College of San Mateo
Official Course Outline

1. **COURSE ID:** CIS 400 **TITLE:** Probability for Computer Scientists
   Units: 4.0 units **Hours/Semester:** 48.0-54.0 Lecture hours; 48.0-54.0 Lab hours; 96.0-108.0 Homework hours; 192.0-216.0 Total Student Learning hours
   Method of Grading: Grade Option (Letter Grade or Pass/No Pass)
   Recommended Preparation:
   CIS 262

2. **COURSE DESIGNATION:**
   Degree Credit
   Transfer credit: CSU; UC
   AA/AS Degree Requirements:
   CSM - COMPETENCY REQUIREMENTS: C1 Math/Quantitative Reasoning Basic Competency
   CSM - GENERAL EDUCATION REQUIREMENTS: E2b. Communication and Analytical Thinking

3. **COURSE DESCRIPTIONS:**
   Catalog Description:
   This foundational course covers probability theory's principles and applications in computer science. It starts with combinatorics, then delves into key probability concepts and distributions, alongside analytical tools. The final part focuses on applying probability in machine learning through real-world cases, fostering practical skills and deeper comprehension for future careers.

4. **STUDENT LEARNING OUTCOME(S) (SLO'S):**
   Upon successful completion of this course, a student will meet the following outcomes:
   1. Apply probability theory to analyze and model situations involving uncertainty,
   2. Demonstrate understanding of random variables, expectation and their use in applications
   3. Write programs to simulate random experiments and to test hypotheses
   4. Apply basic confidence interval formulas to characterize the accuracy of estimates from experimental data
   5. Perform linear regression to estimate one variable from another using experimental data

5. **SPECIFIC INSTRUCTIONAL OBJECTIVES:**
   Upon successful completion of this course, a student will be able to:
   1. Define Combinatorial Theory
   2. Describe Discrete Probability
   3. Apply Discrete Random Variables
   4. Demonstrate Continuous Random Variables
   5. Use Multiple Random Variables
   6. Explain Concentration Inequalities
   7. Apply Statistical Estimation
   8. Apply Statistical Inference

6. **COURSE CONTENT:**
   Lecture Content:
   1. Core Probability
      A. Counting
      B. Combinatorics
      C. Definition of Probability
      D. Equally Likely Outcomes
      E. Probability of OR
      F. Conditional Probability
      G. Independence
      H. Probability of AND
      I. Law of Total Probability
      J. Bayes' Theorem
      K. Log Probability
      L. Many Coin Flips
      M. ApplicationsMLE Normal Demo
         a. Enigma Machine
         b. Serendipity
         c. Random Shuffles
         d. Bacteria Evolution
   2. Random Variables

A. Probability Mass Function
B. Expectation
C. Variance
D. Bernoulli Distribution
E. Bionomial Distribution
F. Poisson Distribution
G. Continues Distribution
H. Uniform Distribution
I. Exponential Distribution
J. Normal Distribtion
K. Bionomial Approximation
L. Applications
    a. Winning Series
    b. Jury Selection
    c. Grading Eye Inflamation
    d. Grades are not Normal
    e. Curse of dimensionality
    f. Probability of Baby Delivery

3. Probabilistic Models
    A. Join probability
    B. Multinomial
    C. Continuous Joint
    D. Inference
    E. Bayesian Nertworks
    F. Independence in Variables
    G. Correlation
    H. General Inference
    I. Applications
        a. Fairness in AI
        b. Federalist Paper Authorship
        c. Name of Age
        d. Bayesian Vision Test
        e. Bridge Distribution
        f. Tracking in 2D
4. Uncertainty Theory
    A. Beta Distribution
    B. Adding Random Variables
    C. Central Limit Theorem
    D. Sampling
    E. Bootstrapping
    F. Algorithmic Analysis
    G. Applications
        a. Thompson Sampling
        b. Night Sight
        c. P-Hacking
        d. Differential Privacy
5. Machine Learning
    A. Parameter Estimation
    B. Maximum Likelihood Estimation
    C. Maximum A Posteriori
    D. Machine Learning
    E. Naïve Bayes
    F. Logistic regression
    G. Applications
        a. MLE Normal Demo
        b. MLE Pareto Distribution
        c. MLE Mixture Model

Lab Content:

1. Counting
2. Discrete Probability and Conditional Probability
3. Independence, and Discrete Random Variables Basics
4. Expectation
5. Discrete Random Variables
6. Continuous Random Variable Basics
7. The Normal Random Variables
8. Transforming Continuous Random Variables
9. Joint Discrete Distributions
10. Conditional Distributions
11. Covariance and Correlation
12. Convolution
13. Moment Generating Functions, and Limit Theorems
14. Method of Moments Estimation, Beta/Dirichlet Distributions
15. Maximum a Posteriori Estimation
16. Introduction to Hypothesis Testing

17. Confidence Intervals

7. **REPRESENTATIVE METHODS OF INSTRUCTION:**
   Typical methods of instruction may include:
   A. Lecture
   B. Lab
   C. Directed Study
   D. Discussion
   E. Other (Specify): Lecture will be used to introduce new topics; Teacher will model problem-solving techniques. Class will solve a problem together, each person contributing a potential "step". Students will participate in short in-class projects (in teacher-organized small groups) to ensure that students experiment with the new topics in realistic problem settings; Teacher will invite questions AND ANSWERS from students, generating discussion about areas of misunderstanding; Teacher will create and manage an internet conference for discussion of course topics; and students will work in small groups on programming assignments.

8. **REPRESENTATIVE ASSIGNMENTS**
   Representative assignments in this course may include, but are not limited to the following:
   Writing Assignments:
   The primary writing opportunity for students in this course is documentation supporting their lab and programming projects. This includes both technical documentation and end-user documentation. The technical documentation describes the problem to be solved, the scope of the project, an overview of the solution, and any limitations of the solution. User documentation will be provided to the client of any reusable code.
   Reading Assignments:
   Weekly textbook readings.
   Other Outside Assignments:
   Weekly exercises from the textbook and lab/programming assignments comprise the majority of the assignments. The lab and programming assignments support learning outcomes. In addition, students will create several substantial programs consisting of 500-600 lines of code.

9. **REPRESENTATIVE METHODS OF EVALUATION**
   Representative methods of evaluation may include:
   A. Exams/Tests
   B. Group Projects
   C. Homework
   D. Lab Activities
   E. Projects
   F. Quizzes
   G. Written examination
   H. Bi-weekly quizzes (short answer-from textbook material) to provide feedback to students and teacher; assessment of student contributions during class discussion and project time; individual programming assignments; Midterm and Final exams (short answer, general problem solving (similar to in-class work), short program segments (similar to programming assignments); Assessment of group participation on course projects, including peer assessment of participation and contribution to the group effort.

10. **REPRESENTATIVE TEXT(S):**
    Possible textbooks include:
    A. Alex Tsun. *Probability & Statistics with Applications to Computing*, 1 ed. Alex Tsun, 2020
    B. David Forsyth. *Probability and Statistics for Computer Science*, 1 ed. Springer International Publishing, 2018
    C. Jose Unpingco. *Python for Probability, Statistics, and Machine Learning*, 3 ed. Springer International Publishing, 2022
    D. Sheldon Ross. *Introduction to Probability and Statistics for Engineers and Scientists*, 6 ed. Academic Press, 2021

Origination Date: April 2023
Curriculum Committee Approval Date: September 2023
Effective Term: Fall 2024
Course Originator: Kamran Eftekhari