VIETNAM GENERAL CONFEDERATION OF LABOUR

**TON DUC THANG UNIRVERSITY**

FACULTY OF INFORMATION TECHNOLOGY



**MIDTERM PROJECT**

**INTRODUCTION TO MACHINE LEARNING**

*Supervisor*: **Lê Anh Cường**

*Author*: **Nguyễn Công Minh Thành – 520K0215**

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Class **: 20K50301**

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**HO CHI MINH CITY, 2022**

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*Ho Chi Minh City, January 7th , 2022 Authors*

*Nguyễn Công Minh Thành – Trịnh Bảo Toàn*

# ABSTRACT

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# LIST OF SYMBOLS AND ABBREVIATIONS

## LIST OF SYMBOLS

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# Problem 1:

# Problem 2:

1. Using Correlation based methods.

Since the correlation-based feature selection (CFS) technique is a filter method, it is unrelated to the chosen classification model. As implied by the name, correlations are the sole intrinsic qualities used to assess feature subsets.

Finding a feature subset with low feature-feature correlation, which prevents redundancy, and high feature-class correlation, which preserves or boosts predictive power, is the objective.

To do so, the method uses the following equation to estimate the worth of a subset s with k features:

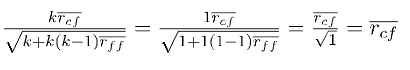


average feature-feature correlation.

 average feature-class correlation.

number of features of that subset.

The search begins with a subset that is empty and assesses each feature's quality in relation to the empty set. The feature-feature correlation may be disregarded for this phase since the denominator of the equation above can be simplified to 1 because k = 1.



The assessment is therefore purely focused on the feature-class correlation for the initial iteration. The as-yet-empty subset receives the addition of the feature with the highest feature-class correlation. The feature that forms the best subset with the one that was already included is preserved after all features, excluding the one that was already introduced, are once again assessed.

The technique loops back to the next best unexpanded subset whenever a feature expansion does not result in an improvement. This method explores the whole feature subset space without any restrictions. Therefore, the amount of backtracking must be controlled. The feature subset that produced the greatest merit up until this point is returned by the algorithm after it reaches this limit.

The association between the features is found out by using the correlation method. There are two broad categories that can be used to measure the correlation between two random variables. One is based on classical linear correlation and the other is based on information theory. Out of these two, the most familiar measure is linear correlation coefficient. As per the standard literature, for a pair of variables (X, Y), the linear correlation coefficient ‘r’ is given by:

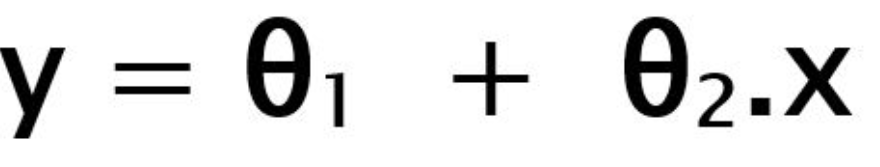


1. MAE and Linear Regression
2. Linear Regression

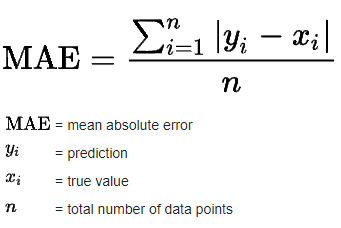
Linear Regression is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting. Different regression models differ based on – the kind of relationship between dependent and independent variables they are considering, and the number of independent variables getting used.

Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). Hence, the name is Linear Regression. In the figure above, X (input) is the work experience and Y (output) is the salary of a person. The regression line is the best fit line for our model.

Hypothesis function for Linear Regression :



1. MAE

Mean absolute error (MAE) is a popular metric because, as with Root [mean squared error](https://www.sciencedirect.com/topics/engineering/mean-squared-error) (RMSE), see next subsection, the error value units match the predicted target value units. Unlike [RMSE](https://www.sciencedirect.com/topics/engineering/root-mean-square-error), the changes in MAE are linear and therefore intuitive. [MSE](https://www.sciencedirect.com/topics/engineering/mean-square-error) and RMSE penalize larger errors more, inflating or increasing the mean error value due to the square of the error value. In MAE, different errors are not weighted more or less, but the scores increase linearly with the increase in errors. The MAE score is measured as the average of the absolute error values. The Absolute is a mathematical function that makes a number positive. Therefore, the difference between an expected value and a predicted value can be:

The formula may look a little daunting, but the steps are easy:

1. Find all of your absolute errors, xi – x.
2. Add them all up.
3. Divide by the number of errors. For example, if you had 10 measurements, divide by 10.

