
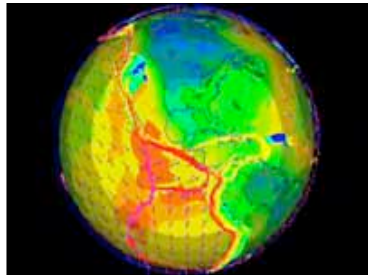
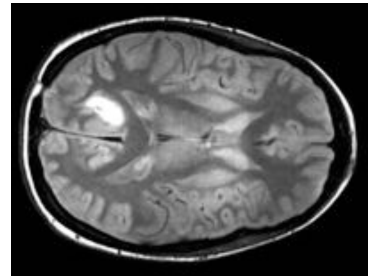



APPLIED AND COMPUTATIONAL MATHEMATICS

A NEW DEGREE FOR 21ST CENTURY DISCOVERY AND INNOVATION

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- BYU Department of Mathematics
- Savvysherpa and UnitedHealth Group

Ideal Job Description for BS in Math

NONE OF THESE ACTUALLY EXIST

What do real jobs look like?

Data Scientist

Google

Responsibilities

- Work with large, complex data sets. Solve difficult, non-routine analysis problems, applying advanced analytical methods as needed. Conduct end-to-end analysis that includes data gathering and requirements specification, processing, analysis, ongoing deliverables, and presentations.
- Build and prototype analysis pipelines iteratively to provide insights at scale. Develop comprehensive understanding of Google data structures and metrics, advocating for changes where needed for both products development and sales activity.
- Interact cross-functionally with a wide variety of people and teams. Work closely with engineers to identify opportunities for, design, and assess improvements to google products.
- Make business recommendations (e.g. cost-benefit, forecasting, experiment analysis) with effective presentations of findings at multiple levels of stakeholders through visual displays of quantitative information.
- Research and develop analysis, forecasting, and optimization methods to improve the quality of Google's user facing products; example application areas include ads quality, search quality, end-user behavioral modeling, and live experiments.

Qualifications

Minimum qualifications:

- MS degree in a quantitative discipline (e.g., statistics, operations research, bioinformatics, economics, computational biology, computer science, mathematics, physics, electrical engineering, industrial engineering).
- 2 years of relevant work experience in data analysis or related field. (e.g., as a statistician / data scientist / computational biologist / bioinformatician).
- Experience with statistical software (e.g., R, Julia, MATLAB, pandas) and database languages (e.g., SQL).

Data Scientist

Machine Learning Data Scientist

Apple

Job Description

We are looking for engineers and technologists to help build the next-generation of systems, tools and features for Apple's cutting-edge devices and platforms that support billions of transactions. This team is the focal point in our work bringing the latest in search and discovery ideas to production at large scale.

Key Qualifications

- 2+ years commercial machine learning experience (not necessarily in a production engineering role).
- A strong understanding of machine learning theory.
- Mid-level programming experience. You do not have to be able to write highly scalable production code (you will be working with engineers who can do that) but you do need to be able to build prototypes and be able to understand the existing code base. Python, Java or C++ experience is highly desired.
- A principled approach to solving algorithmic problems with a focus on what will make users happy.
- A pragmatic approach to rapidly evaluating new algorithmic ideas.
- A very high attention to detail and ability to thoroughly think through problems.
- Excellent written and oral communication skills on both technical and non-technical topics.

Description

As a Machine Learning Data Scientist within the cross-functional Search and Measurement team, you'll have the opportunity to solve challenging search problems across a broad range of Apple products. You'll apply machine learning techniques to improve Apple's search algorithms, which may include iTunes search, App Store search and Maps search. You'll partner with engineers to implement your ideas in production and statisticians and analysts to evaluate and validate your improvements.

Education

BA/BS or higher in Computer Science Masters or PhD in Machine Learning or Statistics highly desired.

Data Scientist

Minimum Qualification

- 2+ years experience doing quantitative analysis
- BA/BS in Computer Science, Math, Physics, Engineering, Statistics or other technical field
- Experience in SQL or other programming languages
- Development experience in any scripting language (PHP, Python, Perl, etc.)
- Ability to communicate the results of analyses with product and leadership teams to influence the strategy of the product
- Understanding of statistics (e.g., hypothesis testing, regressions)
- Experience manipulating data sets through statistical software (ex. R, SAS) or other methods

What’s a Data Scientist?

