UNIVERSIDAD DE CÓRDOBA

acreditada INSTITUCIONALMENTE

Using the Monte Carlo Method to Estimate Student Motivation in Scientific Computing

Isaac Caicedo-Castro, Oswaldo Vélez-Langs, and Rubby Castro-Púche

IARIA

Patterns 2025

University of Córdoba in Colombia: Striving for Quality, Innovation, and Inclusivity to Transform Our Region.

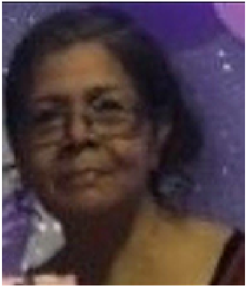
Who am I?

- Isaac Caicedo-Castro
- Full Professor in the Department of Systems Engineering at the University of Córdoba in Colombia
- Ph.D. in Informatics - University of Grenoble Alpes in France
- Ph.D. in Systems and Computing Engineering - National University of Colombia
- Corresponding author: **isacaic@correo.unicordoba.edu.co**

My team mates 1/2

- Oswaldo Vélez-Langs
- Full Professor in the Department of Systems Engineering at the University of Córdoba in Colombia
- Ph.D. in software engineering, systems, and languages - Polytechnic University of Madrid in Spain

My team mates 2/2



- Rubby Castro-Púche
- Full Professor in the Department of Social Science at the University of Córdoba in Colombia
- M.Sc. in Education - La Salle University in Colombia

Agenda

Agenda

Introduction

Collecting and Preprocessing the Dataset

Finding the Functional Relation Among Variables

Calculating the Probability of Each Motivation Level

Reducing the Dimensionality of the Input Space

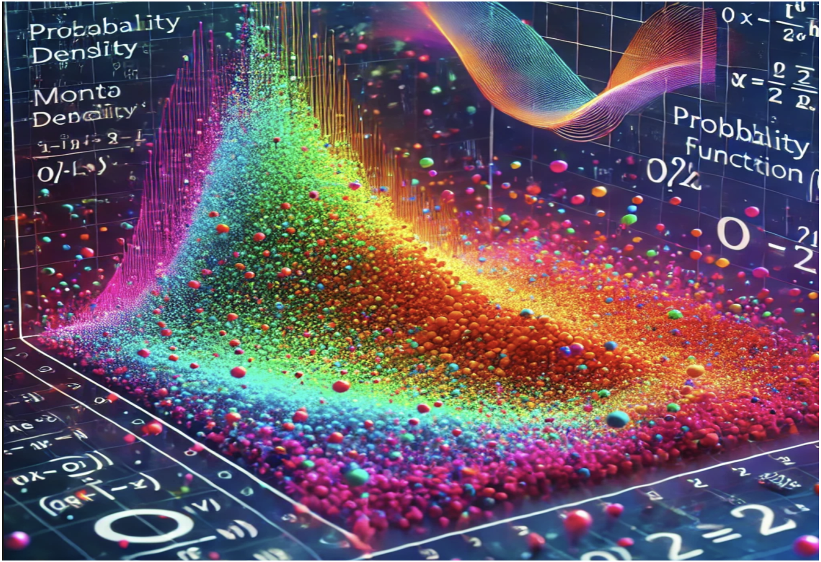
Results and Discussion

Conclusion and Future Work

Question and Answer Session

Introduction

Introduction



Introduction

Scientific Computing Courses:

- Numerical Methods

Introduction

Scientific Computing Courses:

- Numerical Methods
- Linear Programming (aka, Linear Optimization)

Introduction

Scientific Computing Courses:

- Numerical Methods
- Linear Programming (aka, Linear Optimization)
- Nonlinear Programming (aka, Nonlinear Optimization)

Introduction

Scientific Computing Courses:

- Numerical Methods
- Linear Programming (aka, Linear Optimization)
- Nonlinear Programming (aka, Nonlinear Optimization)
- Simulation

Introduction

Scientific Computing Courses:

- Numerical Methods
- Linear Programming (aka, Linear Optimization)
- Nonlinear Programming (aka, Nonlinear Optimization)
- Simulation
- Machine Learning (optional course)

Introduction

What's Scientific Computing after all?

"Numerical analysis is concerned with the design and analysis of algorithms for solving mathematical problems that arise in many fields, especially science and engineering. For this reason, ***numerical analysis*** *has more recently also become known as* ***scientific computing****.* ***Scientific computing*** *is distinguished from most other parts of* ***computer science*** *in that it deals with quantities that are* ***continuous****, as opposed to discrete."*
[Heath, 2018]

Introduction

Learning Scientific Computing is challenging!!

- Research $\rightarrow$ aimed at predicting which students are at risk of failing these courses [Caicedo-Castro et al., 2023, Caicedo-Castro, 2023, Caicedo-Castro, 2024b, Caicedo-Castro, 2024a]

Introduction

Learning Scientific Computing is challenging!!

- Research $\rightarrow$ aimed at predicting which students are at risk of failing these courses [Caicedo-Castro et al., 2023, Caicedo-Castro, 2023, Caicedo-Castro, 2024b, Caicedo-Castro, 2024a]
- mathematics

Introduction

Learning Scientific Computing is challenging!!

- Research $\rightarrow$ aimed at predicting which students are at risk of failing these courses [Caicedo-Castro et al., 2023, Caicedo-Castro, 2023, Caicedo-Castro, 2024b, Caicedo-Castro, 2024a]
- mathematics
- programming skills, and

Introduction

Learning Scientific Computing is challenging!!

- Research $\rightarrow$ aimed at predicting which students are at risk of failing these courses [Caicedo-Castro et al., 2023, Caicedo-Castro, 2023, Caicedo-Castro, 2024b, Caicedo-Castro, 2024a]
- mathematics
- programming skills, and
- knowledge of science (e.g., physics) for application purposes

Introduction

Studying the factors influencing the learning of mathematics has been a subject of interest in prior research:

- Basic educational levels [Ayebale et al., 2020, Gómez-García et al., 2020, Trujillo-Torres et al., 2020, Maamin et al., 2022]

Introduction

Studying the factors influencing the learning of mathematics has been a subject of interest in prior research:

- Basic educational levels [Ayebale et al., 2020, Gómez-García et al., 2020, Trujillo-Torres et al., 2020, Maamin et al., 2022]
- Higher education [Brezavščček et al., 2020, Martinez-Villarraga et al., 2021, Park et al., 2023, Batista-Toledo and Gavilan, 2023, Charalambides et al., 2023]

Introduction

Studying the factors influencing the learning of mathematics has been a subject of interest in prior research:

- Basic educational levels [Ayebale et al., 2020, Gómez-García et al., 2020, Trujillo-Torres et al., 2020, Maamin et al., 2022]
- Higher education [Brezavšček et al., 2020, Martinez-Villarraga et al., 2021, Park et al., 2023, Batista-Toledo and Gavilan, 2023, Charalambides et al., 2023]
- Doctoral levels [Wijaya et al., 2023]

Introduction

Studying the factors influencing the learning of mathematics has been a subject of interest in prior research:

