Table of Contents

Dedication

Copyright

Preface

"Learn JavaScript: Beginner's Edition" is a book that offers a comprehensive exploration of JavaScript, positioning it as a vital language in the ever-changing digital landscape. With a focus on foundation and practicality, this resource caters to everyone who wishes to learn the JavaScript programming language.

The book begins by covering the fundamental aspects of JavaScript, gradually progressing towards more advanced techniques. It addresses key topics such as variables, data types, control structures, functions, object-oriented programming, closures, promises, and modern syntax. Each chapter builds upon the previous one, providing a solid foundation for learners and facilitating the comprehension of complex concepts.

A standout feature of "Learn JavaScript" is its practical approach. The book offers hands-on exercises, coding challenges, and real-world problems that allow readers to apply their knowledge and develop essential skills. By engaging with tangible examples, readers gain the confidence to tackle common web development problems and unlock JavaScript's potential for innovative solutions.

Complex ideas such as closures and asynchronous programming are demystified through intuitive explanations and practical examples. The emphasis on clarity and simplicity enables learners of all levels to grasp and retain the key concepts effectively. The book is structured into three parts, with the first 14 chapters delving into the core concepts. The subsequent four chapters elaborate on the utilization of JavaScript for web browser programming, followed by miscellaneous, server side and exercises. The Miscellaneous section explores significant themes and scenarios pertaining to JavaScript programming, followed by exercises for practice.

The course covers bonus topics such as interview questions, design patterns, file system concepts, and ES6 to provide a comprehensive understanding of the language. The focus is on writing efficient, maintainable code, which is valuable for job seekers and personal projects.

In conclusion, "Learn JavaScript: Beginner's Edition" is an essential companion for those seeking to master JavaScript and excel in web development. With its comprehensive coverage, practical approach, clear explanations, real-world application focus, and commitment to ongoing learning, this book serves as a valuable resource. By immersing themselves in its content, readers will gain the skills and knowledge necessary to build dynamic and interactive web applications, unlocking their full potential as JavaScript developers.

Introduction

Basics

Comments

Variables

Types

Equality

==Logistic regression models the log-odds of the probability as a linear function of the input features.==

It models the probability of an input belonging to a particular class using a logistic (sigmoid) function.

The model establishes a decision boundary (threshold) in the feature space.

Logistic regression is best suited for cases where the decision boundary is approximately linear in the feature space.

Logistic [[Regression]] can be used for [[Binary Classification]]tasks.

Related Notes:

- [[Logistic Regression Statsmodel Summary table]]
- [[Logistic Regression does not predict probabilities]]
- [[Interpreting logistic regression model parameters]]
- [[Model Evaluation]]
- To get [[Model Parameters]] use [[Maximum Likelihood Estimation]]

In [[ML_Tools]], see:

- [[Regression_Logistic_Metrics.ipynb]]

Key Concepts of Logistic Regression

Logistic Function (Sigmoid Function)

Logistic regression models the probability that an input belongs to a particular class using the logistic (sigmoid) function. This function maps any real-valued input into the range (0,1), representing the probability of belonging to the positive class (usually class 1).

The sigmoid function is defined as:

$$ \sigma(z) = \frac{1}{1 + e^{-z}} $$

where

$$ z = \mathbf{w} \cdot \mathbf{x} + b $$

Thus, the logistic regression model is given by:

$$ P(y=1 \mid \mathbf{x}) = \sigma(z) $$

Log odds: Transforming from continuous to 0-1

Logistic regression is based on the ==log-odds== (logit) transformation, which expresses probability in terms of odds:

$$ \text{Odds} = \frac{P(y=1 \mid \mathbf{x})}{1 - P(y=1 \mid \mathbf{x})} $$

Taking the natural logarithm of both sides gives the logit function:

$$ \log \left(\frac{P(y=1 \mid \mathbf{x})}{1 - P(y=1 \mid \mathbf{x})} \right) = \mathbf{w} \cdot \mathbf{x} + b $$

This equation shows that ==logistic regression models the log-odds of the probability as a linear function of the input features.==

Decision Boundary

- Similar to [[Support Vector Machines]], logistic regression defines a decision boundary that separates the two classes.
- The logistic function determines the probability of a data point belonging to a specific class. If this probability exceeds a given ==threshold== (typically 0.5), the model assigns the point to the positive class; otherwise, it is classified as negative.

[[Binary Classification]]

- Logistic regression is primarily used for binary classification tasks, where the target variable has only two possible values (e.g., "0" and "1").
- It can handle multiple independent variables (features) and assigns probabilities to the target classes based on the feature values.
- Examples include:
    - Predicting whether a tumor is malignant or benign (Breast Cancer dataset).
    - Determining whether a passenger survived the Titanic disaster (Titanic dataset).

No Residuals

- Unlike [[Linear Regression]], logistic regression does not compute standard residuals.
- Instead, [[Model Evaluation]] is performed by comparing predicted probabilities with actual class labels using metrics such as accuracy, precision, recall, and the [[Confusion Matrix]].

Also see:

Related terms:

- Cost function for logistic regression
- Gradient computation in logistic regression
- Regularized logistic regression
- Cost function for regularized logistic regression

Logistic regression can be extended to handle non-linear decision boundaries through:

- Polynomial features to capture more complex relationships.
- Regularization techniques to improve generalization.

Explaining logistic regression

Comments

Statsmodel has this summary table unlike [[Sklearn]]

Explanation of summary

The dependent variable is 'duration'. The model used is a Logit regression (logistic in common lingo), while the method

- Maximum Likelihood Estimation ([[MLE]]). It has clearly converged after classifying 518 observations.
- The Pseudo R-squared is 0.21 which is within the 'acceptable region'.
- The duration variable is significant and its coefficient is 0.0051.
- The constant is also significant and equals: -1.70 (p value close to 0)
- High p value, suggests to remove from model, drop one by one, ie [[Feature Selection]].

Specifically a graph such as, ![[Pasted image 20240124095916.png]]

$$\mathbb{N}$$