A Personal and Historical View of Computational Mathematics

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King Abdullah University of Science and Technology

Math-IMS, CUHK, April 30, 2021

What is CM?

• Wiki: "involves mathematical research in areas of science where computing plays a central and essential role, emphasizing algorithms, numerical methods, and symbolic methods."

• Newton, Gauss, Richardson, Von Neumann,..

Modern History

- CM modern history after WWII
 - Inst of Numer Analysis at UCLA 1947-1954
- SIAM founded April 1952
 - Main professional society promoting CAM
 - Journals: SINUM, SISC, MMS, SIIMS (AMS Comp Math)
 - Conferences, SIAGs, reports
- Algorithms "founded" circa 1952
 - SOR, CG, ADI, Simplex

CM & TC

- My UG/Grad CAM:
 - WKB, singular perturbation, asymptotics
 - Laplace/Fourier transforms, separation of variables, tensor analysis, game theory
 - NA from Issacson & Keller, Conte & De Boor, Dahlquist & Bjorck (GVL being written); NODE from Gear, NPDE from Mitchell, K&O; CS algs; some CFD
 - Hardware: PDP 11, IBM 360 (cards!), HP35C, HP2000, arpanet
 - Software: JCL, Fortran, Basic, APL, ALGOL
 - Algorithms: Least sq, SVD, fast Poisson solvers, quasi-newton methods, ALM
- I have worked on/participated in:
 - NPDE, NLA, MG, DD, CG, //, IP, Brain mapping, VLSI
 - Competition between finite difference vs finite elements for PDEs
 - NLA: Matrix factorizations, LS, QR, SVD, Lanczos, CG (GMRES etc), on Householder Symp Comm 1993-2005.
 - MG: From Brandt 78 MLAT paper on, MG for bifurcation probs, unstructured grids; EMG confs
 - DD: Chaired DD2 at UCLA 1988, on DDM Committee until DD12.
 - //: main frames, vector machines (Alliant), parallel machines (CM, Cosmic Cube, Ncube), GPU
 - Software: EISPACK, LINPACK, Matlab (before MathWork), Mathematica, Petsc
 - Applications:
 - CFD: MG/DD for unstructured meshes;
 - IP: TV, level set, L1, Compressed sensing
 - Brain mapping: Ricci flow, Yamabe eq, conformal mapping, Beltrami coef
 - VLSI opt: new paradigm, widely adopted in industry, hypergraphs
- Math I should have learned in school:
 - nonlinear analysis, differential geometry, stochasticity, BV, L1, Baysean

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TOP 10 Sites for June 2016

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tps://www.top500.org/lists/2016/06/

For more information about the sites and systems in the list, click on the links or view the complete list.

Rank	Site	System	Cores	Rmax (TFlop/s)	Rpeak (TFlop/s)	Power (kW)
1	National Supercomputing Center in Wuxi China	Sunway TaihuLight - Sunway MPP, Sunway SW26010 260C 1.45GHz, Sunway NRCPC	10,649,600	93,014.6	125,435.9	15,371
2	National Super Computer Center in Guangzhou China	Tianhe-2 (MilkyWay-2) - TH-IVB-FEP Cluster, Intel Xeon E5-2692 12C 2.200GHz, TH Express-2, Intel Xeon Phi 31S1P NUDT	3,120,000	33,862.7	54,902.4	17,808
3	DOE/SC/Oak Ridge National Laboratory United States	Titan - Cray XK7, Opteron 6274 16C 2.200GHz, Cray Gemini interconnect, NVIDIA K20x Cray Inc.	560,640	17,590.0	27,112.5	8,209
4	DOE/NNSA/LLNL United States	Sequoia - BlueGene/Q, Power BQC 16C 1.60 GHz, Custom IBM	1,572,864	17,173.2	20,132.7	7,890
5	RIKEN Advanced Institute for Computational Science (AICS) Japan	K computer, SPARC64 VIIIfx 2.0GHz, Tofu interconnect Fujitsu	705,024	10,510.0	11,280.4	12,660
6	DOE/SC/Argonne National Laboratory United States	Mira - BlueGene/Q, Power BQC 16C 1.60GHz, Custom IBM	786,432	8,586.6	10,066.3	3,945
7	DOE/NNSA/LANL/SNL United States	Trinity - Cray XC40, Xeon E5-2698v3 16C 2.3GHz, Aries	301,056	8,100.9	11,078.9	

