**Using neural networks to determine factors causing heart attacks**

**Abstract**

According to the CDC, someone in the US suffers a heart attack every 40 seconds. Heart disease is the leading cause of death for both men and women across ethnicities. Early action can help prevent many of these fatalities. We attempt to predict the factors associated with heart attacks and enable patients to take early action. In this paper, we will use concepts of machine learning such as neural networks to develop the model, as well as predicting the likelihood that a patient will have a heart attack.

**Introduction**

Machine Learning is a subfield of Artificial Intelligence that uses data to develop computational models that make predictions and help make decisions. The branch of machine learning we will use is called supervised learning. Here is part of the dataset we used:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Sex | Age | Type of chest pain | Cholesterol | Did the patient have a heart attack? |
| Male | 63 | 3 | 233 | Yes |
| Male | 37 | 2 | 250 | Yes |
| Female | 41 | 1 | 204 | Yes |
| Male | 57 | 0 | 131 | No |
| Female | 57 | 1 | 236 | No |

In the machine learning language, each patient is called an example. This set is called the training set. We have two types of information we have about each example, the features and labels. The goal is to develop a model that will predict the label in terms of the features. In the above tables, the features are sex, age, type of chest pain, and cholesterol and the label is the if the patient is at risk or not risk of having a heart attack.

Note that, for the examples in the data set we are given, as illustrated by the above table, both the features and labels are known. The goal of supervised learning (and our goal) is to develop a model that can predict the label of a new example, not in the data set originally given, when only the features of that example are known (in our case, the model will predict the if a patient is at risk of a heart attack once the model knows its features, i.e. sex, age, type of chest pain, and cholesterol).

The sex, age, type of chest pain, and cholesterol are collectively called “features”, and the “label” is whether or not the patient had a heart attack. The goal of our model is to predict the label of a new example given only the features.

Heart attack data

A picture containing calendar

Description automatically generated

Our data set, shown above, contains information about several patients. This includes the patient’s age, sex, the type of chest pain, resting blood pressure, cholesterol levels, whether blood sugar is higher than 120 mg/dl, resting electrocardiographic results, and maximum heart rate achieved. These are the features that will be inputted into the model. The last column - “output” - shows whether the person had a heart attack and is the label that our model tries to predict.

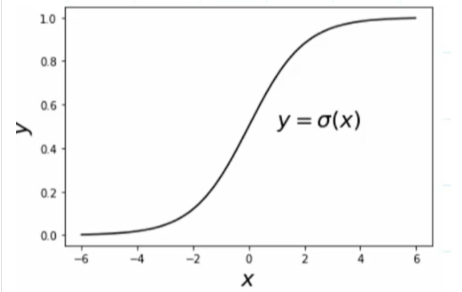
Since each example belongs to one of two categories (person had a heart attack and person did not have a heart attack), this is classified as a binary classification problem.

The machine learning algorithm takes all the features, denoted as , and comes up with a function that outputs a number between 0 and 1. We denote this number with ( is the model’s prediction of a label). In our case, this number represents the probability that a patient has a heart attack. If this number is greater than 0.5, the prediction is category 1 (patient had a heart attack), and if the number is less than 0.5, the prediction is category 0 (patient did not have a heart attack). Since the model is a function, we can write = . For binary classification problems, we can use either logistic regression or neural networks to create the model.

Logistic Regression

Logistic regression is a machine learning technique that is used for binary classification problems.

Logistic regression uses the sigmoid function, denoted by σ. The sigmoid function is:



A notable property is that for all .

Generally, the logistic regression model assumes the prediction is in the following form:

are the features of the examples and are the parameters. These parameters determine the model (when the parameters change, the model also changes). The method of logistic regression selects the parameters that make the binary cross entropy error on the training set as small as possible.

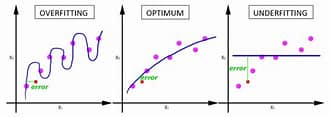
Binary Cross Entropy Error

In binary classification problems such as this one, we use the binary cross entropy error to measure how good the model’s predictions are. Let be the labels of a set of examples (in this case, whether or not the patient has a heart attack) and let be the predictions of the labels by the model (these predicted labels represent the probability, according to the model, that the patient had a heart attack). The binary cross entropy error is

The lower the value of J, the better the model’s predictions.

Training Set and Validation Set

We do not want the algorithm to come up with a function that crosses through all the points; we want the model to see the general relationship and not capture all the noise. When the function captures all the noise and is needlessly complex, it is known as “overfitting”.

[](https://www.bing.com/images/search?q=overfitting+example&id=D13476A172A709FA69A533473CC0211AFB787A83&FORM=EQNAMI)

To overcome this, we split the examples in the dataset into the “training” and “validation” sets (around 75% in the training set and around 25% in the validation set). We use the training set to train the model and the validation set to measure the model’s accuracy.

Analysis of data

We used several of Python’s libraries, including numpy, pandas, mathplotlib, sklearn, and keras to read the dataset and develop the model. Using logistic regression, our model correctly predicted whether a patient had a heart attack 83% of the time. But we went further and decided to find out which of the features has the greatest effect on the model. We looked at one feature at a time and ran the algorithm again. In the following table, we show the accuracies on the validation set for each of the models. This allows us to quantitatively see which features have the highest and lowest effects on the model

|  |  |
| --- | --- |
| All features | 0.83 |
| “age” | 0.64 |
| “sex” | 0.57 |
| “cp” | 0.79 |
| “trtbps” | 0.55 |
| “chol” | 0.57 |
| “fbs” | 0.57 |
| “restecg” | 0.57 |
| “thalachh” | 0.75 |
| “exng” | 0.76 |
| “oldpeak” | 0.67 |
| “slp” | 0.64 |
| “caa” | 0.71 |
| “thall” | 0.75 |

The removal of all features apart from the type of chest pain only dropped the accuracy of the model by 4 percentage points. It is by far the feature that has the greatest effect on whether or not the patient has a heart attack. Other features that had a significant effect on the accuracy were the maximum heart rate achieved (“thalachh”) and whether or not the patient had exercise induced angina (“exng”).

Conclusion

Machine learning has many uses in several different fields. Here, we explored applying machine learning to heart attack data. Our end result was a model that correctly predicted whether a patient had a heart attack 83% of the time and we found that three factors that are correlated to heart attacks are the type of chest pain, the maximum heart rate, and whether or not the patient had exercise induced angina. An 83% accuracy is far better than random guessing (50%), but is not accurate enough for the model to be the only diagnosis tool. To improve the accuracy of the model, we suggest adding more examples. The model is not meant to predict with 100% certainty whether patients have a heart attack, it is just meant to be used in addition to other diagnostic tools.

References

[1] Andriy Burkov. *The hundred-page machine learning book*, volume 1. Andriy Burkov Canada, 2019.

[2] Jerome Friedman, Trevor Hastie, Robert Tibshirani, et al. *The elements of statistical learning*, volume 1. Springer series in statistics New York, 2001.

[3] Tom M Mitchell et al. Machine learning. 1997.

[4] Toby Segaran. *Programming collective intelligence: building smart web 2.0 applications*. ” O’Reilly Media, Inc.”, 2007.