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CLASSIFICATION VS REGRESSION



Regression

i.e., **predicting** a continuous value by learning **relationship** between **dependent** and **independent** variables.

Output is numeric value.

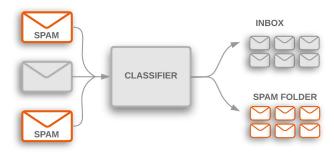




Classification

Identifying which of the category a new observation belong.

Output is class label.



Logistic Regression



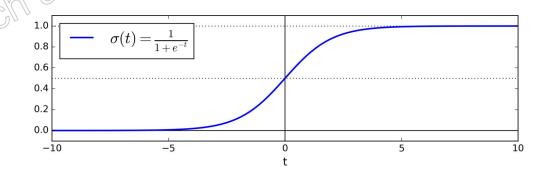
Logistic Regression estimates probability that an instance belongs to a particular class.

Just like linear regression, logistic regression also finds weighted sum of the inputs but instead of the continuous value, it outputs its sigmoid result.

$$\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \ldots + \theta_n x_n$$
 Linear Regression (Multivariate)

$$\hat{p} = h_{\mathbf{\theta}}(\mathbf{x}) = \sigma(\mathbf{\theta}^T \mathbf{x})$$

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





Logistic Regression model prediction (binary classifier)

$$\hat{p} = h_{\mathbf{\theta}}(\mathbf{x}) = \sigma(\mathbf{\theta}^T \mathbf{x})$$

$$\hat{y} = \begin{cases} 0 & \text{if } \hat{p} < 0.5 \\ 1 & \text{if } \hat{p} \ge 0.5 \end{cases}$$

No analytical solution

It is a convex function

Cost function to optimize

Gradient descent can be used to solve the problem.

$$J(\mathbf{\theta}) = \sum_{i=1}^{m} \left[y^{(i)} log(\hat{p}^{(i)}) + (1 - y^{(i)}) log(1 - \hat{p}^{(i)}) \right]$$



SOFTMAX REGRESSION

SOFTMAX REGRESSION



Softmax regression is logistic regression extended for multiple classes.

Logistic regression

Logistic regression supports only binary classification.

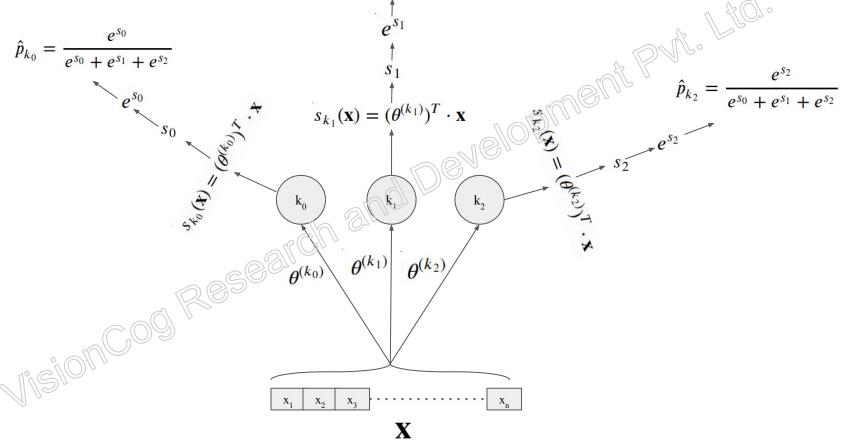
Softmax regression:

- For each class k, a score is estimated.
- Then estimates probability of each class by applying softmax function.
- The predicted class is the one with highest estimated probability.

SOFTMAX REGRESSION

$$\hat{p}_{k_1} = \frac{e^{s_1}}{e^{s_0} + e^{s_1} + e^{s_2}}$$





SOFTMAX REGRESSION



Score

$$s_k(\mathbf{x}) = (\mathbf{\theta}^{(k)})^T \mathbf{x}$$

Probability

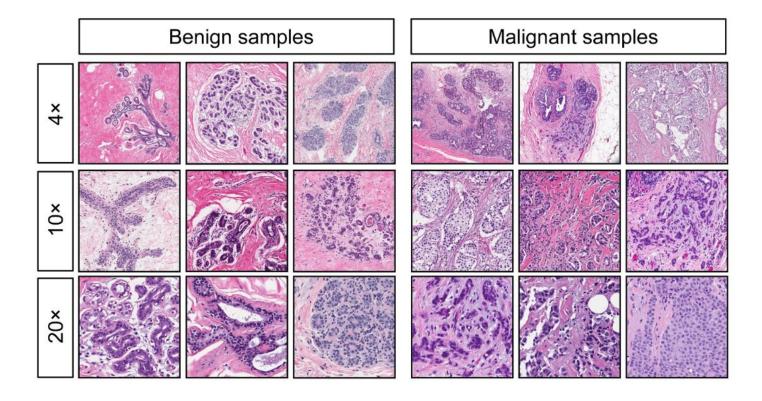
$$\hat{p}_k = \sigma(\mathbf{s}(\mathbf{x}))_k = \frac{\exp(s_k(\mathbf{x}))}{\sum_{j=1}^K \exp(s_j(\mathbf{x}))}$$