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Rank	Site RIKEN Center for	System	Cores	Rmax (TFlop/s)	Rpeak (TFlop/s)	Power (kW) 29.899	5	NVIDIA Corporation United States	Selene - NVIDIA DGX A100, AMD EPYC 7742 64C 2.25GHz, NVIDIA	555,520	63,460.0	79,215.0	2,646
	Computational Science Japan	Fugaku - Supercomputer Fugaku, A64FX							HDR Infiniband Nvidia				
		48C 2.2GHz, Tofu interconnect D Fujitsu					6	National Super Computer Center in Guangzhou	Tianhe-2A - TH- IVB-FEP Cluster, Intel Xeon E5-	4,981,760	61,444.5	100,678.7	18,48
2	DOE/SC/Oak Ridge National Laboratory United States	Summit - IBM Power System AC922, IBM POWER9 22C	2,414,592	148,600.0	200,794.9	10,096		China	2692v2 12C 2.2GHz, TH Express-2, Matrix-2000 NUDT				
		Volta GV100, Dual-rail Mellanox EDR Infiniband IBM					7	Forschungszentrum Juelich (FZJ) Germany	JUWELS Booster Module - Bull Sequana XH2000, AMD EPYC 7402 24C 2.8GHz, NVIDIA A100,	449,280	44,120.0	70,980.0	1,764
3	DOE/NNSA/LLNL United States	Sierra - IBM Power System AC922, IBM POWER9 22C 3.1GHz, NVIDIA	1,572,480	94,640.0	125,712.0	7,438			Mellanox HDR InfiniBand/ParTec ParaStation ClusterSuite Atos				
		Volta GV100, Dual-rail Mellanox EDR Infiniband IBM / NVIDIA / Mellanox					8	Eni S.p.A. Italy	HPC5 - PowerEdge C4140, Xeon Gold 6252 24C 2.1GHz, NVIDIA Tesla V100, Mellanox	669,760	35,450.0	51,720.8	2,252
4	National Supercomputing	Sunway TaihuLight -	10,649,600	93,014.6	125,435.9	15,371			HDR Infiniband Dell EMC				
	Center in Wuxi China	Sunway MPP, Sunway SW26010 260C 1.45GHz, Sunway NRCPC					9	Texas Advanced Computing Center/Univ. of Texas United States	Frontera - Dell C6420, Xeon Platinum 8280 28C 2.7GHz, Mellanox InfiniBand HDR	448,448	23,516.4	38,745.9	
5	NVIDIA Corporation United States	Selene - NVIDIA DGX A100, AMD EPYC 7742 64C 2.25GHz, NVIDIA	555,520	63,460.0	79,215.0	2,646	10	Saudi Aramco Saudi Arabia	Dell EMC Dammam-7 - Cray CS-Storm,	672,520	22,400.0	55,423.6	
		A100, Mellanox HDR Infiniband							V 0-14 (0/0		6	J	

CSE2000 Top 10 Algorithms

- Monte Carlo
- Simplex
- Krylov
- Matrix decomposition
- Fortran optimizing compiler
- Francis QR
- Quicksort
- FFT
- Integer relation detection
- Fast multipole method
- No update as of 1/28/2021

Other New Algorithmic Paradigms

- Multigrid
- DD
- Multiscale
- Uncertainty
- Continuous vs discrete: Diff Equ vs graphs

• 2021: Deep Neural Networks?

Criteria

- Speed (flops, comp complexity, time)
- Accuracy
- Scalability
- Parallelism, communication/latency
- Memory efficiency
- Impact (internal and external)

Top 10 Most Cited Recent CM Papers (TC 04/30/21)

Ref: Golub-Van Loan (4th ed 2012): 52717/72912 citations! Metropolis et al (1953, J Chem Phys) 31807 citations. Hestenes-Stiefel Conjugate Gradient (1952 JBS) 6379 citations.

