i^T \mathbf{x}}}$$

Sigmoid vs. Softmax

- ▶ **Sigmoid** function: $\sigma(\mathbf{w}^T \mathbf{x}) = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}}}$
- ▶ **Softmax** function: $\sigma(\mathbf{w}_j^T \mathbf{x}) = \frac{e^{\mathbf{w}_j^T \mathbf{x}}}{\sum_{i=1}^k e^{\mathbf{w}_i^T \mathbf{x}}}$
 - Calculate the probabilities of each target class over all possible target classes.
 - The softmax function for two classes is equivalent to the sigmoid function.



How Does Softmax Work? - Step 1

- For each instance $\mathbf{x}^{(i)}$, computes the **score** $\mathbf{w}_j^T \mathbf{x}^{(i)}$ for each **class** j .

$$\mathbf{w}_j^T \mathbf{x}^{(i)} = w_{0,j} x_0^{(i)} + w_{1,j} x_1^{(i)} + \cdots + w_{n,j} x_n^{(i)}$$

- Note that each class j has its **own dedicated parameter** vector \mathbf{w}_j .

$$\mathbf{W} = \begin{bmatrix} [w_{0,1}, w_{1,1}, \cdots, w_{n,1}] \\ [w_{0,2}, w_{1,2}, \cdots, w_{n,2}] \\ \vdots \\ [w_{0,k}, w_{1,k}, \cdots, w_{n,k}] \end{bmatrix} = \begin{bmatrix} \mathbf{w}_1^T \\ \mathbf{w}_2^T \\ \vdots \\ \mathbf{w}_k^T \end{bmatrix}$$



- $$\hat{y}_j^{(i)} = p(y^{(i)} = j \mid \mathbf{x}^{(i)}; \mathbf{w}_j) = \sigma(\mathbf{w}_j^T \mathbf{x}^{(i)}) = \frac{e^{\mathbf{w}_j^T \mathbf{x}^{(i)}}}{\sum_{l=1}^k e^{\mathbf{w}_l^T \mathbf{x}^{(i)}}}$$



How Does Softmax Work? - Step 3

- Predicts the class with the **highest estimated probability**.

Softmax Model Estimation and Prediction - Example (1/2)

- Assume we have a **training set** consisting of $m = 4$ instances from $k = 3$ **classes**.

$$\mathbf{x}^{(1)} \rightarrow \text{class1}, \mathbf{y}^{(1)\top} = [1 \ 0 \ 0]$$

$$\mathbf{x}^{(2)} \rightarrow \text{class2}, \mathbf{y}^{(2)\top} = [0 \ 1 \ 0]$$

$$\mathbf{x}^{(3)} \rightarrow \text{class3}, \mathbf{y}^{(3)\top} = [0 \ 0 \ 1]$$

$$\mathbf{x}^{(4)} \rightarrow \text{class3}, \mathbf{y}^{(4)\top} = [0 \ 0 \ 1]$$

$$\mathbf{Y} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

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$$\mathbf{Y} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

- Assume **training set** \mathbf{X} and random parameters \mathbf{W} are as below:

$$\mathbf{X} = \begin{bmatrix} 1 & 0.1 & 0.5 \\ 1 & 1.1 & 2.3 \\ 1 & -1.1 & -2.3 \\ 1 & -1.5 & -2.5 \end{bmatrix}$$

$$\mathbf{W} = \begin{bmatrix} 0.01 & 0.1 & 0.1 \\ 0.1 & 0.2 & 0.3 \\ 0.1 & 0.2 & 0.3 \end{bmatrix}$$

Softmax Model Estimation and Prediction - Example (2/2)

► Now, let's compute the softmax activation:

$$\hat{y}_j^{(i)} = p(y^{(i)} = j \mid \mathbf{x}^{(i)}; \mathbf{w}_j) = \sigma(\mathbf{w}_j^T \mathbf{x}^{(i)}) = \frac{e^{\mathbf{w}_j^T \mathbf{x}^{(i)}}}{\sum_{l=1}^k e^{\mathbf{w}_l^T \mathbf{x}^{(i)}}}$$

$$\hat{\mathbf{Y}} = \begin{bmatrix} \mathbf{y}^{(1)T} \\ \mathbf{y}^{(2)T} \\ \mathbf{y}^{(3)T} \\ \mathbf{y}^{(4)T} \end{bmatrix} = \begin{bmatrix} 0.29 & 0.34 & \mathbf{0.36} \\ 0.21 & 0.33 & \mathbf{0.46} \\ \mathbf{0.43} & 0.33 & 0.24 \\ \mathbf{0.45} & 0.33 & 0.22 \end{bmatrix}$$

$$\text{the predicted classes} = \begin{bmatrix} 3 \\ 3 \\ 1 \\ 1 \end{bmatrix}$$

$$\text{The correct classes} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 3 \end{bmatrix}$$

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- What is the cost function?



