# ANTONIUS' COMPENDIUM

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Volume II: Neural Nucleus
Version 0.003


Compiled by: Antonius W. Torode[1]
1. Applied Research Laboratories - University Of Texas: Austin

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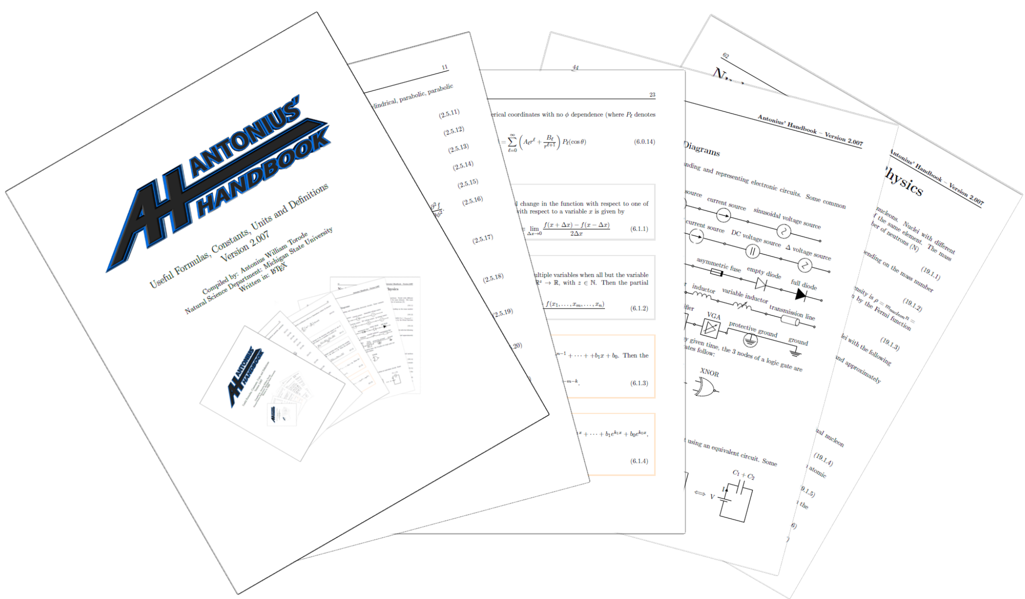

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The current maintainer of this work is: Antonius Torode.

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## Preface

This document is a compilation of ideas, scratch work, derivations, useful formulas, definitions, constants, and general information used for my own studies as a reference while furthering self education. These are my notes. It's purpose is to provide a complete 'compendium' per say of various ideas used often. All the material in this document was either directly copied from one of the references listed at the end or derived from scratch. On occasion *typos may exist* due to human error but will be corrected when discovered.

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## Topics Covered In This Book

- Machine Learning
- Artificial Intelligence
- Modeling
- Psychology

The information in this book is in no way limited to the topics listed above. They serve as a simple guideline to what you will find within this document. For more information about this book or details about how to obtain your own copy please visit:

https://torodean.github.io/

> "Scientific theories deal with concepts, not with reality. All theoretical results are derived from certain axioms by deductive logic. In physical sciences the theories are so formulated as to correspond in some useful sense to the real world, whatever that may mean. However, this correspondence is approximate, and the physical justification of all theoretical conclusions is based on some form of inductive reasoning." - Athanasios Papoulis (Probability, Random Variables, and Stochastic Processes book)

## Disclaimer

This book contains formulas, definitions, and theorems that by nature are very precise. Due to this, some of the material in this book was taken directly from other sources such as but not limited to Wolfram Mathworld. This is only such in cases where a change in wording could cause ambiguities or loss of information quality. Following this, all sources used are listed in the references section and cited when used.

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# Contents


**1 Modeling** **1**
- 1.1 Introduction . . . 1
- 1.2 Markov Models . . . 1
  - 1.2.1 Overview . . . 1
  - 1.2.2 First-Order Markov Model . . . 1
  - 1.2.3 A Larger Example . . . 2
  - 1.2.4 Predicting Input Size . . . 3
  - 1.2.5 Higher-Order Markov Model . . . 4

**2 Artificial Intelligence** **5**
- 2.1 Introduction . . . 5

**3 Psychology** **6**
- 3.1 Introduction . . . 6

**4 resources** **7**

**References** **7**

# Modeling

## 1.1 Introduction

Modeling is the process of constructing abstract representations of real-world systems, behaviors, or phenomena. These representations—whether mathematical, statistical, or computational—enable analysis, simulation, prediction, and understanding of complex structures and dynamics.