- Basic educational levels [Ayebale et al., 2020, Gómez-García et al., 2020, Trujillo-Torres et al., 2020, Maamin et al., 2022]
- Higher education [Brezavšček et al., 2020, Martinez-Villarraga et al., 2021, Park et al., 2023, Batista-Toledo and Gavilan, 2023, Charalambides et al., 2023]
- Doctoral levels [Wijaya et al., 2023]
- Colombia $\rightarrow$ algebra courses (engineering curricula) [Martinez-Villarraga et al., 2021]

Introduction

Problem $\rightarrow g(x_i) \approx y_i = k$

Introduction

Problem $\rightarrow g(x_i) \approx y_i = k$, where $k = 1, \ldots, 10$

Introduction

Problem $\rightarrow g(x_i) \approx y_i = k$, where $k = 1, \ldots, 10$

$g : \mathcal{X} \rightarrow \mathcal{Y}$

Introduction

Problem $\rightarrow g(x_i) \approx y_i = k$, where $k = 1, \ldots, 10$

$$g : \mathcal{X} \rightarrow \mathcal{Y} \implies P(y_i = k) = \int_{\mathcal{X}} P(g(x_i) = k | x_i) P(x_i) dx_i$$

Agenda

Collecting and Preprocessing the Dataset

How did we collect the dataset

- Population sample: 117 engineering students enrolled in scientific computing courses in 2024

Collecting and Preprocessing the Dataset

How did we collect the dataset

- Population sample: 117 engineering students enrolled in scientific computing courses in 2024
- Courses: numerical methods and nonlinear programming

Collecting and Preprocessing the Dataset

How did we collect the dataset

- Population sample: 117 engineering students enrolled in scientific computing courses in 2024
- Courses: numerical methods and nonlinear programming
- 15 independent variables (1 to 5) $\rightarrow$15 out of 27 factors that determine motivation - some from prior research [Batista-Toledo and Gavilan, 2023, Charalambides et al., 2023]

Collecting and Preprocessing the Dataset

How did we collect the dataset

- Population sample: 117 engineering students enrolled in scientific computing courses in 2024
- Courses: numerical methods and nonlinear programming
- 15 independent variables (1 to 5) $\rightarrow$15 out of 27 factors that determine motivation - some from prior research [Batista-Toledo and Gavilan, 2023, Charalambides et al., 2023]
- Target variable $\rightarrow$ motivation level (1 to 10)

Collecting and Preprocessing the Dataset

We chose (F-test) independent variables such as (p-value < 0.05):

- The extent to which the student has enjoyed the course

Collecting and Preprocessing the Dataset

We chose (F-test) independent variables such as (p-value < 0.05):

- The extent to which the student has enjoyed the course
- The extent to which the student would like to recommend the course to other peers

Collecting and Preprocessing the Dataset

We chose (F-test) independent variables such as (p-value < 0.05):

- The extent to which the student has enjoyed the course
- The extent to which the student would like to recommend the course to other peers
- The extent to which the student perceives the university has up-to-date equipment

Collecting and Preprocessing the Dataset

We chose (F-test) independent variables such as (p-value < 0.05):

- The extent to which the student has enjoyed the course
- The extent to which the student would like to recommend the course to other peers
- The extent to which the student perceives the university has up-to-date equipment
- The extent to which the course has been encouraged students to study with classmates

Collecting and Preprocessing the Dataset

We didn't (F-test) select factors such as (p-value ≥ 0.05):

- The student's average grade in previous mathematics courses

Collecting and Preprocessing the Dataset

We didn't (F-test) select factors such as
(p-value ≥ 0.05):

- The student's average grade in previous mathematics courses
- The extent to which the student considers it imperative to study the course

Collecting and Preprocessing the Dataset

We didn't (F-test) select factors such as
(p-value $\geq$ 0.05):

- The student's average grade in previous mathematics courses
- The extent to which the student considers it imperative to study the course
- The extent to which the student considers it imperative to study mathematics courses

Collecting and Preprocessing the Dataset

We didn't (F-test) select factors such as (p-value ≥ 0.05):

- The student's average grade in previous mathematics courses
- The extent to which the student considers it imperative to study the course
- The extent to which the student considers it imperative to study mathematics courses
- The extent to which the student considers it wrong not to study the course

Collecting and Preprocessing the Dataset

Mathematical notation:

- $x_i \in \mathcal{X} \subset \mathbb{R}^D \rightarrow$ *i*th student

Collecting and Preprocessing the Dataset

Mathematical notation:

- $x_i \in \mathcal{X} \subset \mathbb{R}^D \rightarrow i$th student
- Where the jth component $x_{ij} \rightarrow j$th input variable associated with a specific factor

Collecting and Preprocessing the Dataset

Mathematical notation:

- $x_i \in \mathcal{X} \subset \mathbb{R}^D \rightarrow i$th student
- Where the jth component $x_{ij} \rightarrow j$th input variable associated with a specific factor
- $D = 15$

Collecting and Preprocessing the Dataset

Mathematical notation:

- $x_i \in \mathcal{X} \subset \mathbb{R}^D \rightarrow i$th student
- Where the jth component $x_{ij} \rightarrow j$th input variable associated with a specific factor
- $D = 15$
- $y_i \in \mathcal{Y} \subset \mathbb{R} \rightarrow i$th student's course motivation level

Collecting and Preprocessing the Dataset

Mathematical notation:

- $x_i \in \mathcal{X} \subset \mathbb{R}^D \rightarrow i$th student
- Where the jth component $x_{ij} \rightarrow j$th input variable associated with a specific factor
- $D = 15$
- $y_i \in \mathcal{Y} \subset \mathbb{R} \rightarrow i$th student's course motivation level
- $\mathcal{D} = \{(x_i, y_i) \,|\, x_i \in \mathcal{X} \wedge y_i \in \mathcal{Y},\, i = 1, \ldots, N\} = \{(x_i, y_i)\}_{i=1}^{N}$

Collecting and Preprocessing the Dataset

Mathematical notation:

- $x_i \in \mathcal{X} \subset \mathbb{R}^D \rightarrow i$th student
- Where the jth component $x_{ij} \rightarrow j$th input variable associated with a specific factor
- $D = 15$
- $y_i \in \mathcal{Y} \subset \mathbb{R} \rightarrow i$th student's course motivation level
- $\mathcal{D} = \{(x_i, y_i) \,|\, x_i \in \mathcal{X} \wedge y_i \in \mathcal{Y},\, i = 1, \ldots, N\} = \{(x_i, y_i)\}_{i=1}^{N}$
- $N = 117$

Collecting and Preprocessing the Dataset

Mathematical notation:

- $x_i \in \mathcal{X} \subset \mathbb{R}^D \rightarrow i$th student
- Where the jth component $x_{ij} \rightarrow j$th input variable associated with a specific factor
- $D = 15$
- $y_i \in \mathcal{Y} \subset \mathbb{R} \rightarrow i$th student's course motivation level
- $\mathcal{D} = \{(x_i, y_i) \mid x_i \in \mathcal{X} \wedge y_i \in \mathcal{Y}, i = 1, \ldots, N\} = \{(x_i, y_i)\}_{i=1}^{N}$
- $N = 117$
- $\mathcal{X} = \mathbb{X}_1 \times \mathbb{X}_2 \times \cdots \times \mathbb{X}_j \times \cdots \times \mathbb{X}_D$