Multinomial Logistic Regression - Cost Function (1/2)

- ▶ The **objective** is to have a model that estimates a **high probability** for the target class, and consequently a **low probability** for the other classes.

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- ▶ **Cost function**: the **cross-entropy** between the **correct classes** and **predicted class** for all classes.

$$J(\mathbf{w}_j) = -\frac{1}{m} \sum_{i=1}^m \sum_{j=1}^k y_j^{(i)} \log(\hat{y}_j^{(i)})$$

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- ▶ $y_j^{(i)}$ is 1 if the target class for the i th instance is j , otherwise, it is 0.



Multinomial Logistic Regression - Cost Function (2/2)

- If there are two classes ($k = 2$), this cost function is equivalent to the **logistic regression's cost function**.

$$J(\mathbf{w}) = -\frac{1}{m} \sum_{i=1}^m [y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)})]$$



How to Learn Model Parameters \mathbf{W} ?

- Goal: find \mathbf{W} that minimizes $J(\mathbf{W})$.



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- ▶ **Goal:** find \mathbf{W} that **minimizes** $J(\mathbf{W})$.
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 2. Choose a **step size** η

How to Learn Model Parameters \mathbf{W} ?

- ▶ **Goal:** find \mathbf{W} that **minimizes** $J(\mathbf{W})$.
- ▶ Start at a **random point**, and repeat the following **steps**, until the **stopping criterion** is satisfied:
 1. Determine a **descent direction** $\frac{\partial J(\mathbf{W})}{\partial \mathbf{w}}$
 2. Choose a **step size** η
 3. **Update** the parameters: $\mathbf{w}^{(\text{next})} = \mathbf{w} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{w}}$ (**simultaneously** for **all** parameters)



Multinomial Logistic Regression in Spark

```
val training = spark.read.format("libsvm").load("multiclass_data.txt")
```



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```
import org.apache.spark.ml.classification.LogisticRegression
```

```
val lr = new LogisticRegression().setMaxIter(10).setRegParam(0.3).setElasticNetParam(0.8)  
val lrModel = lr.fit(training)
```



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import org.apache.spark.ml.classification.LogisticRegression
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val lr = new LogisticRegression().setMaxIter(10).setRegParam(0.3).setElasticNetParam(0.8)  
val lrModel = lr.fit(training)
```

```
println(s"Coefficients: \n${lrModel.coefficientMatrix}")  
println(s"Intercepts: \n${lrModel.interceptVector}")
```

Performance Measures



Performance Measures

- ▶ Evaluate the performance of a model.
- ▶ Depends on the application and its requirements.
- ▶ There are many different types of classification algorithms, but the evaluation of them share similar principles.

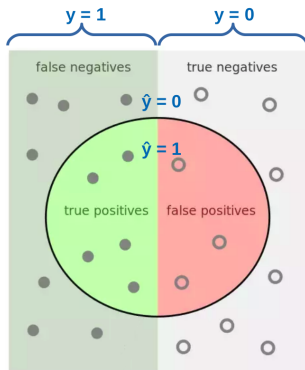


Evaluation of Classification Models (1/3)

- ▶ In a **classification problem**, there exists a **true output y** and a **model-generated predicted output \hat{y}** for each data point.
- ▶ The results for each instance point can be assigned to one of **four categories**:
 - True Positive (TP)
 - True Negative (TN)
 - False Positive (FP)
 - False Negative (FN)

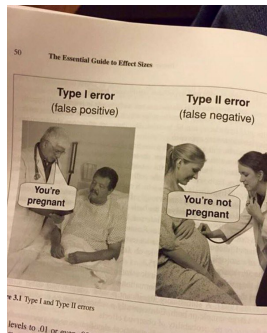
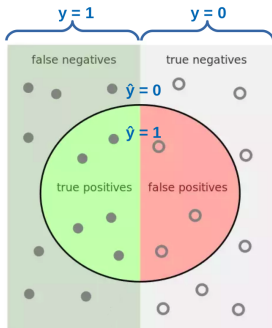
Evaluation of Classification Models (2/3)

- ▶ True Positive (TP): the label y is positive and prediction \hat{y} is also positive.
- ▶ True Negative (TN): the label y is negative and prediction \hat{y} is also negative.