- 2014 1(15794/?) Donoho, Compressed Sensing, IEEE TIT 2006 1.
 - 2(12242/17463) Osher-Sethian, level set, JCP 1988 2.
 - 3. 3(10162/?) Donoho, Soft Thresholding, IEEE TIT 1995
 - 6(10157/17084) Candes-Romberg-Tao, Compr Sensing, IEEE TIT 2006 4.
 - 8(9281/15826) Rudin-Osher-Fatemi, TV denoising, Physica D 1992 5.
 - 5(9576/13061) Saad-Schultz, GMRES, SISC 1986 6.
 - 9(8223/12715) Chan-Vese, Segmentation, IEEE TIP 2001 7.
 - 4(9370/11937) Daubechies, Ortho Basis for Wavelets, CPM 1984 8.
 - 9. 7(8795/?) Donoho-Johnstone, wavelet shrinkage, Biometrika 1994
 - 10. 10(4296/5803) Greengard-Rokhlin, Fast Multipole, JCP 1987
 - (3772/?) Brandt, Multigrid, Math Comp 1977 11.

Dec

Most citations above are not by "peers" but by "users".

LeCun, Bengio, Hinton "Deep Learning", Nature 2015. 38352 citations!

Hinton "Image classification with Deep Convolution Neural Networks", 2012. 85306 cites!

Computational Linear Algebra

- EISPACK, LINPACK, LAPACK, Matlab
- Matrix factorizations: QR, SVD, RRQR,
- Tensors
- Least sqs: LS, TLS
- Sparsity: GE, ordering, fill-ins
- Iterative meths: CG, Lanczos, GMRES, preconditioners
- Revived twice by: parallelism, search/Google, completion/Netflix

Multigrid/Domain Decompositon

- A paradigm shift
- Russian influence
 - motivated by efficient use of limited computer power
- MLAT Brandt
- DD motivated by parallel computers
- Subspace decomposition & correction (Xu)
- Fast Multipole Method particle simulation

CFD to IP

- FD has provided a challenging testbed for CM for several decades
- Multi-dim, multi-component, mutli-scale, nonlinear, discontinuities, complex geometry/mesh, time-dep,
- IP is "new CFD": all of above (except reg mesh)

Imaging science

- Relatively new to Math Community
- SIIMS founded 2007.
- Imaging journals:
 SIAM SIIMS
 IEEE TIP
 JMIV
 IJCV



- Imaging conferences.
 SIAM Imaging conference Scale-Space conference IEEE ICIP
- The new "CFD". Part of " Data May 20 22, 2012





May 20 - 22, 2012 DoubleTree by Hilton Hotel Philadelphia Center City Philadelphia, Pennsylvania, USA



May 12 -14, 2014 Hong Kong Baptist University Hong Kong



2012 IEEE International Conference on Image Processing

September 30 – October 3, 2012 Disney's Coronado Springs Resort • Orlando, Florida, U.S.A.



Computer Science 12

Bart for Baar Romeny Luc Florack Jan Koenderink Max Viergever (Eds.)

Scale-Space Theory in Computer Vision



Springs

SIAM Board of Trustees Regular Session July 15, 2006 Agenda Item 8 Page 1 of 9

Report of the SIAM Journal Committee on "Proposal for a New SIAM Journal on Imaging Sciences",

submitted by Tony Chan and Kirk Jordan

hai issue in Margaret Cheney "typic" journel. Edward Olmstead Mac Hyman NOT "Traging as a topic Tim Kelley (SIAM Vice-President for Publications) Tom Manteuffel En ward on backward Nick Trefethen Benjamin White Ceder? David Williamson Margaret Wright (chair) +CM. IEEG long Some La conss. July 2, 2006 or concern ?

1 Committee Charge; Review Process

Following an extended discussion at the July 2005 SIAM annual meeting in New Orleans, the SIAM Council requested that Tony Chan and Kirk Jordan prepare a proposal for a new SIAM journal in imaging sciences. The proposal was received by SIAM on April 20, 2006. The SIAM Journal Committee was then asked by the Vice-President for Publications, Tim Kelley, to review the proposal and prepare a report. This report summarizes that review and will be presented to the SIAM Council in Boston on July 13, 2006.