This chapter will introduces several types of models used across disciplines, with a focus on those that capture structure, uncertainty, and sequential behavior. Topics include deterministic models, probabilistic frameworks, and data-driven models. The goal is to present models not only as tools for approximation or prediction, but as frameworks for organizing knowledge and reasoning about systems.

## 1.2 Markov Models

### 1.2.1 Overview

In a previous project I was working on for Dungeons & Dragons, I created a model for generating random names and character sequences. That project code can be found here:

`https://github.com/torodean/DnD/blob/main/templates/creator.py`.

The functionality was based on transition patterns between characters of preexisting names. I only later found out that this was referred to as a Markov model. The features related to this will be discussed here in a more generalized form. These models can be used to create elements which follow a similar pattern of an input sequence (such as creating predictive text).

### 1.2.2 First-Order Markov Model

This section contains an explanation of how the markov model functions. Consider some set of sequences $S$ for some arbitrary type, where each element is denoted by a capitalized letter. For example, let

$$S = \{ABC, ABD, BAD\} \tag{1.2.1}$$

. The probability matrix $P$ is constructed by determining all of the elements which follow another, and at what probability that element has of following the others (The probabilities of elements following some element $K$ is $P_K$). that is $P(S) = \{K : P_K \forall K \in S\}$.

The set of elements which exist in $S$ are $A, B, C, D, \emptyset$, where $\emptyset$ denotes the absence of an element (or beginning/end of a sequence). Starting with $A$, we can see that the $A$ element is followed only by $B$ (twice), and $D$ (once) in $S$. The total number of elements ever following an $A$ is thus three. The probabilities following an element $A$ is thus

$$P_A = \begin{cases} B & : \text{twice} \\ D & : \text{once} \end{cases} \implies P_A = \begin{cases} B & : 66.\overline{6}\% \\ D & : 33.\overline{3}\% \end{cases} = \{B : 0.\overline{6}, D : 0.\overline{3}\} \tag{1.2.2}$$

Following this same process for the other elements gives

$$P_B = \{A : 0.\overline{3}, C : 0.\overline{3}, D : 0.\overline{3}\} \tag{1.2.3}$$

$$P_C = P_D = \{\emptyset : 1.0\} \tag{1.2.4}$$

$$P_\emptyset = \{A : 0.\overline{6}, B : 0.\overline{3}\}. \tag{1.2.5}$$

The total probability matrix for this set of sequences would then be

$$P(S) = \{A : P_A, B : P_B, C : P_C, D : P_D, \emptyset : P_\emptyset\} = \begin{cases} A : \{B : 0.\overline{6}, D : 0.\overline{3}\} \\ B : \{A : 0.\overline{3}, C : 0.\overline{3}, D : 0.\overline{3}\} \\ C : \{\emptyset : 1.0\} \\ D : \{\emptyset : 1.0\} \\ \emptyset : \{A : 0.\overline{6}, B : 0.\overline{3}\}. \end{cases} \tag{1.2.6}$$

The $\emptyset$ is a special case in that it represents the first character of a sequence (there is never a character after the last). This format may not look like a matrix at all, but it can be re-written to matrix format. First, note that there are a total of 5 elements ($A$, $B$, $C$, $D$, $\emptyset$) which will give a $5 \times 5$ matrix for all possible combinations. The matrix is configured such that both the rows and columns span from $A \to \emptyset$, covering all the elements of the set. The matrix value of $a, b$ then represents the probability that element $a$ will be proceeded by element $b$.

$$P(S) = \begin{bmatrix} 0 & 0.\overline{3} & 0 & 0 & 0.\overline{6} \\ 0.\overline{6} & 0 & 0 & 0 & 0.\overline{3} \\ 0 & 0.\overline{3} & 0 & 0 & 0 \\ 0.\overline{3} & 0.\overline{3} & 0 & 0 & 0 \\ 0 & 0 & 1.0 & 1.0 & 0 \end{bmatrix} \tag{1.2.7}$$

This probability matrix thus represents the probability of an element proceeding another in one of the given sequences. Each column of the matrix should total to 1.0, as they represent the total set of elements proceeding another. It can be used to generate new sequences which adhere to similar patterns of the input sequences. With larger data sets, more possibilities of sequences typically arise as probable outputs.

One important feature of these models is that under low-entropy (the model is derived from a deterministic source), a uniquely resolvable input set (You can reconstruct exactly one input set) and with enough metadata (initial state, model size, model order, etc), the model can be used to reconstruct the original data.