Collecting and Preprocessing the Dataset

Mathematical notation:

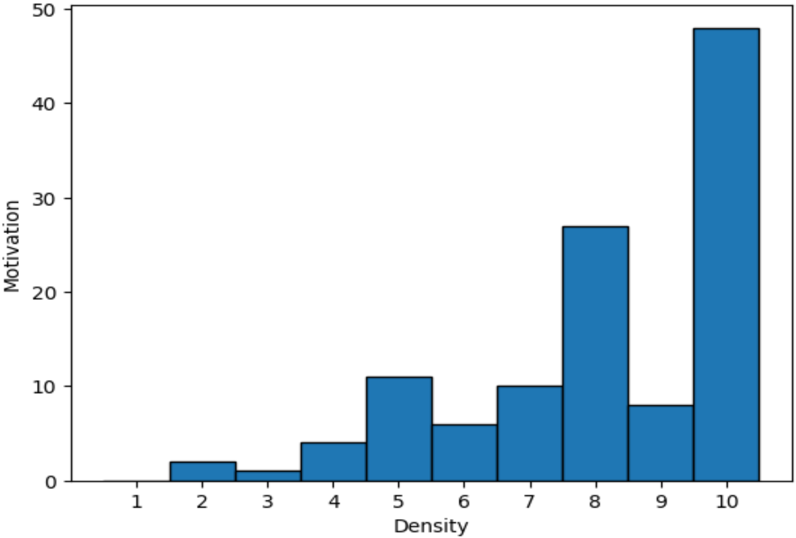
- $x_i \in \mathcal{X} \subset \mathbb{R}^D \rightarrow i$th student
- Where the jth component $x_{ij} \rightarrow j$th input variable associated with a specific factor
- $D = 15$
- $y_i \in \mathcal{Y} \subset \mathbb{R} \rightarrow i$th student's course motivation level
- $\mathcal{D} = \{(x_i, y_i) \,|\, x_i \in \mathcal{X} \wedge y_i \in \mathcal{Y},\, i = 1, \ldots, N\} = \{(x_i, y_i)\}_{i=1}^{N}$
- $N = 117$
- $\mathcal{X} = \mathbb{X}_1 \times \mathbb{X}_2 \times \cdots \times \mathbb{X}_j \times \cdots \times \mathbb{X}_D$
- $\mathbb{X}_j = \{a \in \mathbb{N} \,|\, 1 \leq a \leq 5\}, \quad \text{for } j = 1, \ldots, D$

Collecting and Preprocessing the Dataset

Mathematical notation:

- $x_i \in \mathcal{X} \subset \mathbb{R}^D \to i$th student
- Where the jth component $x_{ij} \to j$th input variable associated with a specific factor
- $D = 15$
- $y_i \in \mathcal{Y} \subset \mathbb{R} \to i$th student's course motivation level
- $\mathcal{D} = \{(x_i, y_i) \,|\, x_i \in \mathcal{X} \wedge y_i \in \mathcal{Y},\, i = 1, \ldots, N\} = \{(x_i, y_i)\}_{i=1}^N$
- $N = 117$
- $\mathcal{X} = \mathbb{X}_1 \times \mathbb{X}_2 \times \cdots \times \mathbb{X}_j \times \cdots \times \mathbb{X}_D$
- $\mathbb{X}_j = \{a \in \mathbb{N} \,|\, 1 \leq a \leq 5\}, \quad \text{for } j = 1, \ldots, D$
- $\mathcal{Y} = \{a \in \mathbb{N} \,|\, 1 \leq a \leq 10\}$

Collecting and Preprocessing the Dataset



Agenda

Finding the Functional Relation

Problem definition:

- Find the function g

Finding the Functional Relation

Problem definition:

- Find the function g
- the dataset $\mathcal{D}$

Finding the Functional Relation

Problem definition:

- Find the function g
- the dataset $\mathcal{D}$
- $g(x_i) \approx y_i$

Finding the Functional Relation

Problem definition:

- Find the function g
- the dataset $\mathcal{D}$
- $g(x_i) \approx y_i$
- $g : \mathcal{X} \to \mathcal{Y}$

Finding the Functional Relation

Problem definition:

- Find the function g
- the dataset $\mathcal{D}$
- $g(x_i) \approx y_i$
- $g : \mathcal{X} \to \mathcal{Y}$
- $g(x_i) = w_0 + w_1 x_{i1} + w_2 x_{i2} + \cdots + w_D x_{iD} = w^T \hat{x}_i$

Finding the Functional Relation

Problem definition:

- Find the function g
- the dataset $\mathcal{D}$
- $g(x_i) \approx y_i$
- $g : \mathcal{X} \to \mathcal{Y}$
- $g(x_i) = w_0 + w_1 x_{i1} + w_2 x_{i2} + \cdots + w_D x_{iD} = w^T \hat{x}_i$
- $\hat{x}_{i0} = 1$, whereas $\hat{x}_{ij} = x_{ij}$ for $j = 1, \ldots, D$

Finding the Functional Relation

Problem definition:

- Find the function g
- the dataset $\mathcal{D}$
- $g(x_i) \approx y_i$
- $g : \mathcal{X} \to \mathcal{Y}$
- $g(x_i) = w_0 + w_1 x_{i1} + w_2 x_{i2} + \cdots + w_D x_{iD} = w^T \hat{x}_i$
- $\hat{x}_{i0} = 1$, whereas $\hat{x}_{ij} = x_{ij}$ for $j = 1, \ldots, D$
- $w \in \mathbb{R}^{D+1}$

Finding the Functional Relation

Problem definition:

- Find the function g
- the dataset $\mathcal{D}$
- $g(x_i) \approx y_i$
- $g : \mathcal{X} \rightarrow \mathcal{Y}$
- $g(x_i) = w_0 + w_1 x_{i1} + w_2 x_{i2} + \cdots + w_D x_{iD} = w^T \hat{x}_i$
- $\hat{x}_{i0} = 1$, whereas $\hat{x}_{ij} = x_{ij}$ for $j = 1, \ldots, D$
- $w \in \mathbb{R}^{D+1}$
- $\min_w f(w) = ||Xw - y||^2 + \lambda ||w||^2$

Finding the Functional Relation

Problem definition:

- Find the function g
- the dataset $\mathcal{D}$
- $g(x_i) \approx y_i$
- $g : \mathcal{X} \rightarrow \mathcal{Y}$
- $g(x_i) = w_0 + w_1 x_{i1} + w_2 x_{i2} + \cdots + w_D x_{iD} = w^T \hat{x}_i$
- $\hat{x}_{i0} = 1$, whereas $\hat{x}_{ij} = x_{ij}$ for $j = 1, \ldots, D$
- $w \in \mathbb{R}^{D+1}$
- $\min_w f(w) = ||Xw - y||^2 + \lambda ||w||^2$
- $X_{ij} = 1$ if $j = 1$, and $X_{ij} = \hat{x}_{i,j-1}$ for $j = 2, \ldots, D + 1$