In conducting its review of the proposal, each member of the Journal Committee was asked by Margaret Wright (its chair) to send comments on the proposal. Her email of April 21, 2006, to the committee said:

It is now our job to make a recommendation to the SIAM Council (which will meet in mid-July at the annual meeting) as to whether SIAM should establish such a journal.

What Math brings to IP



Filtering in the Frequency Domain 164

4.4 Obtaining Frequency Domain Filters from Spatial Filters 180

- 4.5 Generating Filters Directly in the Frequency Domain 185
- 4.6 Highpass (Sharpening) Frequency Domain Filters 194
- 4.7 Selective Filtering 199

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- 5.7 Wiener Filtering 240
- 5.8 Constrained Least Squares (Regularized) Filtering 244
- 5.9 Iterative Nonlinear Restoration Using the Lucy-Richardson Algorithm 246

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II Image Segmentation 535

11.1 Point, Line, and Edge Detection 536 11.1.1 Point Detection **536**

- 11.1.2 Line Detection 538
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- 11.2 Line Detection Using the Hough Transform 549

IEEE TRANSACTIONS ON IMAGE PROCESSING A PUBLICATION OF THE IEEE SIGNAL PROCESSING SOCIETY

Volume 7, Number 3, March 1998

Vicent Caselles, Jean-Michel Morel:

Introduction To The Special Issue On Partial Differential Equations And Geometry-driven Diffusion In Image Processing And Analysis. 269-273

Françoise Dibos: Projective analysis of 2-D images. 274-279

Scott T. Acton: Multigrid anisotropic diffusion. 280-291

Georges-Henri Cottet, Mokamed El-Ayyadi: A Volterra type model for image processing, 292-303

Peter Blomgren, Tony F. Chan: Color TV: total variation methods for restoration of vector-valued images. 304-309

<u>Nir A. Sochen, Ron Kimmel, Ravi Malladi</u>: A general framework for low level vision. 310-318

Antonin Chambolle, Ronald A. DeVore, Nam-Yong Lee, Bradley J. Lucier:

Nonlinear wavelet image processing: variational problems, compression, and noise removal through wavelet shrinkage. 319-335

Olivier D. Faugeras, Renaud Keriven:

Variational principles, surface evolution, PDEs, level set methods, and the stereo problem. 336-344

Anthony J. Yezzi Jr.:

Modified curvature motion for image smoothing and enhancement. 345-352

René A. Carmona, Sifen Zhong: Adaptive smoothing respecting feature directions. 353-358

Chenyang Xu, Jerry L. Prince: Snakes, shapes, and gradient vector flow. 359-369

Tony F. Chan, Chiu-Kwong Wong: Total variation blind deconvolution. 370-375

Vicent Caselles, Jean-Michel Morel, Catalina Sbert: An axiomatic approach to image interpolation. 376-386

Sylvic Teboul, Laure Blanc-Féraud, Gilles Aubert, Michel Barlaud: Variational approach for edge-preserving regularization using coupled PDEs

Joachim Weickert, Bart M. ter Haar Romeny, Max A. Viergever:

Efficient and reliable schemes for nonlinear diffusion filtering, 398-410

Lionel Moisan:

Affine plane curve evolution: a fully consistent scheme. 411-420 <u>Michael J. Black, Guillermo Sapiro, David H. Marimont, David Heeger</u>: Robust anisotropic diffusion. 421-432

Kaleem Siddiqi, Yves Bérubé Lauzière, Allen Tannenbaum, Steven W. Zucker: Area and length minimizing flows for shape segmentation. 433-443

Frederic Guichard: A morphological, affine, and Galilean invariant scale-space for movies. 444-456 <u>Pietro Perona</u>: Orientation diffusions. 457-467

Francis H. Y. Chan, Francis K. Lam, Hui Zhu:

Adaptive thresholding by variational method. 468-473

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Uncertainty and	
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Image Processing and Applied Maths

PDEs (CFD, viscosity solution) Calculus of variations Differential geometry (level set method) Smooth & non-smooth functional analysis (wavelets/Besov, total variation/BV)



Compressed sensing, L1 optimization (Bregman) Convexification for geometric problems Relaxation for graph optimization problems Compressed Sensing Candes, Donoho, Romberg, Tao 2006

- Sparsity: L0
- Convexity: L1
- Randomness: Restricted Isometry Property
- Exact recovery
- IPAM origin
- TV Wavelet Inpainting connection

TV Wavelet inpainting [Chan, Shen & Zhou '04]

Can you recognize this person?