DATA

Data Scientist: The Sexiest Job of the 21st Century

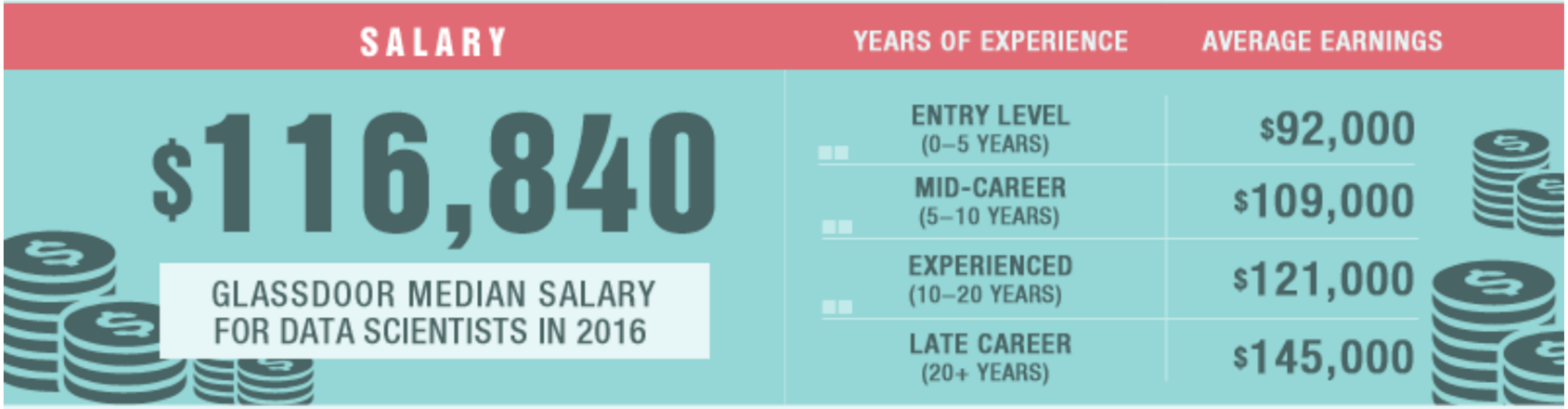
by Thomas H. Davenport and D.J. Patil

FROM THE OCTOBER 2012 ISSUE

Meet the people who can coax treasure out of messy, unstructured data.
by Thomas H. Davenport and D.J. Patil

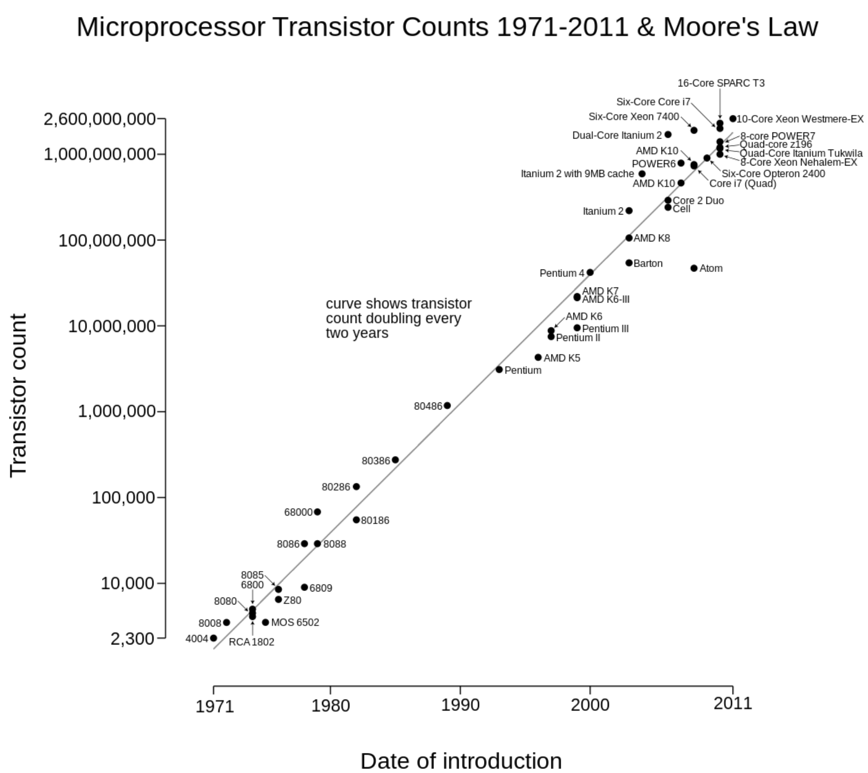
When Jonathan Goldman arrived for work in June 2006 at LinkedIn, the business networking site, the place still felt like a start-up. The company had just under 8 million accounts, and the number was growing quickly as existing members invited their friends and colleagues to join. But users weren't seeking out connections with the people who were already on the site at the rate executives had expected. Something was apparently missing in the social experience. As one LinkedIn manager put it, "It was like arriving at a conference reception and realizing you don't know anyone. So you just stand in the corner sipping your drink—and you probably leave early."