Compare the difference between feature sets through Mean Absolute Error:

In this session we use ‘Diabetes.csv’ (include these attribute: 'Insulin', 'Glucose', 'BloodPressure', 'SkinThickness', 'BMI', 'DiabetesPedigreeFunction', 'Age')

|  |  |
| --- | --- |
| Attribute | MAE |
| Insulin | 0.412 |
| Glucose | 0.344 |
| Blood Pressure | 0.424 |
| Skin Thickness | 0.421 |
| BMI | 0.391 |
| Diabetes Pedigree Function | 0.409 |
| Age | 0.418 |

# Problem 3:

1. ***Stochastic Gradient Descent Algorithm***

* Stochastic gradient descent is an optimization algorithm often used in machine learning applications to find the model parameters that correspond to the best fit between predicted and actual outputs. It’s an inexact but powerful technique.
* Stochastic gradient descent is widely used in machine learning applications.
* Stochastic gradient descent algorithms are a modification of gradient descent. In stochastic gradient descent, you calculate the gradient using just a random small part of the observations instead of all of them. In some cases, this approach can reduce computation time.
* Online stochastic gradient descent is a variant of stochastic gradient descent in which you estimate the gradient of the cost function for each observation and update the decision variables accordingly. This can help you find the global minimum, especially if the objective function is convex.
* Batch stochastic gradient descent is somewhere between ordinary gradient descent and the online method. The gradients are calculated and the decision variables are updated iteratively with subsets of all observations, called minibatches. This variant is very popular for training neural networks.
* You can imagine the online algorithm as a special kind of batch algorithm in which each minibatch has only one observation. Classical gradient descent is another special case in which there’s only one batch containing all observations.

1. **Minibatches in Stochastic Gradient Descent**

Stochastic gradient descent begins with an initial vector of choice variables and updates it over a number of iterations, much like in the case of the ordinary gradient descent. What takes place during the iterations differs between the two:

* Minibatches are generated at random from the collection of data via stochastic gradient descent.
* The gradient is calculated and the vector is moved for each minibatch.
* You declare that an iteration, or epoch, is complete when all minibatches have been consumed and go on to the next one.

1. **Momentum in Stochastic Gradient Descent**

As you've previously seen, the gradient descent outcome may be significantly influenced by the learning rate. During the execution of the algorithm, you may modify the learning rate using a variety of alternative tactics. Additionally, you may add momentum to your algorithm.

Momentum can be used to offset the impact of learning rate. The concept is to keep track of the vector's most recent update and use it to determine the following one. Although you don't always move the vector in the direction of the negative gradient, you usually maintain the prior move's direction and magnitude.

The decay rate or decay factor parameter determines how significant the preceding update's impact is.

1. **Random Start Values**

For stochastic gradient descent, the beginning point is frequently less crucial than for standard gradient descent. Additionally, it could present an unneeded challenge for a user, especially when there are several potential outcomes. Imagine having to manually establish the parameters for a neural network with thousands of biases and weights to get an idea.

1. ***Adam Optimization Algorithm***

Adam is an optimization algorithm that can be used instead of the classical stochastic gradient descent procedure to update network weights iterative based in training data.

The attractive benefits of using Adam on non-convex optimization problems, as follows:

* Straightforward to implement.
* Computationally efficient.
* Little memory requirements.
* Invariant to diagonal rescale of the gradients.
* Well suited for problems that are large in terms of data and/or parameters.
* Appropriate for non-stationary objectives.
* Appropriate for problems with very noisy/or sparse gradients.
* Hyper-parameters have intuitive interpretation and typically require little tuning.

Compared to traditional stochastic gradient descent, Adam is unique.

For all weight updates, stochastic gradient descent maintains a constant learning rate (referred to as alpha), which does not fluctuate throughout training.

As learning progresses, a learning rate is maintained and independently adjusted for each network weight (parameter).

Adam as combining the advantages of two other extensions of stochastic gradient descent. Specifically:

Adaptive Gradient Algorithm (AdaGrad) that maintains a per-parameter learning rate that improves performance on problems with sparse gradients (e.g. natural language and computer vision problems).

Root Mean Square Propagation (RMSProp) that also maintains per-parameter learning rates that are adapted based on the average of recent magnitudes of the gradients for the weight (e.g. how quickly it is changing). This means the algorithm does well on online and non-stationary problems (e.g. noisy).

Adam realizes the benefits of both AdaGrad and RMSProp.

Instead of adapting the parameter learning rates based on the average first moment (the mean) as in RMSProp, Adam also makes use of the average of the second moments of the gradients (the uncentered variance).

Specifically, the algorithm calculates an exponential moving average of the gradient and the squared gradient, and the parameters beta1 and beta2 control the decay rates of these moving averages.

* Adam is a replacement optimization algorithm for stochastic gradient descent for training deep learning models.
* Adam combines the best properties of the AdaGrad and RMSProp algorithms to provide an optimization algorithm that can handle sparse gradients on noisy problems.
* Adam is relatively easy to configure where the default configuration parameters do well on most problems.

# REFERENCE