Finding the Functional Relation

Problem definition:

- Find the function g
- the dataset $\mathcal{D}$
- $g(x_i) \approx y_i$
- $g : \mathcal{X} \rightarrow \mathcal{Y}$
- $g(x_i) = w_0 + w_1 x_{i1} + w_2 x_{i2} + \cdots + w_D x_{iD} = w^T \hat{x}_i$
- $\hat{x}_{i0} = 1$, whereas $\hat{x}_{ij} = x_{ij}$ for $j = 1, \ldots, D$
- $w \in \mathbb{R}^{D+1}$
- $\min_w f(w) = ||Xw - y||^2 + \lambda ||w||^2$
- $X_{ij} = 1$ if $j = 1$, and $X_{ij} = \hat{x}_{i,j-1}$ for $j = 2, \ldots, D+1$
- $w = (X^T X + \lambda I)^{-1} X^T y$

Agenda

Probability of Each Motivation Level

We adopted the Monte Carlo numerical method [Metropolis and Ulam, 1949]

- $P(y_i = k) \approx P(g(x_i) = k)$

Probability of Each Motivation Level

We adopted the Monte Carlo numerical method [Metropolis and Ulam, 1949]

- $P(y_i = k) \approx P(g(x_i) = k)$
- $P(g(x_i) = k) = \int_{\mathcal{X}} P(g(x_i) = k \mid x_i) P(x_i)\, dx_i$

Probability of Each Motivation Level

We adopted the Monte Carlo numerical method [Metropolis and Ulam, 1949]

- $P(y_i = k) \approx P(g(x_i) = k)$
- $P(g(x_i) = k) = \int_{\mathcal{X}} P(g(x_i) = k \mid x_i) P(x_i) \, dx_i$
- $P(x_i)$ is the probability density function of the input variables

Probability of Each Motivation Level

We adopted the Monte Carlo numerical method [Metropolis and Ulam, 1949]

- $P(y_i = k) \approx P(g(x_i) = k)$
- $P(g(x_i) = k) = \int_{\mathcal{X}} P(g(x_i) = k \mid x_i) P(x_i) \, dx_i$
- $P(x_i)$ is the probability density function of the input variables
- $x_{ij} \sim \mathcal{U}(1, 5)$ for $j = 1, \ldots, D$

Probability of Each Motivation Level

We adopted the Monte Carlo numerical method [Metropolis and Ulam, 1949]

- $P(y_i = k) \approx P(g(x_i) = k)$
- $P(g(x_i) = k) = \int_{\mathcal{X}} P(g(x_i) = k \mid x_i) P(x_i)\, dx_i$
- $P(x_i)$ is the probability density function of the input variables
- $x_{ij} \sim \mathcal{U}(1, 5)$ for $j = 1, \ldots, D$
- $P(y_i = k) \approx P(g(x_i) = k) \approx \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}(g(x_i) = k)$

Probability of Each Motivation Level

We adopted the Monte Carlo numerical method [Metropolis and Ulam, 1949]

- $P(y_i = k) \approx P(g(x_i) = k)$
- $P(g(x_i) = k) = \int_{\mathcal{X}} P(g(x_i) = k \mid x_i) P(x_i)\, dx_i$
- $P(x_i)$ is the probability density function of the input variables
- $x_{ij} \sim \mathcal{U}(1, 5)$ for $j = 1, \ldots, D$
- $P(y_i = k) \approx P(g(x_i) = k) \approx \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}(g(x_i) = k)$
- N is the number of vectors x_i

Probability of Each Motivation Level

We adopted the Monte Carlo numerical method [Metropolis and Ulam, 1949]

- $P(y_i = k) \approx P(g(x_i) = k)$
- $P(g(x_i) = k) = \int_{\mathcal{X}} P(g(x_i) = k \mid x_i) P(x_i)\, dx_i$
- $P(x_i)$ is the probability density function of the input variables
- $x_{ij} \sim \mathcal{U}(1, 5)$ for $j = 1, \ldots, D$
- $P(y_i = k) \approx P(g(x_i) = k) \approx \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}(g(x_i) = k)$
- N is the number of vectors x_i
- $\mathbf{1}(u) = 1$ if u is true, and $\mathbf{1}(u) = 0$ otherwise

Probability of Each Motivation Level

We adopted the Monte Carlo numerical method [Metropolis and Ulam, 1949]

- $P(y_i = k) \approx P(g(x_i) = k)$
- $P(g(x_i) = k) = \int_{\mathcal{X}} P(g(x_i) = k \mid x_i) P(x_i)\, dx_i$
- $P(x_i)$ is the probability density function of the input variables
- $x_{ij} \sim \mathcal{U}(1, 5)$ for $j = 1, \ldots, D$
- $P(y_i = k) \approx P(g(x_i) = k) \approx \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}(g(x_i) = k)$
- N is the number of vectors x_i
- $\mathbf{1}(u) = 1$ if u is true, and $\mathbf{1}(u) = 0$ otherwise
- N is not the size of the dataset

Probability of Each Motivation Level

We adopted the Monte Carlo numerical method [Metropolis and Ulam, 1949]

- $P(y_i = k) \approx P(g(x_i) = k)$
- $P(g(x_i) = k) = \int_{\mathcal{X}} P(g(x_i) = k \mid x_i) P(x_i)\, dx_i$
- $P(x_i)$ is the probability density function of the input variables
- $x_{ij} \sim \mathcal{U}(1, 5)$ for $j = 1, \ldots, D$
- $P(y_i = k) \approx P(g(x_i) = k) \approx \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}(g(x_i) = k)$
- N is the number of vectors x_i
- $\mathbf{1}(u) = 1$ if u is true, and $\mathbf{1}(u) = 0$ otherwise
- N is not the size of the dataset
- $SE = \frac{\sigma}{\sqrt{N}}$