Evaluation of Classification Models (3/3)

- **False Positive (FP)**: the **label y** is **negative** but **prediction \hat{y}** is **positive** (**type I error**).
- **False Negative (FN)**: the **label y** is **positive** but **prediction \hat{y}** is **negative** (**type II error**).





Why Pure Accuracy Is Not A Good Metric?

- **Accuracy**: how **close** the **prediction** is to the **true value**.



Why Pure Accuracy Is Not A Good Metric?

- ▶ **Accuracy**: how **close** the **prediction** is to the **true value**.
- ▶ Assume a highly **unbalanced dataset**
- ▶ E.g., a dataset where **95%** of the data points are **not fraud** and **5%** of the data points are **fraud**.



Why Pure Accuracy Is Not A Good Metric?

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- ▶ Assume a highly **unbalanced dataset**
- ▶ E.g., a dataset where **95%** of the data points are **not fraud** and **5%** of the data points are **fraud**.
- ▶ A **naive classifier** that **predicts not fraud**, regardless of input, will be **95% accurate**.

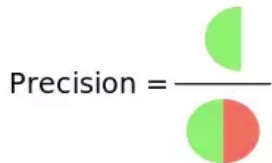
Why Pure Accuracy Is Not A Good Metric?

- ▶ **Accuracy**: how **close** the **prediction** is to the **true value**.
- ▶ Assume a highly **unbalanced dataset**
- ▶ E.g., a dataset where **95%** of the data points are **not fraud** and **5%** of the data points are **fraud**.
- ▶ A **naive classifier** that **predicts not fraud**, regardless of input, will be **95% accurate**.
- ▶ For this reason, metrics like **precision** and **recall** are typically used.

Precision

- It is the **accuracy** of the **positive predictions**.

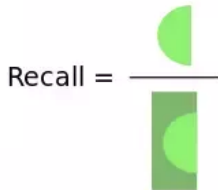
$$\text{Precision} = p(y = 1 \mid \hat{y} = 1) = \frac{TP}{TP + FP}$$

A Venn diagram illustrating the components of precision. It consists of two overlapping circles. The top circle is entirely green. The bottom circle is split vertically, with the left half being green and the right half being red. A horizontal line is drawn across the middle of the two circles, representing the equation Precision = (green area) / (total green area).
$$\text{Precision} = \frac{\text{Green Area}}{\text{Total Green Area}}$$

Recall

- ▶ Is the **ratio** of **positive instances** that are **correctly detected** by the classifier.
- ▶ Also called **sensitivity** or **true positive rate (TPR)**.

$$\text{Recall} = p(\hat{y} = 1 \mid y = 1) = \frac{TP}{TP + FN}$$

A Venn diagram illustrating the concept of Recall. It consists of a large green rectangle representing the total number of positive instances (y=1). Inside this rectangle, there is a smaller green circle representing the number of positive instances correctly detected by the classifier (TP). The word 'Recall =' is placed to the left of the diagram, followed by a horizontal line that aligns with the top of the circle, indicating the ratio of the circle's area to the rectangle's area.
$$\text{Recall} = \frac{\text{Area of Circle}}{\text{Area of Rectangle}}$$

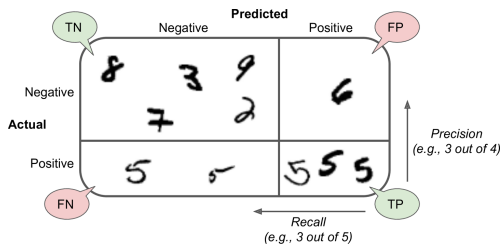
F1 Score

- ▶ **F1 score**: combine precision and recall into a single metric.
- ▶ The **F1 score** is the harmonic mean of precision and recall.
- ▶ Whereas the regular mean treats all values equally, the harmonic mean gives much more weight to low values.
- ▶ F1 only gets high score if both recall and precision are high.

$$F1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}}$$

Confusion Matrix

- ▶ The **confusion matrix** is $K \times K$, where K is the **number of classes**.
- ▶ It shows the **number of correct and incorrect predictions** made by the classification model **compared to the actual outcomes** in the data.