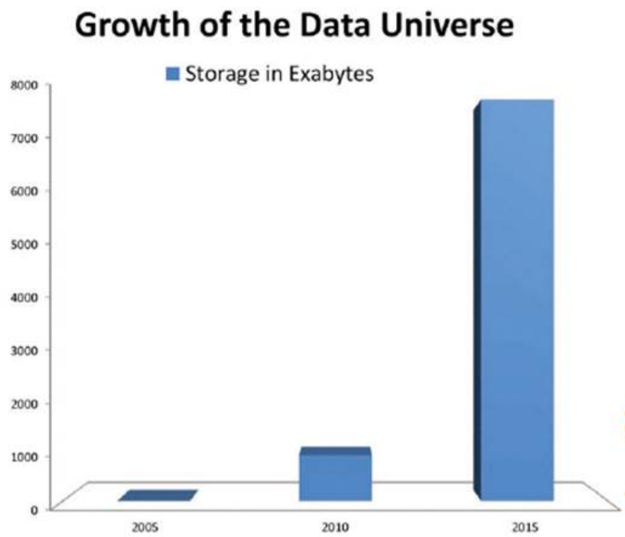
Data Science Salaries

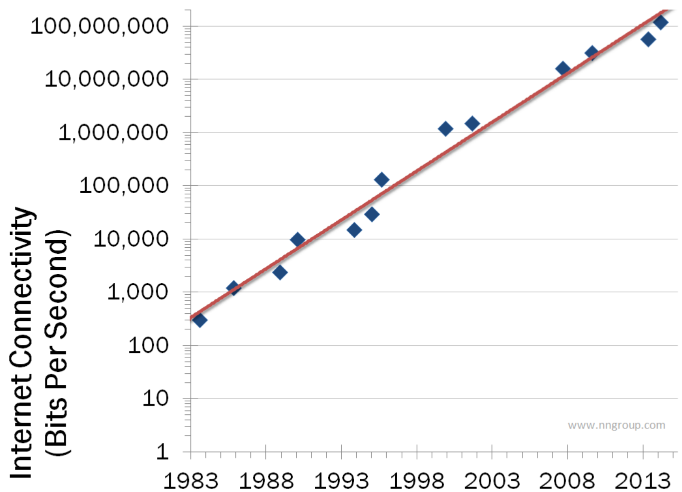


What’s driving this?

Rapid Growth in Computation, Data, and Communication







What should we do about it?

Problems Revamping the Math Major

- Typical BS in math focuses on 19^{th} Century and early 20^{th} Century content (Ring theory, circa 1920).
- Many mathematicians are often embarrassingly disconnected from STEM disciplines and the needs of industry.
- Math departments have a “service department” mentality that leads to a doomed business model.
- Sustainability is difficult. Innovations often die out do to burnout, retirement, and administrative assignments.
- Systemic changes will probably require an “off the shelf” solution.

If you could design a degree from the ground up, how would you do it?

Desired Outcomes

Want the students to

- Become sophisticated mathematically
- Develop strong technical and computational skills
- Be engaged and foster a strong work ethic
- Learn to be world class thinkers and problem solvers
- To become leaders and work well in interdisciplinary teams
- To get top career and graduate program placements
- Forge strong bonds that translate into vibrant alumni relations
- Learn to discern truth (!)
- To use their powers for good (!)