Original image downloaded from internet Damaged image: 50% of wavelet coefficients (including low frequencies) are randomly lost.

• Model I (for noise-less images):

$$\min_{\beta_{j,k}} \int |\nabla u| \quad \text{s.t. } u = \sum_{j,k} \beta_{j,k} \Phi_{j,k}, \quad \beta_{j,k} = \beta_{j,k}^0 \quad \text{(observed coefs)}$$
wavelets

No parameters. Problem dimension << #coefs.

• Model II (for noisy images):

$$\min_{\beta_{j,k}} \int |\nabla u| + \lambda_I ||u - u_0||^2 \ (u_0 \text{ observed image})$$



Restoration result



Original image

50

100



Damaged image, 50% of wavelet coefficients are randomly lost. PSNR = 10.9



150

200

250



Inpainted image by TV-Wavelets



Model II: Recovered image, keeping undamaged coefficients unchanged. PSNR 18.8. Inpainted image by TV-Wavelets

100 200



PSNR vs %Coefs Retained

X-axis: percentage of randomly retained wavelet coefficients Y-axis: improvements in PSNR after inpainted by Model I (green) and Model II (red). As less coefficients are missed, the improvement in PSNR becomes larger.

An Extreme Example

Upper left: Original clear square.

Upper right: Lost all but one nonzero coefficients in the low-low frequency subband, while keep all high frequencies (PSNR=11.2dB).

Lower left: Recovered by Model I. Perfect reconstruction (PSNR=61dB).

Lower Right: Cross-section at x=128. The inpainted profile is visually indistinguishable from the original.

A preview of Compressed Sensing!





Compressed Sensing in IP [Candes, Romberg & Tao '06, Donoho '06]

Reconstruct the signal u in \mathbb{R}^n from m measurements f with m $\leq n$:

 $f = Au, \ u \in \mathbb{R}^n, \ f \in \mathbb{R}^m, \ A \in \mathbb{R}^{n \times m}$ (system is underdetermined)

Assume u is sparse then the problem is: $\min_{u} \|\Psi u\|_0 \ s.t. \ f = Au$

Theorem: For m>=c.log n, the signal u can be reconstructed exactly (under reasonable assumptions) solving the problem:

$$\min_{u} \|\Psi u\|_{1} \ s.t. \ f = Au \qquad \text{L1 relaxation (tight)}$$

For $\|\Psi u\|_1 = TV(u) = \int |\nabla u|$ and $A = R\Phi \begin{bmatrix} \Phi : \text{ sensing basis (wavelet, Fourier)} \\ R: \text{ measurement extractor} \end{bmatrix}$ => The CS problem is equivalent to the TV wavelet inpairing problem.

Algorithm Connections, Old and New



Uzawa's Method

 \leftrightarrow

 \leftrightarrow

Proximal Forward Backward Splitting \longleftrightarrow

Arrow-Hurwicz

Preconditioned Method of Multipliers/ Proximal Method of Multipliers

Preconditioned ADMM (Linearization of penalty also related to surrogate function and optimization transfer)

Newton-like Methods

 \leftrightarrow





Penalty method (Reformulates total variation penalty as constrained optimization problem) [Wang, Yin, Zhang 2007]

Linearized Bregman (Efficient for large scale problems) [Darbon, Osher, Yin, Goldfarb 2007]

Fixed Point Continuation (FPC) and many related iterative thresholding methods for L1 minimization [Hale, Yin, Zhang 2007]

Primal Dual Hybrid Gradient (PDHG) (Excellent for TV denoising) [Zhu, Chan 2008]

Bregman Operator Splitting (BOS) (Proposed for nonlocal TV; very generally applicable) [Zhang, Burger, Bresson, Osher 2009]