Confusion Matrix - Example

| | | Predicted | | |
|--------|----------|--|-------------|---|
| | | Negative | Positive | |
| Actual | Negative | 8 3 9 | 6 | <div>TP</div> <div>Precision (e.g., 3 out of 4)</div> |
| | Positive | 5 5 5 | 5 5 5 | |
| | | <div>Recall (e.g., 3 out of 5)</div> | | |

$$TP = 3, TN = 5, FP = 1, FN = 2$$

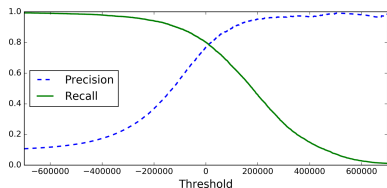
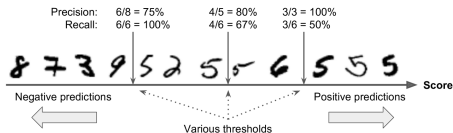
$$\text{Precision} = \frac{TP}{TP + FP} = \frac{3}{3 + 1} = \frac{3}{4}$$

$$\text{Recall (TPR)} = \frac{TP}{TP + FN} = \frac{3}{3 + 2} = \frac{3}{5}$$

$$\text{FPR} = \frac{FP}{TN + FP} = \frac{1}{5 + 1} = \frac{1}{6}$$

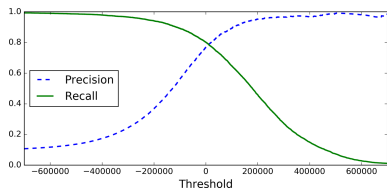
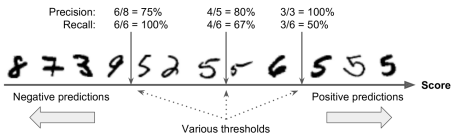
Precision-Recall Tradeoff

- Precision-recall tradeoff: increasing precision reduces recall, and vice versa.



Precision-Recall Tradeoff

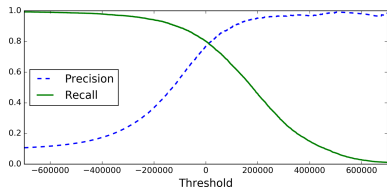
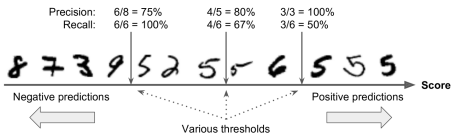
- **Precision-recall tradeoff:** increasing precision reduces recall, and vice versa.
- Assume a classifier that detects number 5 from the other digits.
 - If an instance score is greater than a threshold, it assigns it to the positive class, otherwise to the negative class.



-
- Precision: $\frac{6}{8} = 75\%$ $\frac{4}{5} = 80\%$ $\frac{3}{3} = 100\%$
 Recall: $\frac{6}{6} = 100\%$ $\frac{4}{6} = 67\%$ $\frac{3}{6} = 50\%$
- 8 7 3 9 5 2 5 5 6 5 5 5
- Negative predictions Positive predictions Score
- Various thresholds

Precision-Recall Tradeoff

- **Precision-recall tradeoff**: increasing precision reduces recall, and vice versa.
- Assume a classifier that detects number 5 from the other digits.
 - If an instance score is greater than a threshold, it assigns it to the positive class, otherwise to the negative class.
- Raising the threshold (move it to the arrow on the right), the false positive (the 6) becomes a true negative, thereby increasing precision.
- Lowering the threshold increases recall and reduces precision.

