

#### **HANDOUTS**

# "The Sum of the Parts is other than the whole"

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#### Bayes' Theorem

Bayes' rule is a rigorous method for interpreting evidence in the context of previous experience or knowledge.

$$Pr(A|X) = \frac{Pr(X|A) Pr(A)}{Pr(X|A) Pr(A) + Pr(X|not A) Pr(not A)}$$

#### **Decision Tree**

The classification technique is a systematic approach to build classification models from input data. The decision tree classifiers organize a series of test questions and conditions in a tree structure. So, a decision tree is a graph that uses a branching method to illustrate every possible decision outcome.

The root and internal nodes contain attribute test conditions that are used to separate records showing different characteristics. To each terminal node a class label is assigned. During the test phase, starting from the root node, we apply the test condition to the input and follow the appropriate branch based on the test outcome. When it reaches the leaf node, the class label associated with the leaf node is then assigned to the input.

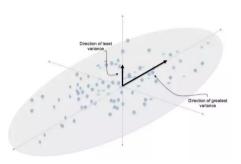
#### **Singular Value Decomposition**

The singular value decomposition (SVD) is a factorization of a real or complex matrix.

The directions along which there is greatest variance are referred to as the "principal components".

Geometrically, the SVD means that spheres of the proper dimension in the domain are transformed

into ellipsoids in the codomain. Since the transformation may not be injective, the dimension of the ellipsoid is at most the dimension of the sphere. So you get some distortion along some axes and some collapsing along other axes.





#### **Principal Component Analysis**

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components

#### When do we use SVD and when PCA?

PCA is used for finding the directions where most of the energy of the vectors lies, whereas SVD is a factorization of matrix into ortho-normal spaces.

There is a very direct mathematical relation between SVD (Singular Value Decomposition) and PCA (Principal Component Analysis).

But, even if the two algorithms deliver essentially the same result (a set of "new axes" constructed from linear combinations of the original feature space axes in which the dataset is plotted), and formally both solutions can be used to calculate the same principal components and their correspondent to singular values, the extra step of calculating the covariance matrix can lead to numerical rounding errors when calculating the vectors.

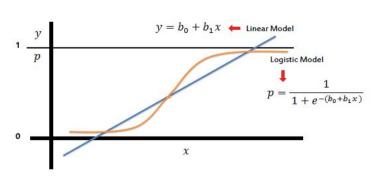
#### **Logistic Regression**

The logistic regression is a predictive analysis used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables. The task is to estimate the log odds of an event. Mathematically, logistic regression estimates a multiple linear regression function defined as:

$$= \log \left( \frac{p(y=1)}{1 - (p=1)} \right) = \beta_0 + \beta_1 \cdot x_2 + \beta_2 \cdot x_2 + \dots + \beta_p \cdot x_m$$

In linear regression we try to predict the value of y(i) for the ith example x(i) using a linear function  $y=h\theta(x)$ .

The function  $\sigma(z)$  is an S-shaped function that "squashes" the value of x into the range [0,1], so that we may interpret  $h\theta(x)$  as a probability. The probability  $P(y=1|x)=h\theta(x)$  is large when x belongs to the "1" class and



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small when x belongs to the "0" class.

#### **Linear Regression**

Linear regression uses the general linear equation  $Y=b0+\sum(biXi)+\epsilon Y$ , where Y is a dependent variable and independent variables Xi. Both Y and X are continuous variables. The term  $\epsilon$  is the variance that is not explained by the model and is usually just called "error".

# What is the difference between linear regression and logistic regression?

Logistic regression is a generalized linear model (GLM) procedure using the same basic formula of Linear Regression. However, instead of the continuous YY, it is regressing for the probability of a categorical outcome.

#### **Support Vector Machine**

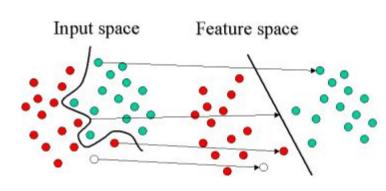
Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects



Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal separation (which is more complex than a line). Classification tasks based on drawing separating lines to distinguish between objects of



different class memberships are known as hyperplane classifiers. Support Vector



Machines are particularly suited to handle such tasks. Data are mapped (rearranged) using a set of mathematical functions. kernels. Support known as Vector Machine (SVM) primarily a classier method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different

class labels. SVM supports both regression and classification tasks.





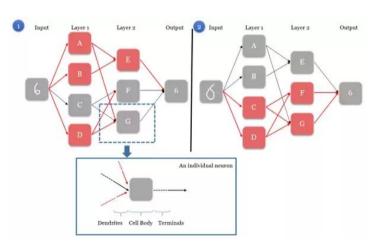


#### **Kernel functions**

The kernel function, represents a dot product of input data points mapped into the higher dimensional feature space by transformation  $\phi$ . Gamma is an adjustable parameter of certain kernel functions. The RBF is by far the most popular choice of kernel types used in Support Vector Machines. This is mainly because of their localized and finite responses across the entire range of the real x-axis.