Split Inexact Uzawa, Modified PDHG, Chambolle/Pock Method, He/Yuan Variants... (Many versions of this very versatile method) [Zhang, Burger, Osher, Esser, Chan, Chambolle, Pock...2009]

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CGM [Chan, Golub & Mulet '95]

Semismooth Newton for TV [Hintermuller, Stadler] (Uses second order information, can be superlinearly convergent)

Lessons

- 1. Right model more important than fast algorithm
- 2. Simplicity trumps everything else
- 3. Proof is good (but not absolutely necessary) but good idea is a must
- 4. Old methods can find new use: IP opt
- 5. New applications can inspire new CM: IP, search
- 6. Hardwares change, good ideas last: Hypercubes, Connection Machine
- 7. Ideas for one problem can be useful for another
 - 1. TVD for shock capturing -> TV for IP
- 8. What appears different may be related
 - 1. IP: PDE vs graph modelling & algorithms
- 9. New Math plus old tricks differential geometry + ALM
- 10. Be the first to spot a math idea or a rich application

Future

• Plenty of challenges in basic S&E

- Biology (genetics, brain, diseases,....)
- Big data (mining, learning,...)
- Uncertainty (Quantization, randomization...)
- IP to Vision, Comp Photography,..

- New math; New applications
- 2021: Machine Learning the new CFD?

Back to the Future?



11:56 PM Wed Jan 27

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Thirty years of Applied Mathematics

Abstract

The 50's to the 80's saw tremendous growth of applied math, driven mainly by PDEs and numerical algorithms. The integration of the two produced the "Courant School", which has had a far-reaching impact on applied math and beyond, particularly in the area of fluid mechanics.

Since the 90's, the Courant school has faced some serious challenges. On one hand, a lot of the basic problems in numerical analysis and PDEs were already solved, the ones left proved to be truly difficult. On the other hand, efforts to move beyond fluid mechanics have not reproduced the kind of success that applied math had in fluid mechanics. In fact, during this period of time, applied math benefited more from the growth of signal processing, such as wavelets, image processing and compressed sensing.

Machine learning has come to the rescue for the Courant school, and it also provides the platform for the natural integration between the first principle-driven PDE school and the data-driven harmonic analysis/statistics school. The integration of these two schools of thoughts will give rise to unprecedented power for solving the problems we have faced in applied math and computational science. At the same time, it also provides the final missing component for applied math to become a mature scientific discipline with a unified scope and curriculum that will boost our ability to attract and educate young talents.

Prof. Weinan E Princeton University

Date: 11 Nov 2020, Wednesday

Time: **2pm – 3pm**

Venue: Online via Zoom

Biography Professor Weinar

Professor Weinan E obtained his BS degree from the University of Science and Technology of China in 1982 and his PhD from the University of California at Los Angeles in 1989. He is currently a professor in the Department of Mathematics and Program in Applied and Computational Mathematics at Princeton University. Professor E has made tremendous contributions to homogenization theory, theoretical models of turbulence, stochastic partial differential equations, electronic structure analysis, multiscale methods, computational fluid dynamics, and machine learning

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Carnegie Initiative on the Doctorate

In 2001 The Carnegie Foundation for the Advancement of Teaching launched a multiyear project to examine the doctoral degree in the United States. Entitled the Carnegie Initiative on the Doctorate (CID), the project aims to stimulate rethinking and renewal of doctoral programs in six disciplines, one of which is mathematics. During 2003 the CID will publish a set of twelve essays, two in each discipline, about doctoral education. And earlier this year, thirty-two "partner departments", including eight mathematics departments, were chosen as participants in the initiative.

Founded by Andrew Carnegie in 1905, the Carnegie Foundation has a long tradition of carrying out research and policy studies in education. One of its most famous and influential projects was the 1910 "Flexner report", a tough indictment of medical schools in the United States that led to widespread reform. It was partly because of his fame as author of that report that Abraham Flexner became the founding director of the Institute for Advanced Study. Although the Flexner report is sometimes mentioned in connection with the CID, the similarity is not strong. "Of course we would like [the CID] to be influential," remarked Chris Golde, research director for the CID. The difference is that Flexner clearly had an agenda in mind when he wrote his report, while the CID does not. "We are committed to that [agenda] needing to arise from the disciplines," Golde said.