Agenda

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i1} = u_1^T x_i$, $u_1^T u_1 = 1$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i1} = u_1^T x_i$, $u_1^T u_1 = 1$
- $\text{var}(z_{i1}) = u_1^T S u_1$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i1} = u_1^T x_i$, $u_1^T u_1 = 1$
- $\text{var}(z_{i1}) = u_1^T S u_1$
- $S \in \mathbb{R}^{D \times D}$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i1} = u_1^T x_i$, $u_1^T u_1 = 1$
- $\mathrm{var}(z_{i1}) = u_1^T S u_1$
- $S \in \mathbb{R}^{D \times D}$
- $S = \frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})(x_i - \bar{x})^T$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i1} = u_1^T x_i$, $u_1^T u_1 = 1$
- $\mathrm{var}(z_{i1}) = u_1^T S u_1$
- $S \in \mathbb{R}^{D \times D}$
- $S = \frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})(x_i - \bar{x})^T$
- $\max_{u_1} J(u_1) = u_1^T S u_1 - \lambda_1 (u_1^T u_1 - 1)$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i1} = u_1^T x_i$, $u_1^T u_1 = 1$
- $\mathrm{var}(z_{i1}) = u_1^T S u_1$
- $S \in \mathbb{R}^{D \times D}$
- $S = \frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})(x_i - \bar{x})^T$
- $\max_{u_1} J(u_1) = u_1^T S u_1 - \lambda_1 (u_1^T u_1 - 1)$
- $\lambda_1 = u_1^T S u_1 = \mathrm{var}(z_{i1})$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i2} = u_2^T x_i$, $u_2^T u_2 = 1$, and $u_2^T u_1 = 0$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i2} = u_2^T x_i$, $u_2^T u_2 = 1$, and $u_2^T u_1 = 0$
- $\mathrm{var}(z_{i2}) = u_2^T S u_2$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i2} = u_2^T x_i$, $u_2^T u_2 = 1$, and $u_2^T u_1 = 0$
- $\mathrm{var}(z_{i2}) = u_2^T S u_2$
- $\max_{u_2} J(u_2) = u_2^T S u_2 - \lambda_2(u_2^T u_2 - 1) - \alpha u_2^T u_1$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i2} = u_2^T x_i$, $u_2^T u_2 = 1$, and $u_2^T u_1 = 0$
- $\mathrm{var}(z_{i2}) = u_2^T S u_2$
- $\max_{u_2} J(u_2) = u_2^T S u_2 - \lambda_2(u_2^T u_2 - 1) - \alpha u_2^T u_1$
- $\lambda_2 = u_2^T S u_2 = \mathrm{var}(z_{i2})$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i2} = u_2^T x_i$, $u_2^T u_2 = 1$, and $u_2^T u_1 = 0$
- $\text{var}(z_{i2}) = u_2^T S u_2$
- $\max_{u_2} J(u_2) = u_2^T S u_2 - \lambda_2(u_2^T u_2 - 1) - \alpha u_2^T u_1$
- $\lambda_2 = u_2^T S u_2 = \text{var}(z_{i2})$
- Calculate all basis vectors u_j for $j = 1, \ldots, D$,

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i2} = u_2^T x_i$, $u_2^T u_2 = 1$, and $u_2^T u_1 = 0$
- $\mathrm{var}(z_{i2}) = u_2^T S u_2$
- $\max_{u_2} J(u_2) = u_2^T S u_2 - \lambda_2(u_2^T u_2 - 1) - \alpha u_2^T u_1$
- $\lambda_2 = u_2^T S u_2 = \mathrm{var}(z_{i2})$
- Calculate all basis vectors u_j for $j = 1, \ldots, D$,
- Producing d principal components, where $d < D$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i2} = u_2^T x_i$, $u_2^T u_2 = 1$, and $u_2^T u_1 = 0$
- $\text{var}(z_{i2}) = u_2^T S u_2$
- $\max_{u_2} J(u_2) = u_2^T S u_2 - \lambda_2(u_2^T u_2 - 1) - \alpha u_2^T u_1$
- $\lambda_2 = u_2^T S u_2 = \text{var}(z_{i2})$
- Calculate all basis vectors u_j for $j = 1, \ldots, D$,
- Producing d principal components, where $d < D$
- Resulting the transformed vector $z_i \in \mathbb{R}^d$

Reducing the Dimensionality

We adopted Principal Component Analysis [Bishop, 2006]

- $z_{i2} = u_2^T x_i$, $u_2^T u_2 = 1$, and $u_2^T u_1 = 0$
- $\text{var}(z_{i2}) = u_2^T S u_2$
- $\max_{u_2} J(u_2) = u_2^T S u_2 - \lambda_2(u_2^T u_2 - 1) - \alpha u_2^T u_1$
- $\lambda_2 = u_2^T S u_2 = \text{var}(z_{i2})$
- Calculate all basis vectors u_j for $j = 1, \ldots, D$,
- Producing d principal components, where $d < D$
- Resulting the transformed vector $z_i \in \mathbb{R}^d$
- $\rho = 100 \cdot \frac{\sum_{j=1}^{d} \lambda_j}{\sum_{k=1}^{D} \lambda_k} \%$

Agenda

Results and Discussion

$$
\begin{aligned}
g(x_i) = 0.0220 &+ 0.1678 x_{i,1} + 0.1751 x_{i,2} + 0.1992 x_{i,3} + \dots \\
&\dots + 0.1989 x_{i,4} + 0.1018 x_{i,5} + 0.1111 x_{i,6} + \dots \\
&\dots + 0.1592 x_{i,7} + 0.1157 x_{i,8} + 0.1597 x_{i,9} + \dots \\
&\dots + 0.1557 x_{i,10} + 0.1765 x_{i,11} + \dots \\
&\dots + 0.0895 x_{i,12} - 0.0049 x_{i,13} + \dots \\
&\dots + 0.0744 x_{i,14} + 0.0749 x_{i,15}
\end{aligned} \tag{1}
$$

Results and Discussion

$$
\begin{aligned}
g(x_i) = {} & 0.0220 + 0.1678x_{i,1} + 0.1751x_{i,2} + 0.1992x_{i,3} + \dots \\
& \dots + 0.1989x_{i,4} + 0.1018x_{i,5} + 0.1111x_{i,6} + \dots \\
& \dots + 0.1592x_{i,7} + 0.1157x_{i,8} + 0.1597x_{i,9} + \dots \\
& \dots + 0.1557x_{i,10} + 0.1765x_{i,11} + \dots \\
& \dots + 0.0895x_{i,12} - 0.0049x_{i,13} + \dots \\
& \dots + 0.0744x_{i,14} + 0.0749x_{i,15}
\end{aligned} \tag{1}
$$

- The *i*th student's satisfaction ($x_{i,4}$) with the scientific computing course
- The *i*th student's enjoyment ($x_{i,3}$) with the scientific computing course

Results and Discussion

$$
\begin{aligned}
g(x_i) = 0.0220 &+ 0.1678x_{i,1} + 0.1751x_{i,2} + 0.1992x_{i,3} + \dots \\
&\dots + 0.1989x_{i,4} + 0.1018x_{i,5} + 0.1111x_{i,6} + \dots \\
&\dots + 0.1592x_{i,7} + 0.1157x_{i,8} + 0.1597x_{i,9} + \dots \\
&\dots + 0.1557x_{i,10} + 0.1765x_{i,11} + \dots \\
&\dots + 0.0895x_{i,12} - 0.0049x_{i,13} + \dots \\
&\dots + 0.0744x_{i,14} + 0.0749x_{i,15}
\end{aligned} \tag{1}
$$

A negative weight for $x_{i,13}$ indicates that students who perceive mathematics courses as more useful for their careers tend to have slightly lower motivation levels in scientific computing courses