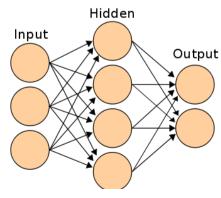
#### **Artificial Neural Network**

Artificial neural networks (ANNs) is a computational model able to be any real



function. It does that taking the biological model as example. ANNs simply map inputs to outputs. They do so by adding biases to the inputs as well as multiplying those inputs with weights. Those weights and biases together are known as a model, which is responsible for the guesses the ANN makes about inputs. The weights and biases can and will be adjusted, depending on how accurate they

are with their guesses. Using a loss function, we measure how wrong each guess is by contrasting it with a ground-truth answer. Then we take the error produced by the loss function, and we use it to adjust the weights and biases. Each neuron makes a single decision by a weighted approach. The inputs are weighted because some inputs are more important than others.



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Two main factors are involved during the training of the model:

- A metric to evaluate the model's accuracy
- Rules that govern whether neurons are activated or not

A common metric to evaluate model accuracy is the sum of the squared errors (SSE).

The ANN model will try to minimize the loss by changing its internal weight coefficients.

#### Rectified linear unit (ReLU) Function

The ReLU is an activation function used in the hidden layers of the network. It is

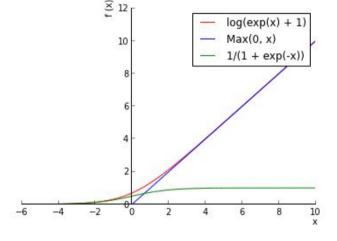
commonly used in classification problems because introduce sparsity among neurons and does not face the gradient vanishing problems (present in the other activation function such sigmoid and tahn.

$$f(x) = \sum_{i=1}^{n} \sigma(x-i+0.5) \approx \log(1+ex)$$

Other common activation function are:

Sigmoid unit : f(x) = 1 + exp(-x)

Tanh unit: f(x)=tanh(x)



# Artificial Neural Networks: Why do we use the softmax function for the output layer?

Simply, sigmoid could work as well but softmax do the job better. The sigmoid function in the final layer works just in case the output admits multiple "true" answers (so, if it is not a probability distribution). Classification problems can take advantage of the fact that the classes are mutually exclusive. Mathematically, using a SoftMax activation function is basically equivalent to use a Logistic Regression over the features extracted from the layer before the final Fully Connected layer. Softmax activation is basically the normalized exponential probability of class observations represented as neuron activations.







#### **Our Results**

| <b>Accuracy</b> |  |
|-----------------|--|
| Accuracy        |  |

| Moduracy |                                   |
|----------|-----------------------------------|
| 0.888    | Bayes                             |
| 0.9004   | Decision Tree                     |
| 0.9146   | Logistic Regression (regul.=1)    |
| 0.9074   | Logistic Regression (regul.=10)   |
| 0.9036   | Logistic Regression (regul.=100)  |
| 0.9004   | Logistic Regression (regul.=1000) |

|                        | Linear<br>Kernel | rbf Kernel |
|------------------------|------------------|------------|
| regul = 1 Gamma = 1    | 0.83220          | 0.845949   |
| regul = 1 Gamma = 10   | 0.83220          | 0.846673   |
| regul = 1 Gamma = 100  | 0.83220          | 0.847878   |
| regul = 10 Gamma = 1   | 0.83220          | 0.846190   |
| regul = 10 Gamma = 10  | 0.83220          | 0.848360   |
| regul = 10 Gamma = 100 | 0.83220          | 0.849083   |





|                          | Linear<br>Kernel | rbf Kernel |
|--------------------------|------------------|------------|
| regul = 100 Gamma = 1    | 0.83220          | 0.8457087  |
| regul = 100 Gamma = 10   | 0.83220          | 0.8488428  |
| regul = 100 Gamma = 100  | 0.83220          | 0.8488428  |
| regul = 1000 Gamma = 1   | 0.83220          | 0.8478784  |
| regul = 1000 Gamma = 10  | 0.83220          | 0.8481195  |
| regul = 1000 Gamma = 100 | 0.83220          | 0.8459498  |

|                        | 1 hidden layer | 2 hidden layer | 3 hidden layer |
|------------------------|----------------|----------------|----------------|
| Accuracy               | 0.967213       | 0.951543       | 0.844021       |
| Neurons first layer    | 500            | 250            | 250            |
| Neurons second layer   | 0              | 125            | 125            |
| Neurons third layer    | 0              | 0              | 25             |
| starting learning rate | 1e-02          | e-02           | e-02           |