Want the program to

- Have a strong national brand
- Develop tight relationships with industry
- Seed other disciplines with exceptional graduate students
- Seed mathematics with exceptional graduate students
- Help mathematics align better with industry and the needs to society
- Provide a national model that elevates mathematics in the STEM community
- Double as a professional development platform for faculty
- Connects faculty and practitioners to other disciplines and resources
- Change the culture of mathematics

Our Approach

- Fresh 21st Century Content
- Students Choose a Concentration
- Capstone Experience
- Lockstep Curriculum (Efficient)
- Cohort Model (Breeds Teamwork and Socialization)
- Internship & Career Placement, Alumni Relations

Fresh 21st Century Content

- Algorithmic Thinking
- Rigorous Mathematics (mostly analysis)
- Tightly Integrated Content
- Mathematical and Statistical Modeling
- Course Sequences with Labs (32 Credits)
  - Mathematical Analysis
  - Algorithms, Approximation, and Optimization
  - Modeling with Uncertainty and Data
  - Modeling with Dynamics and Control
- Labs:
  - Cutting-Edge Computational Training
  - Data Wrangling and Big Data Platforms
  - Pull Broadly from Applications
- Seminars
  - Career Essentials
  - Data Visualization
  - Competitive Coding

Algorithmic Thinking

- An algorithm is a natural extension of a function
- Mathematical analysis is about proving theorems about algorithms
- Often we have to approximate algorithms in order to analyze them
- Every problem is either an optimization problem or a sampling problem
- Best way to learn something is to teach it. Knuth argues the best way to learn something is to teach it to a computer.
- No black boxes! Students in our program aren't allowed to use a package until they have coded the core algorithm(s) themselves. They have to earn the right to use a package!

Algorithms that can and should be included in an undergraduate mathematics curriculum

- Encryption algorithms: probabilistic primes (using Fermat's little theorem), RSA, Euclidian algorithm, Diffie-Hillman key exchange
- Solving Linear Systems and Finding Eigenvalues: Row reduction, Jacobi, Gauss Seidel, Successive over relaxation (SOR), and Krylov methods such as Arnoldi, Lanczos, GMRES
- State Estimation: Kalman, extended Kalman, particle filters, recursive least squares, etc.
- Compression: Huffman, LWZ, wavelet approximation
- Tree Search: AVL trees, Black-White trees, B-trees
- Constrained Optimization: simplex, interior point, \ell^1
- regularization (which includes lasso, group lasso, compressed sensing, etc.)
- Sampling and Markov Chain Monte Carlo: Gibbs, Metropolis, Metropolis-Hastings
- Matrix Decompositions: LU, QR, SVD, etc.
- Graph Algorithms: Minimum Spanning tree, traveling salesman, breadth-first search, depth-first search
- Unconstrained Optimization: Newton, BFGS, conjugate-gradient
- Dynamic programming (backward iteration)
- Classification: Logistic regression, random forests, support vector machines, neural networks
- Multi-armed bandit problems and Markov Decision Processes
- ODE Solvers (RK, RKF, Dormand-Prince)
- PDE solvers: finite difference/element: Most of these are just linear algebra solvers
- Pseudorandom number generation: Mersenne Twister
- Splines/Interpolation: Chebyshev interpolation uses FFT, barycentric Lagrange interpolation
- Time Series: ARMA, ARIMA (these can be done with the Kalman filter, but almost nobody does it this way

Mathematical Rigor: Uniform Contractions

Theorem 7.2.4 (Uniform contraction mapping principle). *Assume that* $(X, \|\cdot\|_X)$ *and* $(Y, \|\cdot\|_Y)$ *are Banach spaces,* $U \subset X$ *and* $V \subset Y$ *are open, and the function* $f : \overline{U} \times V \to \overline{U}$ *is a uniform contraction with constant* $0 \leq \lambda < 1$. *Define a function* $g : V \to \overline{U}$ *that sends each* $\mathbf{y} \in V$ *to the unique fixed point of the contraction* $f(\cdot, \mathbf{y})$. *If* $f \in C^k(\overline{U} \times V; \overline{U})$ *for some* $k \in \mathbb{N}$, *then* $g \in C^k(V; \overline{U})$.

Theorem 7.3.12 (Newton's Method—Vector Version). *Let* $(X, \|\cdot\|)$ *be a Banach space and assume* $f : X \to X$ *is* C^1 *in an open neighborhood* U *of the point* $\bar{\mathbf{x}} \in X$ *and* $f(\bar{\mathbf{x}}) = 0$. *If* $Df(\bar{\mathbf{x}}) \in \mathscr{B}(X)$ *has a bounded inverse and* $Df(\mathbf{x})$ *is Lipschitz on* U, *then the iterative map*

$$\mathbf{x}_{n+1} = \mathbf{x}_n - Df(\mathbf{x}_n)^{-1} f(\mathbf{x}_n) \tag{7.19}$$

converges quadratically to $\bar{\mathbf{x}}$ *whenever* $\mathbf{x}_0$ *is sufficiently close to* $\bar{\mathbf{x}}$.