In fact, the CID does not even take it for granted that doctoral education needs a huge overhaul. "I don't see [the CID] as necessarily dramatically changing what we do," said Kevin Corlette, chair of the University of Chicago mathematics department, one of the CID participating departments. "The idea is to go back to basic questions about what we are trying to accomplish in doctoral education and to think about what we could do differently or better." A sign of the excellence of U.S. doctoral programs is that they attract students from all over the globe. Still, evolution in the societal and academic contexts in which these programs exist has sometimes caused mismatches between the goals of doctoral programs and what is expected of the programs' graduates. The idea of the CID is to ask anew the question. What is the purpose of doctoral education today? George Walker, a theoretical physicist at Indiana University who serves as the CID project director, said the main goal is to "convince people to think carefully and deeply about PhD programs, and then to act on their thoughts, just as they do in their disciplinary research "

An organizing notion for the initiative is that doctoral programs should produce "stewards of the discipline". In addition to having made an original contribution to research in the discipline, a steward possesses perspective on the history of the discipline, on the "big questions" and ideas that drive the field, and on its relations to other areas. A steward should also be a communicator in the broadest sense: someone who not only can teach stuch avg that the tools and ideas of the discipline are available to those outside it. The notion of a steward of the discipline "calls in an ethical dimension," Golder remarked. "It's about integrity. It's about, What are your responsibilities to the discipline?"

The CID is "conceptually based," Golde explained. "Its heart is in ideas, not in very specific practices," The purpose is not, say, to promote the use of interdisciplinary team projects in doctoral programs. Rather, the goad would be to get departments to think carefully about the communication skills that stewards of the discipline should possess. Departments would then consider what kinds of experiences team projects may be one of them—would lead to the development of those skills. As Walker put it, "What experiences should future stewards of the field have in graduate school to allow them to evolve and be effective in a future we can'timagine, a future thirty or fifty years from now"

Six fields were chosen for the CID: chemistry, education, English, history, mathematics, and neuroscience. There were several reasons for choosing these particular disciplines. One was the aim of including disciplines that span a wide area of academe. Carnegie also looked for central, fundamental fields where there are a large number of doctoral programs and students. The inclusion of neuroscience reflected the desire to bring in a multidisciplinary field.

In addition, Carnegie sought areas in which discussions of the doctorate were already taking place, and in that regard mathematics was a natural choice. Over the past decade or so the mathematical community has engaged in intensive discussions about the doctoral program. Among the major stimulants of these discussions were the reports Educatina Mathematical Scientists: Doctoral Study and the Postdoctoral Experience in the United States (National Academy Press, 1992) and Towards Excellence: Leading a Doctoral Mathematics Department in the 21st Century (AMS, 1999). These discussions influenced the establishment of the VIGRE (Vertical Integration of Research and Education in the Mathematical Sciences) program of the National Science Foundation, which has stimulated much innovation and change in doctoral programs.

To begin the CD, Carnegie commissioned the writing of twelve essays, two in each of the six disciplines, that explore the purpose of doctoral education and the notion of "stewards" in the context of each discipline. The essays are not "how-to" manuals for structuring doctoral programs; their purpose is not to tell departments what to do but rather to provoke discussions within disciplines and across academe. The essays in mathematics were written by Hyman Bass of the University of Michigan, who is now past president of the AMS, and Tony Chan of the University of California, Los Angeles (the essays by Bass and Chan will be published in future issues of the Notices). All of the essays are scheduled to be

CID Participating Mathematics Departments Partner Departments

Duke University Ohio State University State University of New York, Stony Brook University of Chicago University of Illinois, Urbana-Champaign University of Michigan, Ann Arbor University of Nebraska, Lincoln University of Southern California

Allied Departments

Howard University Kent State University University of North Carolina, Chapel Hill University of Utah

completed in spring 2003 and will eventually be published together as a book.