### 1.2.3 A Larger Example

Consider the following set of sequences:

$$S = \{ABCDE, ABDEE, AABCD, ACDCE, AABCD\} \tag{1.2.8}$$

The set of all elements of this sequence are $\{A, B, C, D, E, \emptyset\}$. There are a total of 6 elements. This set of sequences has 7 $A$'s, 4 $B$'s, 5 $C$'s, 5 $D$'s, 4 $E$'s, and 5 $\emptyset$'s (beginning of each sequence). The probabilities $P_k$ are then

$$P_A = \{A : 2/7, B : 4/7, C : 1/7, D : 0, E : 0, \emptyset : 0\} \tag{1.2.9}$$
$$P_B = \{A : 0, B : 0, C : 3/4, D : 1/4, E : 0, \emptyset : 0\} \tag{1.2.10}$$
$$P_C = \{A : 0, B : 0, C : 0, D : 4/5, E : 1/5, \emptyset : 0\} \tag{1.2.11}$$
$$P_D = \{A : 0, B : 0, C : 1/5, D : 0, E : 2/5, \emptyset : 2/5\} \tag{1.2.12}$$
$$P_E = \{A : 0, B : 0, C : 0, D : 0, E : 1/4, \emptyset : 3/4\} \tag{1.2.13}$$
$$P_\emptyset = \{A : 5/5, B : 0, C : 0, D : 0, E : 0, \emptyset : 0\} \tag{1.2.14}$$

This gives a probability matrix $P(S)$ of

$$P(S) = \begin{bmatrix} 2/7 & 0 & 0 & 0 & 0 & 5/5 \\ 4/7 & 0 & 0 & 0 & 0 & 0 \\ 1/7 & 3/4 & 0 & 1/5 & 0 & 0 \\ 0 & 1/4 & 4/5 & 0 & 0 & 0 \\ 0 & 0 & 1/5 & 2/5 & 1/4 & 0 \\ 0 & 0 & 0 & 2/5 & 3/4 & 0 \end{bmatrix} \tag{1.2.15}$$

### 1.2.4 Predicting Input Size

A probability matrix for a markov model is generated with a set of sequences. Each sequence $s$ has a size, and the set of all sequences $S$ also has a size. If the size of each sequence $s$ is fixed, there will always be a minimum possible size of the $S$ needed to generate the probability matrix. This analysis will being by using a fixed size for all $s \in S$.

Given an input probability matrix $P$, a limited prediction of the input data size can be made. Suppose $P(S)$ forms an $n \times n$ matrix, implying that it contains $n$ elements. The matrix is formed by some number of combinations of these $n$ elements. For visualization, suppose the matrix looks something like the following:

$$P(S) = \begin{bmatrix} s_{00} & s_{10} & s_{20} & \cdots & s_{n0} \\ s_{01} & s_{11} & s_{21} & \cdots & s_{n1} \\ s_{02} & s_{12} & s_{22} & \cdots & s_{n2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{0n} & s_{1n} & s_{2n} & \cdots & s_{nn} \end{bmatrix} \tag{1.2.16}$$

As mentioned before, the probabilities of each column $k$ (each column represents a different element of $S$, so $k$ here, is just any element $k \in S$) must add to 1, giving

$$P(k) = \sum_{i=0}^{n} s_{in} = 1, \forall k \in S. \tag{1.2.17}$$

Every element $k \in S$ will appear an integer number of times (since an element either appears or does not). This means, that every probability $s$ will be a rational value, $s \in \mathbb{Q}$ (since it is defined as the total occurrences of $k$ over the total possible occurrences of any element). Therefore, we can define $s^*_{ik} \in \mathbb{N}$ such that $s^*_{ik} = s_{ik} N_k$, where $N_k \in \mathbb{N}$. Given that $N_k$ is the least common denominator (LCD) when summing all values of $s_{ik}$ to 1, this value of $N_k$ would then be the minimum possible number of total elements of $k$, denoted $T_k$, in the initial sequence which produced this matrix. This gives

$$\min(T_k) = \sum_{i=0}^{n} s^*_{ik} = N_k, \forall k \in S. \tag{1.2.18}$$

Note that the $\emptyset$ element is a special case here. It is defined as the start or end of a sequence and therefore there will always be $n$ of them from the reference of following an element, and $n$ from the reference of preceding an element.