Theorem 7.4.8 (The Inverse Function Theorem). *Assume that* $(X, \|\cdot\|_X)$ *and* $(Y, \|\cdot\|_Y)$ *are Banach spaces, that* U *and* V *are open neighborhoods of* $\mathbf{x}_0 \in X$ *and* $\mathbf{y}_0 \in Y$, *respectively, and that* $f : U \to V$ *is a* C^k *map for some* $k \in \mathbb{Z}^+$, *satisfying* $f(\mathbf{x}_0) = \mathbf{y}_0$. *If* $Df(\mathbf{x}_0) \in \mathscr{B}(X; Y)$ *has a bounded inverse, then there exist open neighborhoods* $U_0 \subset U$ *of* $\mathbf{x}_0$ *and* $V_0 \subset V$ *of* $\mathbf{y}_0$, *and a unique* C^k *function* $g : V_0 \to U_0$ *that is inverse to* f. *In other words,* $f(g(\mathbf{y})) = \mathbf{y}$ *for all* $\mathbf{y} \in V_0$ *and* $g(f(\mathbf{x})) = \mathbf{x}$ *for all* $\mathbf{x} \in U_0$. *Moreover, for all* $\mathbf{x} \in U_0$, *we have*

$$Dg(\mathbf{y}) = Df(g(\mathbf{y}))^{-1}. \tag{7.25}$$

Theorem 7.4.2 (The Implicit Function Theorem). *Assume that* $(X, \|\cdot\|_X)$, $(Y, \|\cdot\|_Y)$, *and* $(Z, \|\cdot\|_Z)$ *are Banach spaces, that* U *and* V *are open neighborhoods of* $\mathbf{x}_0 \in X$ *and* $\mathbf{y}_0 \in Y$, *respectively, and that* $F : U \times V \to Z$ *is a* C^k *map for some integer* $k \geq 1$. *Let* $\mathbf{z}_0 = F(\mathbf{x}_0, \mathbf{y}_0)$. *If* $D_2F(\mathbf{x}_0, \mathbf{y}_0) \in \mathscr{B}(Y; Z)$ *has a bounded inverse, then there exists an open neighborhood* $U_0 \times V_0 \subset U \times V$ *of* $(\mathbf{x}_0, \mathbf{y}_0)$ *and a unique* C^k *function* $f : U_0 \to V_0$ *such that* $f(\mathbf{x}_0) = \mathbf{y}_0$ *and*

$$\{(\mathbf{x}, \mathbf{y}) \in U_0 \times V_0 \mid F(\mathbf{x}, \mathbf{y}) = \mathbf{z}_0\} = \{(\mathbf{x}, f(\mathbf{x})) \mid \mathbf{x} \in \mathrm{U}_0\}. \tag{7.21}$$

Moreover, the derivative of f *satisfies*

$$Df(\mathbf{x}) = -D_2F(\mathbf{x}, f(\mathbf{x}))^{-1} D_1F(\mathbf{x}, f(\mathbf{x})) \tag{7.22}$$

on U_0.

Mathematical Rigor: The Danielle Integral

Theorem 5.7.6 (Continuous Linear Extension Theorem). *Let $(Z, \|\cdot\|_Z)$ be a normed linear space, $(X, \|\cdot\|_X)$ a Banach space, and $S \subset Z$ a dense subspace of Z. If $T : S \to X$ is a bounded linear transformation, then T has a unique linear extension to $\overline{T} \in \mathscr{B}(Z; X)$ satisfying $\|\overline{T}\| = \|T\|$.*

Definition 5.10.4. *The* integral *of a step function $f \in S([a,b]; X)$ of the form (5.13) is defined to be*

$$I(f) = \sum_{i=1}^{N} \mathbf{x}_i (t_i - t_{i-1}). \tag{5.15}$$

This is a map from $S([a,b]; X)$ to X. We often write $I(f)$ as $\int_a^b f(t)\,dt$.

Proposition 5.10.5. *The integral map $I : S([a,b]; X) \to X$ is a bounded linear transformation with induced norm $\|I\| = (b-a)$.*

Theorem 5.10.6 (Single-variable Banach-valued Integration). *Let $L^\infty([a,b]; X)$ be given the L^∞-norm. The linear map $I : S([a,b]; X) \to X$ can be extended uniquely to a bounded linear (hence uniformly continuous) transformation*

$$\overline{I} : \overline{S([a,b]; X)} \to X,$$

with $\|\overline{I}\| = \|I\| = (b-a)$.