The second part of the CID began in early 2003 with the selection of thirty-two "partner departments". These departments have made a commitment to undertake a thorough examination of their doctoral programs. The intention is that the commissioned essays will stimulate the departments' discussions. CID staff will visit the partner departments, not for the purpose of evaluating them, but rather to encourage discussions and bring in new ideas. There will also be periodic meetings of partner department representatives, the first one taking place in July 2003 at the Carnegie headquarters on the campus of Stanford University. After the initial conceptual phase, the departments will experiment with new ways of designing doctoral programs. In the "research and dissemination" stage, departments will evaluate the outcomes of their experiments and share them with colleagues at other institutions: the Carnegie Foundation will also help to publicize ideas and results growing out of the CID.

The departments were chosen after a call for applications was issued last fall. Because there were more worthy applications than it could accommodate, Carnegie also selected some "allied departments" that can participate in discussions and receive materials but which will not have site visits or support for attending CID meetings. (See the sidebar for a listing of partner and allied mathematics departments.)

The VIGRE program has had an enormous effect on mathematics departments across the country, spawning innovations in education at the undergraduate and graduate levels. One reason for the large impact is that the goals of VIGRE are backed by grant dollars. By contrast, the CID provides essentially no funding to its partner departments

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The Mathematics Doctorate: A Time for Change?

Tony F. Chan

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The Carnegie Foundation commissioned a collection of essays as part of the Carnegie Initiative on the Doctorate (CID). Essays and essayists represent six disciplines that are part of the CID: chemistry, education, English, history, mathematics, and neuroscience. Intended to engender conversation about the conceptual foundation of doctoral education, the essays are a starting point and not the last word in disciplinary discussions. Those faculty members, students, and administrators who work in the discipline are the primary among multiple audiences for each of these essays. © 2003 by the Carnegie Foundation for the Advancement of Teaching. Reprinted with permission.

Comments on the essays and on the CID are welcome and may be sent to cid@ carnegiefoundation.org. Further information may be found at the website http://www.carnegiefoundation.org/cid and in the article "The Carnegie Initiative on the Doctorate", by Allyn Jackson, Notices, May 2003, pages 566-8.

The other Carnegie essay about mathematics, by Hyman Bass, appeared in the August 2003 issue of the Notices, pages 767-76.

—Allyn Jackson

ne can argue, with ample evidence, that in U.S. universities the system of producing mathematics doctorates is doing very well and needs no major overhaul. It is widely recognized that however poor our K-12 mathematics educationand perhaps also our undergraduate mathematics education-might be, our graduate programs in mathematics are the best and the envy of the world. Top students from around the world are still beating on our doors to get into our doctoral programs. We train them well, and many of these students become international leaders in their research fields. Take, for example, the two 2002 Fields Medalists and the Nevalinna Prize winner. Even though the press (at least the press in Beijing, where I read the news) referred to them as French, Russian, and Indian, two received their doctoral training at U.S. universities. We also seem to be succeeding in getting new support from the federal government for mathematical sciences. The recent increase in

Tony F. Chan is professor of mathematics and the dean of the Division of Physical Sciences at the University of California, Los Angeles. His email address is chan@math. ucla.edu. funding for the NSF [National Science Foundation] specifically targets the Division of Mathematical Sciences, and doctoral training, in particular for U.S. students, is a core part of this new funding program. Even Hollywood seems to be working in our favor, in view of the generally positive image of mathematics generated by movies such as *A Beautiful Mind*.

However, there are many signs that not all is well with our doctoral programs. Top, talented students, especially those born in the U.S., are choosing fields other than mathematics for graduate study. Many mathematics departments, especially those outside the "top tier", are having trouble filling their graduate programs with reasonably prepared and talented students. As a field of science, mathematics is underfunded compared to other sciences. Most of our doctoral students are supported by teaching assistantships rather than by fellowships or research assistantships. Our doctoral students are taking too long to get their degrees, and they are not sufficiently and broadly trained for career paths outside of academia. Other scientists and academic administrators perceive us as an insular and, worse, irrelevant community.

- 1. Ensuring Our Source of Quality Doctoral Students
- 2. Ensuring That Mathematics Is Part of Science
- 3. Ensuring Societal Support for Mathematics Doctoral Education
- 4. Ensuring That Mathematics Doctoral Education Meets Its Goals

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Thank you!