Results and Discussion

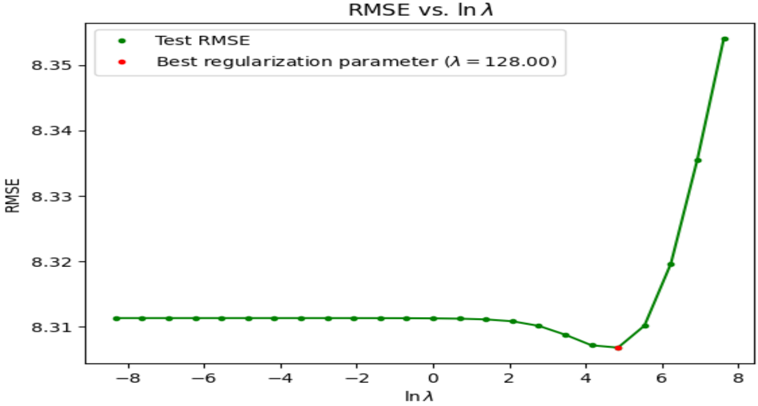
- Coefficient of determination (R^2): 0.37

Results and Discussion

- Coefficient of determination (R^2): 0.37
- root-mean-squared-error: 1.62

Results and Discussion

- Coefficient of determination (R^2): 0.37
- root-mean-squared-error: 1.62



Results and Discussion

- The most probable level according to the Monte Carlo method is 4.908 with a standard error of 6.8×10^{-4}

Results and Discussion

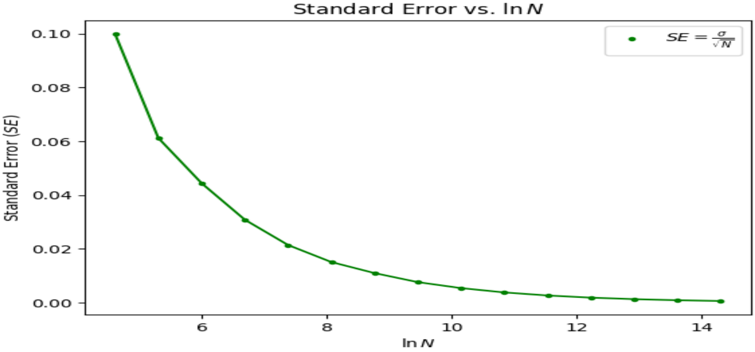
- The most probable level according to the Monte Carlo method is 4.908 with a standard error of 6.8×10^{-4}
- This outcome was obtained with 95% confidence (alpha = 0.05), within the interval (4.90, 4.91)

Results and Discussion

- The most probable level according to the Monte Carlo method is 4.908 with a standard error of 6.8×10^{-4}
- This outcome was obtained with 95% confidence (alpha = 0.05), within the interval (4.90, 4.91)
- We performed rounding to the nearest even number for halfway cases

Results and Discussion

- The most probable level according to the Monte Carlo method is 4.908 with a standard error of 6.8×10^{-4}
- This outcome was obtained with 95% confidence (alpha = 0.05), within the interval (4.90, 4.91)
- We performed rounding to the nearest even number for halfway cases

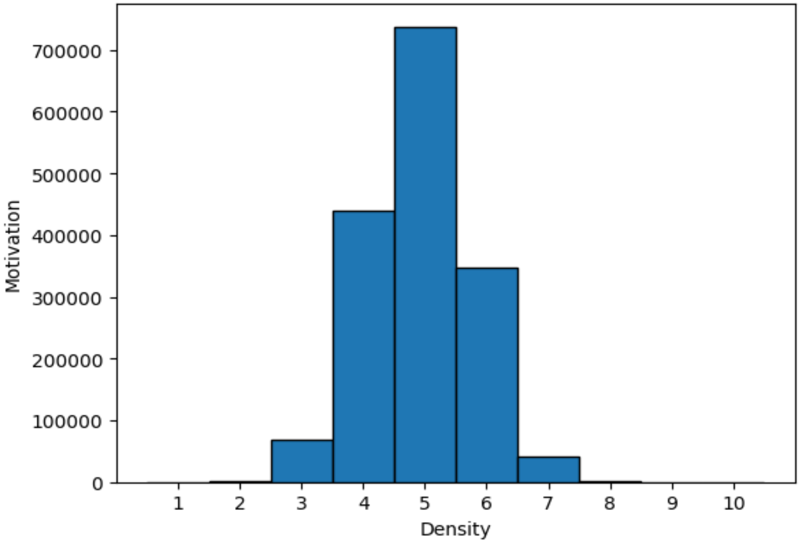


Results and Discussion

Probability of Every Motivation Level Calculated with the Monte Carlo Method

Level	***Probability***
1	$P(y = 1.0) = 5.49 \times 10^{-4}\%$
2	$P(y = 2.0) = 1.34 \times 10^{-1}\%$
3	$P(y = 3.0) = 4.17\%$
4	$P(y = 4.0) = 26.86\%$
5	$P(y = 5.0) = 45.03\%$
6	$P(y = 6.0) = 21.21\%$
7	$P(y = 7.0) = 2.55\%$
8	$P(y = 8.0) = 5.57 \times 10^{-2}\%$
9	$P(y = 9.0) = 6.10 \times 10^{-5}\%$

Results and Discussion



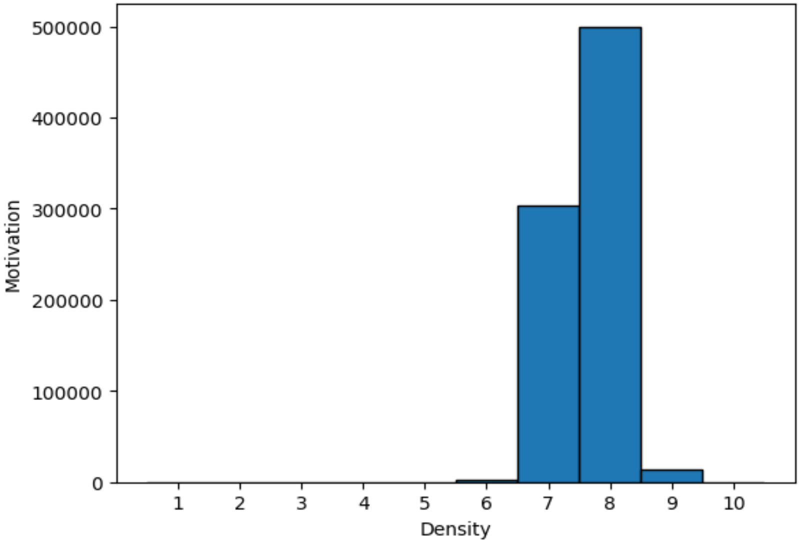
Results and Discussion

Probability of Every Motivation Level Calculated with the Monte Carlo Method from the Best Simulation Setting

Level	***Probability***
6	P(y = 6.0) = 2.5×10^{-1}%
7	P(y = 7.0) = 36.98%
8	P(y = 8.0) = 61.03%
9	P(y = 9.0) = 1.74%

Results and Discussion

$x_{ij} \sim \mathcal{U}(3,5)$ for $1 \leq j \leq 12$ – $x_{i,12} = 0$ – $x_{ij} \sim \mathcal{U}(1,5)$ for $j = 13, 14$



Results and Discussion

- The most probable level according to the Monte Carlo method is 7.642 with a standard error of 8.1×10^{-4}

