**Lesson 0**

Machine Learning

Application of AI that provides system the ability to automatically learn from experience without being explicitly programmed.

Machine Learning = Construct a Hypothesis/Model

Machine

Learning

Reinforcement

Learning

Supervised

Learning

Unsupervised

Learning

Classification

Regression

Logistic Regression

Linear Regression

Predict a categorical dependant variable based on values of independent variables

Predicts binary value (0 or 1)

Predict a continuous dependant variable based on values of independent variables

Predicts integer value

**Lesson 1**

Training models

First, let’s understand what overfitting is.

Overfitting

* happens when your model matches the dataset too closely
* This happens because your model is trying too hard to capture the noise in your training dataset
* Noise is the data points that don’t really represent the true properties of your data, but random chance
* To avoid overfitting, we can use regularization

This is a realistic view of the sizes of models on a very large amount of data:

Training Dataset (60%)

Contains outcomes to train a machine

Multiple Prediction Algorithms are applied

Adjusts weight in neural network

Cross Validation Dataset (20%)

compare the performances of the prediction algorithms based on training set (Using Cost Functions)

Aim to minimize over fitting

Original dataset

Test Dataset (20%)

Apply chosen algorithm on real-world data

Training data vs. Testing data

* As a rule of thumb, a dataset (training data) should be 10x it’s dimension (testing data) and independent of the model used
* This is also to say, throwing more data at a problem won’t always get better results

**Lesson 2**

Linear Regression

(graphs drawn using <https://www.desmos.com/calculator>)

Linear Regression is a topic in statistics that is used as a predictive analysis tool.

Regression can be non-linear.

It aims to form relationships between data points and:

* determining the strength of predictors,
* forecasting an effect,
* trend forecasting.

Linear Regression with h(x)

Machine Learning = Construct a Hypothesis/Model

* This topic recycles concepts learned from High-school mathematics and rebrands concepts using terms found in data science.
* Our goal with h(x) is to choose parameters so that our input (x) can predict the corresponding output (y) for our training set.

Number of plot points

Number of samples in dataset

(Input)

Parameters

Hypothesis/Model

(Output)

\* A model is a dataset that represents reality

Steps to calculate linear regression:  
1. Chose a regression model, apply it to dataset

2. Calculate (degree to which the data is explained by the model)

3. Calculate a p-value for (indicates if there is a significant relationship described by the model)

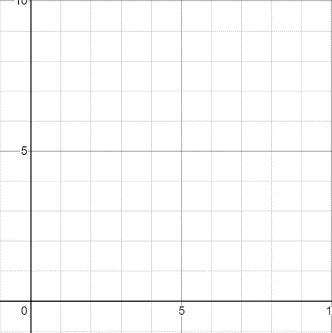
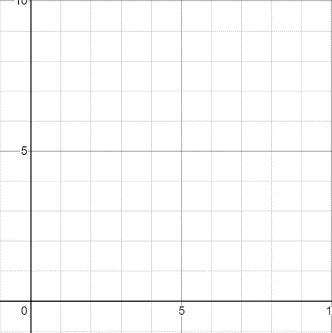
0 - Linear Regression Analysis

x axis : Independent variable

y axis : Dependent variable

graph 1 : positive relationship (m)

graph 2 : positive relationship (-m)



1 - Least-squares regression (line of best fit)

This aims to place a line across as many datapoints as possible, by using formulae to calculate the gradient and intersect with the dataset.

Mathematically, calculating distance from the line to each datapoint is called the residual. The sum of the square of these distances is . tells us how much variation of the dependant variable (y) can be explained by taking the dependant variable (x) into account.

= 1, perfect fit

= 0, no relationship



Higher

Lower

To calculate least squares, we calculate the gradient and intersect of the line of best fit using formulae. The Hypothesis model gives us the full equation for our line of best fit.

Hypothesis

Gradient

Intersect

Example

Dataset:

x = [1, 1, 2, 3, 4, 3, 4, 6, 4]

y = [2, 1, 0.5, 1, 3, 3, 2, 5, 4]



A picture containing cabinet, electronics, furniture

Description automatically generated

1. least-squares

2. Calculate

method 1:

method 2:

Notes:

1. or denotes the “sum of squared residuals”
2. or denotes the “sum of squared residuals around the mean”
3. or denotes the “variance around the mean”
4. or denotes the “variance around the fit or residuals”

3. Calculate p-value for

**Lesson 3**

T-Tests & ANOVA/Analysis of Variance (Using a design matrix)

T-Tests

The goal of a t-test is to compare means and see if they are significantly different from each other.

Steps:

1. Ignore the x-axis and find the overall mean
2. Calculate “sum of squared residuals around the mean”
3. Fit a line to the data (either least squares or the mean)

ANOVA (Analysis of Variance)

The goal of ANOVA is to analyse the differences among group means in a sample

**Lesson 4**

Logistic Regression

Logistic regression can be thought of as a special case of linear regression when the outcome variable is categorical.