Theorem 8.1.9 (Multivariable Banach-valued Integral). *Let $\overline{S([\mathbf{a},\mathbf{b}]; X)}$ be the closure of $S([\mathbf{a},\mathbf{b}]; X)$ in $L^\infty([\mathbf{a},\mathbf{b}]; X)$. The linear transformation $\mathscr{I} : S([\mathbf{a},\mathbf{b}]; X) \to X$ can be extended uniquely to a bounded linear transformation $\overline{\mathscr{I}} : \overline{S([\mathbf{a},\mathbf{b}]; X)} \to X$, and*

$$\|\overline{\mathscr{I}}\| = \lambda([\mathbf{a},\mathbf{b}]).$$

Moreover, we have

$$C([\mathbf{a},\mathbf{b}]; X) \subset \overline{S([\mathbf{a},\mathbf{b}]; X)} \subset L^\infty([\mathbf{a},\mathbf{b}]; X).$$

Definition 8.1.7. *The* integral *of a step function $s = \sum_{I \in \mathscr{P}} \mathbf{x}_I \mathbb{1}_{R_I}$ is*

$$\mathscr{I}(s) = \int_{[\mathbf{a},\mathbf{b}]} s = \sum_{I \in \mathscr{P}} \mathbf{x}_I \lambda(R_I).$$

Tight Integration: Spectral Theory

$$R(z) = (zI - A)^{-1} = \frac{\operatorname{adj}(zI - A)}{\det(zI - A)};$$

Definition 12.4.1. *Let $\lambda \in \sigma(A)$. If Γ is a positively-oriented simple closed curve containing $\lambda \in \sigma(A)$ but no other points of $\sigma(A)$. The* spectral projection *(or* eigenprojection*) of A associated with λ is given by*

$$P_\lambda = \operatorname{Res}_\lambda R(z) = \frac{1}{2\pi i} \oint_\Gamma R(z)dz. \qquad (12.18)$$

Theorem 12.4.6 (Spectral Resolution Formula). *Suppose that $f(z)$ has a power series at $z = 0$ with radius of convergence $b > r(A)$. For any positively-oriented simple closed contour Γ containing $\sigma(A)$, we have*

$$f(A) = \frac{1}{2\pi i} \oint_\Gamma f(z)R(z)dz. \qquad (12.19)$$

Theorem 12.6.12 (Spectral Decomposition Theorem). *For each $\lambda \in \sigma(A)$ let P_λ denote the spectral projection associated to λ and let D_λ denote the corresponding eigennilpotent of order m_λ. The resolvent takes the form*

$$R(z) = \sum_{\lambda \in \sigma(A)} \left[\frac{P_\lambda}{z - \lambda} + \sum_{k=1}^{m_\lambda - 1} \frac{D^k}{(z - \lambda)^{k+1}} \right]. \qquad (12.33)$$

And we have the spectral decomposition

$$A = \sum_{\lambda \in \sigma(A)} \lambda P_\lambda + D_\lambda. \qquad (12.34)$$

- Spectral Mapping Theorem
- Proof of the Power Method
- Perron-Frobenius Theorem
- PageRank Algorithm
- Drazin Inverse
- Basis-Invariant Canonical Form
- Caley-Hamilton Theorem
- Krylov Subspace Theory
- Pseudospectral Analysis
- Lagrange Interpolation $P_\lambda = L_\lambda(A)$

Tight Integration: Other Examples

- Inner Product Spaces:
  - Fourier theory and wavelets
  - Orthogonal polynomials
- Optimization:
  - Almost every problem in machine learning, economics, operations research, engineering design, etc., are optimization problems.
  - After a semester of optimization, students can rapidly learn statistics and several applied fields.
- Kalman Filtering:
  - Formulated as Newton's method on a quadratic form
  - Estimate parameters for ARMA with Kalman
- Logistic Regression:
  - Easy application of convex optimization
  - Nice way to introduce classification methods in Machine Learning
  - Convenient way to introduce Stochastic Gradient Descent
  - Generalizes to Neural Networks

Mathematical & Statistical Modeling = Scientific Method

(where your hypothesis is a mathematical relationship)

Characterization: Graphing relationships, clustering, exploring dimensionality, scaling, unsupervised learning

Formulate Hypothesis: Optimization, differential equation, training supervised learning methods

Prediction/Decision: Forward algorithms, simulations, and feedback control rules

Validation: Measuring, quantifying, and reporting the quality of the results, errors, uncertainty, etc.