Results and Discussion

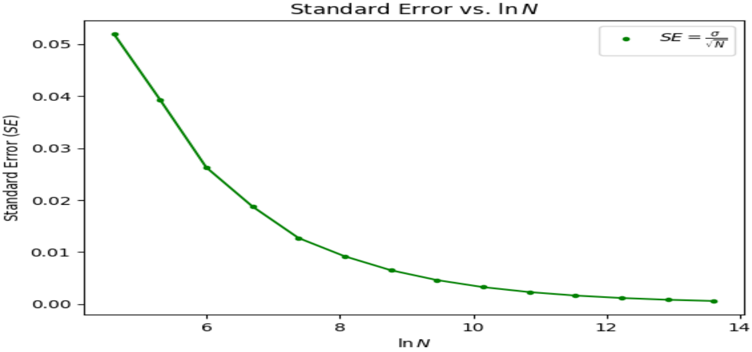
- The most probable level according to the Monte Carlo method is 7.642 with a standard error of 8.1×10^{-4}
- This outcome was obtained with 95% confidence (alpha = 0.05), within the interval (7.641, 7.643)

Results and Discussion

- The most probable level according to the Monte Carlo method is 7.642 with a standard error of 8.1×10^{-4}
- This outcome was obtained with 95% confidence (alpha = 0.05), within the interval (7.641, 7.643)
- We performed rounding to the nearest even number for halfway cases

Results and Discussion

- The most probable level according to the Monte Carlo method is 7.642 with a standard error of 8.1×10^{-4}
- This outcome was obtained with 95% confidence (alpha = 0.05), within the interval (7.641, 7.643)
- We performed rounding to the nearest even number for halfway cases



Results and Discussion

Variance Retained by the Principal Components 1/2

Number of Principal Components	***Retained Variance (%)***
1	44.84%
2	55.43%
3	64.22%
4	71.16%
5	76.19%
6	80.51%
7	84.30%
8	87.74%
9	90.69%
10	92.92%
11	94.77%

Results and Discussion

Variance Retained by the Principal Components 2/2

Number of Principal Components	***Retained Variance (%)***
12	96.50%
13	97.99%
14	99.15%
15	100.00%

Results and Discussion

Regression applied on a two-dimensional space

- Coefficient of determination (R^2): 0.33

Results and Discussion

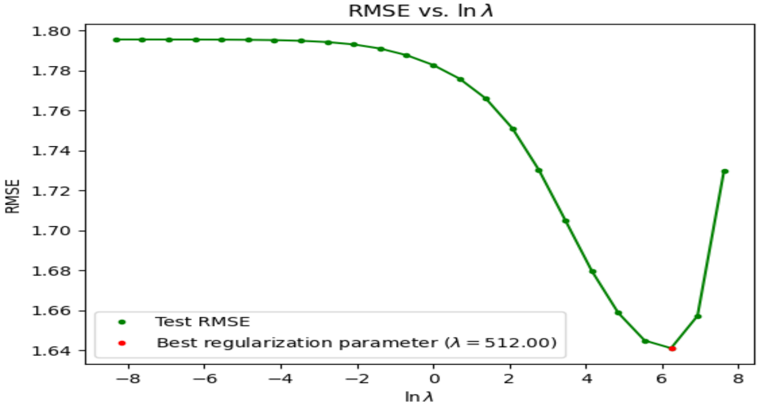
Regression applied on a two-dimensional space

- Coefficient of determination (R^2): 0.33
- root-mean-squared-error: 1.67

Results and Discussion

Regression applied on a two-dimensional space

- Coefficient of determination (R^2): 0.33
- root-mean-squared-error: 1.67



Results and Discussion

- The most probable level according to the Monte Carlo method is 3.84 with a standard error of 1.46×10^{-3}

Results and Discussion

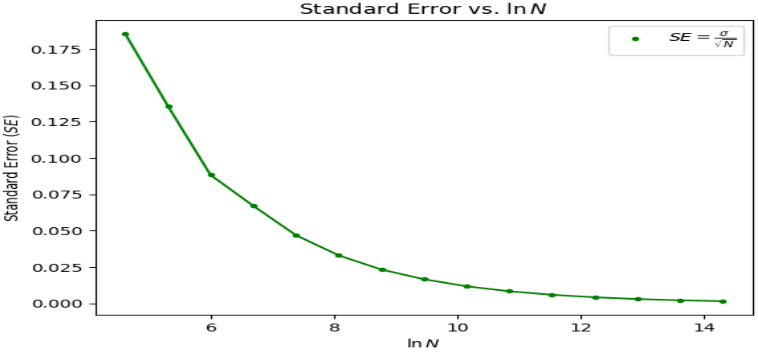
- The most probable level according to the Monte Carlo method is 3.84 with a standard error of 1.46×10^{-3}
- This outcome is within (3.83, 3.84) with a 95% (alpha = 0.05) confidence interval.

Results and Discussion

- The most probable level according to the Monte Carlo method is 3.84 with a standard error of 1.46×10^{-3}
- This outcome is within (3.83, 3.84) with a 95% (alpha = 0.05) confidence interval.
- We performed rounding to the nearest even number for halfway cases

Results and Discussion

- The most probable level according to the Monte Carlo method is 3.84 with a standard error of 1.46×10^{-3}
- This outcome is within (3.83, 3.84) with a 95% (alpha = 0.05) confidence interval.
- We performed rounding to the nearest even number for halfway cases

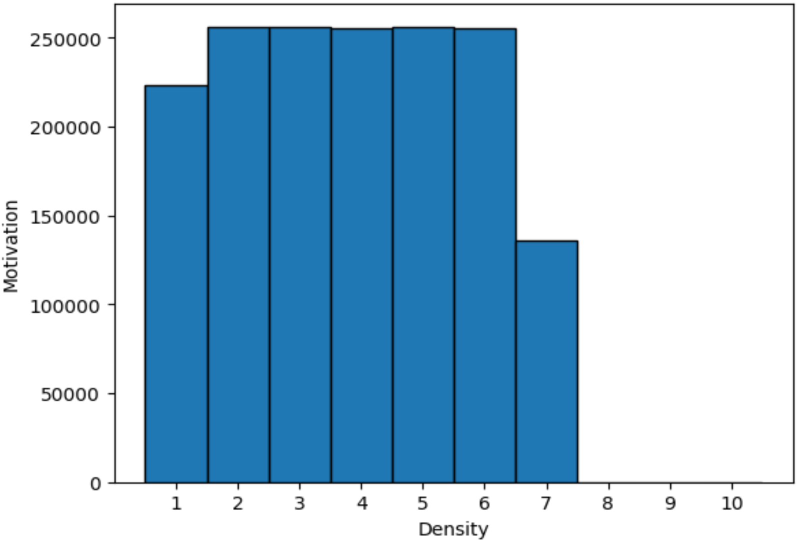


Results and Discussion

Probability of Every Motivation Level Calculated with the Monte Carlo Method Taking into Account Two Principal Components