This is more of an observational conclusion than a formal theorem. Notice in equation 1.2.7, for the first column, we have $\frac{2}{3}$ and $\frac{1}{3}$ as the probabilities. When summed to 1, the LCD of these is 3. This correctly matches the value of the number of $A$ elements (which corresponds to the first column) in the corresponding sequence of $S$ which was used. However, if the initial sequence had 6 elements, and the probabilities were thus $\frac{4}{6} = \frac{2}{3}$ and $\frac{2}{6} = \frac{1}{3}$ (respectively), then the value would have been incorrect because the fractions may have been reduced. This is the reason I say it is $\min(T_k)$ rather than $T_k$. Given that the fractions for the probabilities are left in an non-reduced form, or are irreducible to begin with, this would be $T_k$. But for general purposes, the probabilities are likely always reduced to simplest form and thus we can only determine a minimum value of $T_k$. It will be true that the total number is some multiple of $T_k$, however, which can be valuable information.

There may be some interesting insights to gain from the rows of the probability matrix as well. Given the existence of $N_k$, which has already been established, the sum of the row $R$ for some element $k$ can be written as

$$R(k) = \sum_{i=0}^{n} s_{ki} = \sum_{i=0}^{n} \frac{s_{ki}^*}{N_i} = \frac{s_{k0}^*}{N_0} + \frac{s_{k1}^*}{N_1}\frac{s_{k2}^*}{N_2} + \cdots + \frac{s_{kn}^*}{N_n}. \tag{1.2.19}$$

If $N_i$ is an unreduced LCD for the values of its row, then these coefficients give the total number of elements $k$ in the set of sequences

$$T_k = \sum_{i=0}^{n} s_{ki}^*. \tag{1.2.20}$$

Again, this is more of an observational conclusion than a formal theorem. But this can be seen in the following way. Each element, when appearing in a sequence, will add some minimum amount of probability $p_{min}$ to a corresponding position in the matrix. this amount will always be equal to $1/T_k$. If the elements appear after another element more than once, say, $s_{ki}^*$ times, then this coefficient increments, giving $s_{ki}^*/T_k$. For unreduced fractional forms of each probability, $T_k = N_k$, so $s_{ki}^*/N_k$ is just a count of how many elements there are. Thus, by summing these counters for each case (an element proceeding another element), we have the total number of elements in a set of sequences.

**! Section in Progress !**

### 1.2.5 Higher-Order Markov Model

A higher order Markov model follows similar principals as a first-order Markov model. The difference is how many elements in sequence are tracked and considered when determining another. Consider the same sequence found in 1.2.1. Suppose the order of this model is $O$ (that is a $O$-order Markov model). This would mean that instead of calculating the probability that an element follows another, the probability matrix would instead contain the probability of an element following any sequence of elements from 1 to $O$. For example, suppose we want $O = 2$, giving a second order Markov model. For the sequence in 1.2.1, The possible combinations of any sequence of 1 or 2 elements are the same elements in the first-order Markov model with the union of the additional probabilities of every sequence of 2 elements. The sequence of two elements within $S$ in this case are $AB$ (twice), $BC$ (once), $BD$ (once), $BA$ (once), and $AD$ (once). The probability for a second order is denoted by $P^2$.

# Artificial Intelligence

## 2.1 Introduction

Artificial Intelligence (AI) is the field of study concerned with the design and development of systems capable of performing tasks that typically require human intelligence. These tasks include learning, reasoning, problem-solving, perception, and language understanding. In a sense, this is an attempt to artificially mimic human intelligence while simultaneously combining it with the advantages that modern technological computing powers bring. AI spans a wide range of sub-fields, from symbolic logic and knowledge representation to machine learning and neural networks. It intersects with disciplines such as computer science, mathematics, neuroscience, and philosophy.

Modern AI systems are broadly categorized into two classes: *narrow AI*, designed for specific tasks, and *general AI*, which aspires to emulate human-level cognition across diverse domains. Key concepts include algorithms, data structures, optimization, statistical inference, and computational models of learning. Recent advancements in Large Language Models (LLMs) have demonstrated the ability of transformer-based architectures to generate coherent text, perform reasoning tasks, and interface with complex domains using natural language, which gives an appearance for the foundations of creating a *general AI.* Artificial General Intelligence (AGI) refers to a type of AI that possesses the ability to understand, learn, and apply knowledge across a wide range of tasks at a level comparable to human intelligence, which is the goal of many.

Applications of AI are pervasive, influencing medicine, finance, robotics, language processing, and decision-making systems. Continued advancement in AI raises important technical, ethical, and societal questions, many of which remain open areas of research.

# Psychology

## 3.1 Introduction

Psychology is the scientific study of mind and behavior, encompassing the processes underlying cognition, emotion, perception, and action. It explores how individuals think, feel, and behave across various contexts, integrating insights from biology, sociology, philosophy, and neuroscience. The field is broadly divided into sub-disciplines such as cognitive psychology, behavioral psychology, developmental psychology, clinical psychology, and social psychology. Each examines different aspects of mental processes and behavior, using both experimental and observational methods.