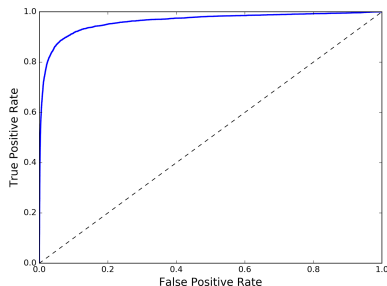
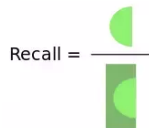


- $$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

FPR = 

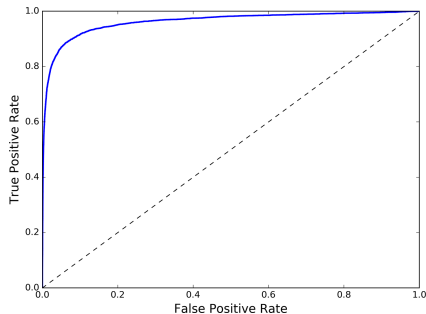
The ROC Curve (1/2)

- ▶ True positive rate (TPR) (recall): $p(\hat{y} = 1 \mid y = 1)$
- ▶ False positive rate (FPR): $p(\hat{y} = 1 \mid y = 0)$
- ▶ The **receiver operating characteristic (ROC)** curves summarize the **trade-off** between the **TPR** and **FPR** for a model using different probability **thresholds**.



The ROC Curve (2/2)

- ▶ Here is a **tradeoff**: the **higher** the **TPR**, the **more** **FPR** the classifier produces.
- ▶ The **dotted line** represents the ROC curve of a **purely random** classifier.
- ▶ A **good classifier** moves toward the **top-left** corner.
- ▶ **Area under the curve (AUC)**





Binomial Logistic Regression Measurements in Spark

```
val lr = new LogisticRegression()  
val lrModel = lr.fit(training)
```

Binomial Logistic Regression Measurements in Spark

```
val lr = new LogisticRegression()
val lrModel = lr.fit(training)

val trainingSummary = lrModel.binarySummary

// obtain the objective per iteration.
val objectiveHistory = trainingSummary.objectiveHistory
objectiveHistory.foreach(loss => println(loss))

// obtain the ROC as a dataframe and areaUnderROC.
val roc = trainingSummary.roc
roc.show()
println(s"areaUnderROC: ${trainingSummary.areaUnderROC}")

// set the model threshold to maximize F-Measure
val fMeasure = trainingSummary.fMeasureByThreshold
val maxFMeasure = fMeasure.select(max("F-Measure")).head().getDouble(0)
val bestThreshold = fMeasure.where($"F-Measure" === maxFMeasure)
    .select("threshold").head().getDouble(0)
lrModel.setThreshold(bestThreshold)
```



Multinomial Logistic Regression in Spark (1/2)

```
val trainingSummary = lrModel.summary

// for multiclass, we can inspect metrics on a per-label basis
println("False positive rate by label:")
trainingSummary.falsePositiveRateByLabel.zipWithIndex.foreach { case (rate, label) =>
  println(s"label $label: $rate")
}

println("True positive rate by label:")
trainingSummary.truePositiveRateByLabel.zipWithIndex.foreach { case (rate, label) =>
  println(s"label $label: $rate")
}
```

Multinomial Logistic Regression in Spark (2/2)

```
println("Precision by label:")
trainingSummary.precisionByLabel.zipWithIndex.foreach { case (prec, label) =>
  println(s"label $label: $prec")
}

println("Recall by label:")
trainingSummary.recallByLabel.zipWithIndex.foreach { case (rec, label) =>
  println(s"label $label: $rec")
}

val accuracy = trainingSummary.accuracy
val falsePositiveRate = trainingSummary.weightedFalsePositiveRate
val truePositiveRate = trainingSummary.weightedTruePositiveRate
val fMeasure = trainingSummary.weightedFMeasure
val precision = trainingSummary.weightedPrecision
val recall = trainingSummary.weightedRecall
```

Summary

Summary

- ▶ Binomial logistic regression
 - $y \in \{0, 1\}$
 - Sigmoid function
 - Minimize the cross-entropy

- ▶ Multinomial logistic regression
 - $y \in \{1, 2, \dots, k\}$
 - Softmax function
 - Minimize the cross-entropy

- ▶ Performance measurements
 - TP, TF, FP, FN
 - Precision, recall, F1
 - Threshold and ROC



Reference

- ▶ Ian Goodfellow et al., Deep Learning (Ch. 4, 5)
- ▶ Aurélien Géron, Hands-On Machine Learning (Ch. 3)
- ▶ Matei Zaharia et al., Spark - The Definitive Guide (Ch. 26)

Questions?