NOTE: Modeling is the process; the model is the hypothesis

50 Shades of Model Uncertainty

Black Box Models

Gray Box Models

White Box Models

Fitting Data

$$\min \sum_{i=1}^{n} \ell(y_i - f(x_i))$$

Purely data driven

Combination of data and first principles

First Principles

$$u_t + \nabla \cdot f(u) = 0$$

Conservation Laws

Summary: Fresh 21st Century Content

- First Year: Design, Analysis, and Optimization of Algorithms
  - Advanced Linear Algebra and Numerical Linear Algebra
  - Advanced Calculus (Multivariable Analysis)
  - Data Structures and Graph Algorithms
  - Approximation Theory and Numerical Analysis
  - Optimization, Optimization, Optimization (!)
- Second Year: Mathematical and Statistical Modeling
  - Probability Theory, Stochastic Modeling
  - Bayesian Statistics and Machine Learning
  - Dynamical Systems (ODE, PDE, SDE)
  - Calculus of Variations and Optimal Control
  - Distributed Computing and Big Data (MPI, Hadoop, noSQL)
  - Data Analytics Platforms (SQL, Python and Pandas)
- Seminars (see GitHub Repo)

INTRODUCING BYU'S APPLIED AND COMPUTATIONAL MATHEMATICS PROGRAM

Program Overview

- Freshman & Sophomore Years
  - General Education Requirements
  - Minor in Mathematics (3 Calculus, Linear Algebra, ODE, proof)
  - Intro Computer Programming (C++)
  - First Semester of Real Analysis (e.g., Abbott)
- Junior Year
  - Mathematical Analysis (Linear and Nonlinear)
  - Algorithms, Approximation & Optimization
  - Work on Concentration
  - Soft-Skills Seminar
- Summer Capstone (Internship or Research)
- Senior Year
  - Modeling w/ Uncertainty & Data
  - Modeling w/ Dynamics & Control
  - Work in Concentration
  - Data Vis and Comp Prog Seminar

LOCKSTEP CORE PROGRAM

STUDENTS ARE IN COHORTS

First Year Sequences

Mathematical Analysis

- Vector Spaces
- Linear Transformations
- Inner Product Spaces
- Spectral Theory
- Metric Topology
- Differentiation
- Contraction Mappings
- Integration
- Integration on Manifolds
- Complex Analysis
- Advanced Spectral Theory
- Krylov Subspaces
- Pseudospectrum

Algorithm Design & Optimization

- Classical Algorithms
- Asymptotic Analysis
- Graph Algorithms
- Discrete Probability
- Fourier Theory
- Wavelets
- Interpolation
- Quadrature
- Unconstrained Optimization
- Convex Analysis
- Linear Optimization
- Nonlinear Optimization
- Dynamic Optimization
- Markov Decision Processes

Selected First-Year Labs

- Python Essentials (10 labs)
  - Intro Python
  - Standard Library
  - OOP
  - Numpy
  - Matplotlib
  - I/O
  - Profiling
  - Unit Testing
  - SymPy
  - Data Visualization
- Kevin Bacon Problem
- Facial Recognition
- Balloon Pop
- PageRank
- Markov Chains
- Many More…

Second Year Sequences

Modeling with Uncertainty & Data

- Probability Spaces
- Random Variables
- Distributions & Expectation
- Limit Theorems
- Markov Processes
- Information Theory
- Kalman Filtering & Time-Series
- Principal Components
- Clustering
- Bayesian Statistics (MCMC)
- Logistic Regression
- Decision Trees & Ensembles
- Support Vector Machines
- Deep Neural Networks

Modeling with Dynamics & Control

- ODE Existence & Uniqueness
- Linear ODE
- Nonlinear Stability
- Boundary-Value Problems
- Hyperbolic PDE
- Parabolic PDE
- Elliptic PDE
- Calculus of Variations
- Optimal Control
- Stochastic Control

Selected Second-Year Labs

- Data Science Essentials (12 labs)
  - Regular Exp
  - Web Technologies
  - SQL 1-2
  - Web Scraping 1-2
  - Pandas 1-4
  - MongoDB
  - MPI
- Machine Learning Labs (16 labs)
  - Bayesian Methods
  - HMM
  - Decision Trees
  - Deep Learning
  - Many More…