Psychological research informs fields like education, mental health, artificial intelligence, and human-computer interaction, providing foundational understanding of human cognition and behavior.

# References


[1] Bauer, W., and Gary D. Westfall. University Physics with Modern Physics. 2nd ed. Vol. 2. New York, NY: McGraw-Hill Companies, 2014. Print.

[2] Boas, Mary L. Mathematical Methods in the Physical Sciences. 3rd ed. New York: John Wiley & Sons, 1984. Print.

[3] http://www.dictionary.com

[4] Griffiths, David J. Introduction to Electrodynamics. 4th ed. N.p.: Pearson India Education Services Pvt, 2015. Print.

[5] Griffiths, David J. Introduction to Quantum Mechanics. 2nd ed. Harlow: Pearson, 2014. Print.

[6] Haberman, R. "Applied Partial Differential Equations: with Fourier series and Boundary Value Problems." 4th ed. Upper Saddle River, New Jersey. 2004. Print.

[7] Judson T. W. "Abstract Algebra: Theory and Applications." Stephen F. Austin State University. August 5, 2017.

[8] Reitz, John Richard. Foundations of Electromagnetic Theory. 4th ed. N.p.: Addison-Wesley, 1992. Print.

[9] Kittel, Charles, and Herbert Kroemer. Thermal Physics. San Francisco: W.H. Freeman, 1980. Print.

[10] Ross, Kenneth A. Elementary Analysis: The Theory of Calculus $2^{\text{nd}}$ edition.

[11] Ryden, Barbara Sue., and Bradley M. Peterson. Foundations of Astrophysics. San Francisco: Addison-Wesley, 2010. Print.

[12] "Table of Isotopic Masses and Natural Abundances." (n.d.): n. pag. NC State University. Web. `https://www.ncsu.edu/chemistry/msf/pdf/IsotopicMass_NaturalAbundance.pdf`.

[13] Taylor, John R. Classical Mechanics. Sausalito, CA: U Science, 2005. Print.

[14] "Wolfram|Alpha: Computational Knowledge Engine." N.p., n.d. Web. 2016 x

[15] "Wolfram MathWorld: The Web's Most Extensive Mathematics Resource." Wolfram MathWorld. N.p., n.d. Web.

[16] Zee, Dennis G. A first Course in Differential Equations with Modeling Applications." Edition 10. Book.

[17] Taylor, John R. (John Robert), 1939. An introduction to error analysis I John R. Taylor.-2nd ed.

[18] The Feynman Lectures on Physics, `https://www.feynmanlectures.caltech.edu/`

[19] IUPAC Periodic Table of the Elements and Isotopes. `https://applets.kcvs.ca/IPTEI/IPTEI.html`

[20] Table Of Nuclides. Nuclear Data Center at KAERI. `https://atom.kaeri.re.kr/nuchart/`

[21] Sakurai, J. J. (Jun John), 1933-1982. Modern quantum mechanics. - 2nd ed. I J.J. Sakurai, Jim Napolitano. p. cm. ISBN 978-0-8053-829 1-4 (alk. paper)

[22] Xavier Lirton, An Introduction to Underwater Acoustics: Principals and Applications, Praxis Publishing, 2004.

[23] Sean M. Carroll, An Introduction to General Relativity: Spacetime and Geometry

[24] Andrew J. S. Hamilton, General Relativity, Black Holes, and Cosmology, 13 January 2020

[25] Newton's Scholium on Time, Space, Place and Motion, `https://plato.stanford.edu/entries/newton-stm/scholium.html`

[26] Being, Nothingness, and the Quantum Vacuum: Revisiting Aether Through Heidegger's Lens, Douglas C. Youvan, March 13, 2024

[27] The Michelson-Morley Experiment, Michael Fowler, UVa, `https://galileoandeinstein.phys.virginia.edu/lectures/michelson.html#Detecting%20the%20Aether%20Wind:%20the%20Michelson-Morley%20Experiment`

[28] The Speed of Light in the Quantum Vacuum Aether: the "Equation of God", Toni Scarmato, May 2023, `https://www.researchgate.net/profile/Toni-Scarmato/publication/371379815_The_Speed_of_Light_in_the_Quantum_Vacuum_Aether_the_Equation_of_God/links/6481e6c62cad460a1bfe15cc/The-Speed-of-Light-in-the-Quantum-Vacuum-Aether-the-Equation-of-God.pdf`

[29] A First Course in Linear Algebra, Robert A. Beezer, Version 3.4. `https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=2d126254474e43b7d300ef5e60752d5e19f287c3`