Class prediction

$$\mathbf{y} = \underset{k}{\operatorname{argmax}} \ \sigma(\mathbf{s}(\mathbf{x}))_{k} = \underset{k}{\operatorname{argmax}} \ s_{k}(\mathbf{x}) = \underset{k}{\operatorname{argmax}} \ ((\mathbf{\theta}^{(k)})^{T}\mathbf{x})$$



Breast cancer wisconsin (diagnostic) dataset





import numpy as np
from sklearn import datasets

cancerDB = datasets.load_breast_cancer()

print(cancerDB.DESCR)

Breast cancer wisconsin (diagnostic) dataset

Data Set Characteristics:

:Number of Instances: 569

:Number of Attributes: 30 numeric, predictive attributes and the class

:Attribute Information:

- radius (mean of distances from center to points on the perimeter)
- texture (standard deviation of gray-scale values)
- area
- smoothness (local variation in radius lengths)
- compactness (perimeter^2 / area 1.0)
- concavity (severity of concave portions of the contour)
- concave points (number of concave portions of the contour)
- symmetry
- fractal dimension ("coastline approximation" 1)

The mean, standard error, and "worst" or largest (mean of the three largest values) of these features were computed for each image, resulting in 30 features. For instance, field 3 is Mean Radius, field 13 is Radius SE, field 23 is Worst Radius.

- class:
 - WDBC-Malignant
 - WDBC-Benign





:Summary Statistics:

| GISTIC REGRESSIC | | | n.A. | |
|------------------|---|-------|-------------------------|--|
| | :Summary Statistics: | | Max = ===== 28.11 39.28 | |
| | | | | |
| | | Min | Max | |
| | radius (mean): | 6.981 | 28.11 | |
| | texture (mean): | 9.71 | 39.28 | |
| | perimeter (mean): | 43.79 | 188.5 | |
| | area (mean): | 143.5 | 2501.0 | |
| | smoothness (mean): | | | |
| | compactness (mean): | 0.019 | 0.345 | |
| | concavity (mean): | 6.0 | 0.427 | |
| | concave points (mean): | 0.0 | 0.201 | |
| | symmetry (mean): | | 0.304 | |
| | fractal dimension (mean): | 0.05 | 0.097 | |
| | radius (standard error): | | 2.873 | |
| | texture (standard error): | 0.36 | 4.885 | |
| | perimeter (standard error): | | 21.98 | |
| | area (standard error): | | 542.2 | |
| | smoothness (standard error): | | 0.031 | |
| | compactness (standard error): | | 0.135 | |
| | concavity (standard error): | 0.0 | 0.396 | |
| | concave points (standard error): | 0.0 | 0.053 | |
| | <pre>symmetry (standard error): fractal dimension (standard error):</pre> | | | |
| | radius (worst): | 7.93 | 36.04 | |
| | texture (worst): | | 49.54 | |
| | perimeter (worst): | | 251.2 | |
| | area (worst): | | 4254.0 | |
| 10 6 10 0 | smoothness (worst): | | 0.223 | |
| VisionCo9 " | compactness (worst): | | 1.058 | |
| | concavity (worst): | 0.0 | 1.252 | |
| ~ | concave points (worst): | 0.0 | 0.291 | |
| | symmetry (worst): | | 0.664 | |
| | fractal dimension (worst): | 0.055 | 0.208 | |



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```
from sklearn.model selection import train test split
# Splitting the dataset into 80% training and 20% testing
X train, X test, y train, y test = train test split(X) y, test size=0.2,
                                                    stratify=y, random state=42)
print(X train.shape)
 (455, 30)
print(X_test.shape)
# (114, 30)
```



```
from sklearn.linear model import LogisticRegression
# Creating an object for LogisticRegression class
model LR = LogisticRegression()
# Training the model to estimate the parameters
model LR.fit(X train, y train)
# Evaluate the accuracy of the model using test set
accuracy = model LR.score(X test, y test)
print(accuracy)
```