Logistic Regression models

(where y is the probability of the hypothesis being true).

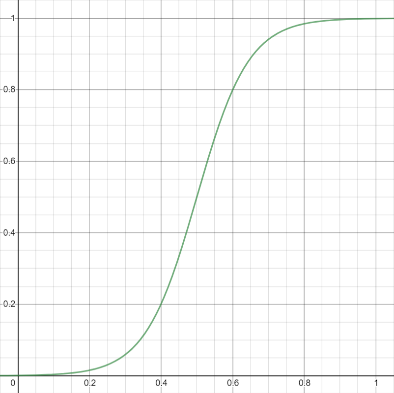
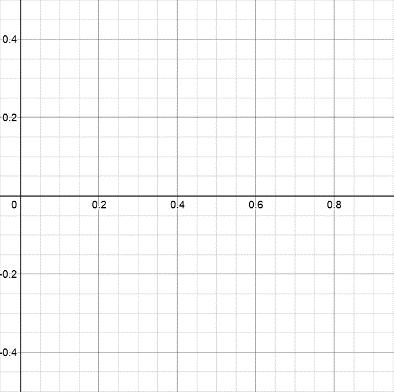
0 – Binary Logistic Regression

This method aims to predict whether something is true or false, instead of predicting something continuous (like price, if it was a dependant variable).

1 – Coefficients (using a continuous variable like weight to predict obesity)

1 true

+ infinity



0 false

- infinity

“Binary logistic model” has datapoints with a probability attached, where if 50% or more, it is categorized as true.

“log odds of y” represents a line which fits the datapoints

At y = 1, true

At y = 0, false

“Log Odds” graph has datapoints only in at positive or negative infinity.

“line of best fit” represents a line which fits the datapoints.

At y = + infinity, true

At y = - infinity, false

The coefficients are represented here by the y-intercept and the slope.

This method cannot use residuals to calculate a line of best fit nor can it calculate . Maximum likelihood is used to calculate Logistic Regression, where the highest Maximum likelihood is used.

**Lesson 5**

Bias and Variance

**Lesson 6**

Other types of Regression

2 – Multiple Linear Regression

This aims to add a plane or higher dimensional object to the data. This just means adding additional data to the model.

3 - Regression with Regularization – How to increase accuracy of learning model

Regularization

* This technique is used for tuning the function by adding an additional penalty term in the error function.
* this technique discourages learning a more complex or flexible model, as to avoid the risk of overfitting.

4 – Isotonic Regression – Equal Stretch Regression

This is a free-form linear model. The model is unique because it is constantly skewed one way or another. It is a complex model which can be found in python

**Lesson 7**

Cost Functions – How to measure the precision of my algorithm

* This function minimizes parameters over the dataset.
* It measures the performance of a Machine Learning model for given data.
* It quantifies the error between predicted values and expected values and presents it in the form of a single real number.

Here are examples of popular cost functions:

Mean Absolute Error (MAE) measures the difference between the estimator (the dataset) and the estimated value (the prediction).

It calculates the average squared difference between the predictions and expected results.

MAE doesn’t add any additional weight to the distance between points — the error growth is linear.

i - index of sample,

ŷ - predicted value,

y - expected value,

m - number of samples in dataset.

i - index of sample,

ŷ - predicted value,

y - expected value,

m - number of samples in dataset.

Mean Squared Error (MSE) measures the difference between the estimator (the dataset) and the estimated value (the prediction).

It calculates the average squared difference between the predictions and expected results.

MSE errors grow exponentially with larger values of distance. It’s a metric that adds a massive penalty to points which are far away and a minimal penalty for points which are close to the expected result

A picture containing sky, map, table, indoor

Description automatically generated

Example - MSE



= estimated value. From using line of best fit

Example – MAE



TODO

* Bias vs. Variance
* Linear Models (Linear Regression, Multiple Regression, GLMs t-tests ANOVA, Design Matrices).

(NOTE: GLM = General Linear Models = Linear + Logistic + Others)

* How many correlations/Cost functions should I use to measure accuracy?
* How do I increase accuracy of my model? >> regularization?

https://stackoverflow.com/questions/47577168/how-can-i-increase-the-accuracy-of-my-linear-regression-modelmachine-learning

* Add [interaction terms](https://en.wikipedia.org/wiki/Interaction_(statistics)#In_regression) to model how two or more independent variables together impact the target variable
* Add [polynomial terms](https://en.wikipedia.org/wiki/Polynomial_regression) to model the nonlinear relationship between an independent variable and the target variable
* Add [spines](http://people.stat.sfu.ca/~cschwarz/Consulting/Trinity/Phase2/TrinityWorkshop/Workshop-handouts/TW-04-Intro-splines.pdf) to approximate piecewise linear models
* Fit [isotonic regression](https://en.wikipedia.org/wiki/Isotonic_regression) to remove any assumption of the target function form
* Fit non-parametric models, such as [MARS](https://en.wikipedia.org/wiki/Multivariate_adaptive_regression_splines)

What does any of this mean? ☹