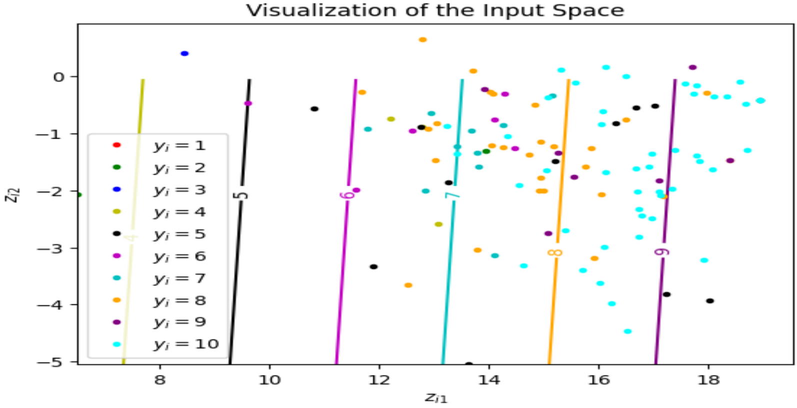
Level	***Probability***
1	P(y = 1.0) = 13.62%
2	P(y = 2.0) = 15.61%
3	P(y = 3.0) = 15.64%
4	P(y = 4.0) = 15.59%
5	P(y = 5.0) = 15.62%
6	P(y = 6.0) = 15.59%
7	P(y = 7.0) = 8.32%

Results and Discussion



Results and Discussion

Visualization of the latent factors derived from the regression model. The contour lines show the lower probability of obtaining the higher motivation levels.



Agenda

Conclusion and Future Work

- We found that engineering students enrolled in scientific computing courses at the University of Córdoba exhibit a moderate level of motivation.

Conclusion and Future Work

- We found that engineering students enrolled in scientific computing courses at the University of Córdoba exhibit a moderate level of motivation.
- This suggests that these students find it challenging to grasp the concepts, foundations, and methods taught in these courses

Conclusion and Future Work

- We found that engineering students enrolled in scientific computing courses at the University of Córdoba exhibit a moderate level of motivation.
- This suggests that these students find it challenging to grasp the concepts, foundations, and methods taught in these courses
- It is essential for lecturers to develop effective motivation strategies tailored to the unique challenges of scientific computing courses

Conclusion and Future Work

- Expanding the dataset to include students from other universities or fields of study could provide a more comprehensive understanding of the factors influencing student motivation.

Conclusion and Future Work

- Expanding the dataset to include students from other universities or fields of study could provide a more comprehensive understanding of the factors influencing student motivation.
- We'll explore nonlinear regression models such as Gaussian processes, Kernel Ridge Regression, and Random Forests, which might uncover more nuanced relationships between the variables

Conclusion and Future Work

- Expanding the dataset to include students from other universities or fields of study could provide a more comprehensive understanding of the factors influencing student motivation.
- We'll explore nonlinear regression models such as Gaussian processes, Kernel Ridge Regression, and Random Forests, which might uncover more nuanced relationships between the variables
- We'll also evaluate alternative models for dimensionality reduction

Agenda

That’s all folks

Now starts the Q ’n’ A session

Praise the name of God forever and ever, for he has all wisdom and power. He controls the course of world events; he removes kings and sets up other kings. He gives wisdom to the wise and knowledge to the scholars. He reveals deep and mysterious things... (Daniel 2:20-22)

References I

Ayebale, L., Habaasa, G., and Tweheyo, S. (2020).
Factors Affecting Students' Achievement in Mathematics in Secondary Schools in Developing countries: A Rapid Systematic Review.
Statistical Journal of the IAOS, 36:1–4.

Batista-Toledo, S. and Gavilan, D. (2023).
Student Experience, Satisfaction and Commitment in Blended Learning: A Structural Equation Modelling Approach.
Mathematics, 11(3).

References II

Bishop, C. M. (2006).
Pattern Recognition and Machine Learning (Information Science and Statistics).
Springer-Verlag, Berlin, Heidelberg.

Brezavšček, A., Jerebic, J., Rus, G., and Žnidaršič, A. (2020).
Factors Influencing Mathematics Achievement of University Students of Social Sciences.
Mathematics, 8(12).

References III

Caicedo-Castro, I. (2023).
Course Prophet: A System for Predicting Course Failures with Machine Learning: A Numerical Methods Case Study.
Sustainability, 15(18).

Caicedo-Castro, I. (2024a).
An Empirical Study of Machine Learning for Course Failure Prediction: A Case Study in Numerical Methods.
International Journal on Advances in Intelligent Systems, 17(1 and 2).

References IV

Caicedo-Castro, I. (2024b).
Quantum Course Prophet: Quantum Machine Learning for Predicting Course Failures: A Case Study on Numerical Methods.
In Zaphiris, P. and Ioannou, A., editors, *Learning and Collaboration Technologies*, pages 220–240, Cham. Springer Nature Switzerland.

Caicedo-Castro, I., Macea-Anaya, M., and Rivera-Castaño, S. (2023).
Early Forecasting of At-Risk Students of Failing or Dropping Out of a Bachelor's Course Given Their Academic History - The Case Study of Numerical Methods.

References V

In *PATTERNS 2023: The Fifteenth International Conference on Pervasive Patterns and Applications*, International Conferences on Pervasive Patterns and Applications, pages 40–51. IARIA: International Academy, Research, and Industry Association.

Charalambides, M., Panaoura, R., Tsolaki, E., and Pericleous, S. (2023).
First Year Engineering Students' Difficulties with Math Courses- What Is the Starting Point for Academic Teachers?
Education Sciences, 13(8).

References VI

Gómez-García, M., Hossein-Mohand, H., Trujillo-Torres, J. M., Hossein-Mohand, H., and Aznar-Díaz, I. (2020).
Technological Factors That Influence the Mathematics Performance of Secondary School Students.
Mathematics, 8(11).

Maamin, M., Maat, S. M., and H. Iksan, Z. (2022).
The Influence of Student Engagement on Mathematical Achievement among Secondary School Students.
Mathematics, 10(1).

References VII

Martinez-Villarraga, E., Lopez-Cobo, I., Becerra-Alonso, D., and Fernández-Navarro, F. (2021).
Characterizing Mathematics Learning in Colombian Higher Distance Education.
Mathematics, 9(15).

Metropolis, N. and Ulam, S. (1949).
The Monte Carlo Method.
Journal of the American Statistical Association, 44(247):335–341.

References VIII

Park, J., Kim, S., and Jang, B. (2023).
Analysis of Psychological Factors Influencing Mathematical Achievement and Machine Learning Classification.
Mathematics, 11(15).

Trujillo-Torres, J.-M., Hossein-Mohand, H., Gómez-García, M., Hossein-Mohand, H., and Hinojo-Lucena, F.-J. (2020).
Estimating the Academic Performance of Secondary Education Mathematics Students: A Gain Lift Predictive Model.
Mathematics, 8(12).

References IX

Wijaya, T. T., Yu, B., Xu, F., Yuan, Z., and Mailizar, M. (2023).
Analysis of factors affecting academic performance of mathematics education doctoral students: A structural equation modeling approach.
International Journal of Environmental Research and Public Health, 20(5).