Growing list of Concentrations

- Animation
- Biology
- Business Management
- Business Strategy
- Chemical Engineering
- Chemistry
- Civil Engineering: Geotechnical
- Civil Engineering: Structures and structural mechanics
- Civil Engineering: Transportation
- Civil Engineering: Water Resources and Environmental
- Computer Science
- Economics
- Electrical and Computer Engineering: Circuits
- Electrical and Computer Engineering: Electromagnetics
- Electrical and Computer Engineering: Signals and Systems
- Financial Markets
- Geological Sciences
- Linguistics
- Manufacturing Systems Design
- Mathematical Biology
- Mathematical Theory
- Mechanical Engineering: Dynamic Systems
- Mechanical Engineering: Fluids and Thermodynamics
- Physics
- Political Science
- Statistics
- Statistics: Actuarial Science
- Statistics: Biostatistics

Career Essentials (soft-skills training)

- Resumes
- Cover Letters
- Interviews
- Internships
- How to give a talk
- Personality Theory
- Listening
- Conflict Management
- Negotiation
- Leadership
- Running a Meeting
- Project Management
- Working in Teams
- Networking

Visiting Companies in Portland, Seattle, Bay Area, DC Area, and elsewhere

- Google
- Amazon
- Nike
- Microsoft
- Boeing
- Zillow
- MITRE
- UnitedHealth
- Milliman
- NSA
- The Gap
- LinkedIn
- Apple
- Raytheon
- Mercer
- Rincon
- Sequoia
- General Dynamics
- CIA

Selected List of Internships

- Apple
- Amazon
- Goldman Sachs
- Google
- Facebook
- Microsoft
- Raytheon
- Lawrence Livermore
- FBI
- EPIC
- Rincon
- Ancestry
- NSA
- Recursion Pharmaceuticals
- Federal Reserve (NY)
- Lincoln Labs
- Sandia NL
- PG&E
- Lucid
- Fast Enterprises
- Los Alamos
- NASA
- Intermountain Health
- UnitedHealth
- Echostar
- Bates White
- Dept Homeland Security

Progress So Far

- Size of Junior Core
  - 15 Graduated April 2015
  - 25 Graduated April 2016
  - 31 Graduated April 2017
  - 36 Graduated April 2018
  - 32 in the Senior Core
  - 77 in the Junior Core (!)
- Won 4 of the last 6 ACM regional coding competitions
- ACME students represent most of the Putnam team
- Excellent job and graduate school placements

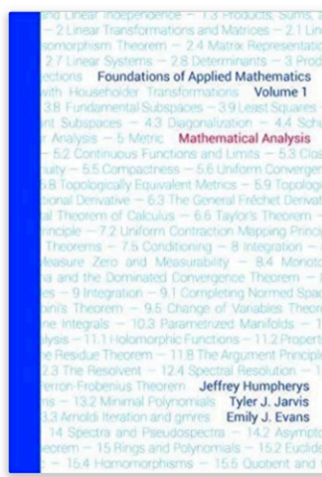
Program Materials

Foundations of Applied Mathematics

- Vol1 Mathematical Analysis (On Display)
- Vol2 Algorithms, Approximation, and Optimization (Spring 19)
- Vol3 Modeling with Uncertainty and Data (TBA)
- Vol4 Modeling with Dynamics and Control (TBA)

- 92 computing labs
- Soft Skills Slides
- Some Lecture Slides

foundations-of-applied-mathematics.github.io



Foundations of Applied Mathematics, Volume 1: Mathematical Analysis

Hardcover – July 7, 2017

by Jeffrey Humpherys (Author), Tyler J. Jarvis (Author), & 1 more

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4 Used from $31.25
4 New from $89.00

Final Talking Points

- Lock-step approach is Powerful
  - Recycle, don't review!
  - Integration across topics
  - Multi-disciplinary perspective
- Cohort Model is Effective
  - Retention
  - Socialization, Team-Building
  - Strong Alumni Base
  - They become BFFs
- Combines to make an Efficient Program
  - Costs 2 FTEs (8 courses/year)
  - A few will stay for graduate school at BYU and become TAs.
- Doubles as a professional development program (!)
  - Theory is taught in the classroom
  - Computation and applications taught in the labs, which are taught by grad students

For more information, see
http://foundations-of-applied-mathematics.github.io