

2015 JSM Session

Big Data: Modeling, Tools, Analytics, & Training

Organizer: Ivo D. Dinov, Statistics Online Computational Resource (SOCR), Michigan
Moderator/Chair: Robin Jeffries, CSU Chico

Logistics:

- o **Date/Time:** Mon, 8/10/2015, 10:30 AM - 12:20 PM
- o **Venue:** Washington State Convention Center, CC-606

Session: #211347, Sponsor: Statistical Computing

Speakers and Topics

- o **Ivo Dinov (Michigan)**, Management, Modeling & Analytic Challenges of Big Biomedical Data
- o **Max Robinson & Gustavo Glusman**, ISB ESPALIERS: A visualization method for Big Data
- o **Moo K. Chung (Wisconsin)**, The computational challenges of constructing and visualizing large-scale brain networks
- o **Ravi Madduri**, Argonne/Chicago, Big Data Services: Globus Online, Galaxy, GridFTP
- o **Barzan Mozafari**, Large-scale Data Intensive Systems, Big Data, Interactive Data Processing


http://wiki.socr.umich.edu/index.php/SOCR_Events_JSS_2015

Management, Modeling & Analytic Challenges of Big Biomedical Data

Ivo D. Dinov

Statistics Online Computational Resource
University of Michigan

www.SOCR.umich.edu

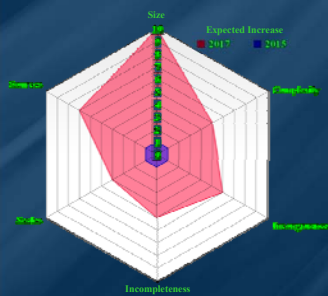


Outline

- Availability, Sharing, Aggregation and Services
- Classical Data Science vs. Innovative Big Data Analytics
 - Amateur Scientists vs. "Experts"
 - Data Scientists vs. Practitioners
 - Domain-specific vs. Trans-disciplinary knowledge
- Commercial vs. Open-source Resourceome
- Rapid Big Data Evolution
- Big Data IT proliferation
- Data democratization
- Big Data is incredibly time, space, protocol, context sensitive
- Big Data Science Training (opportunities and challenges)




Characteristics of Big Data



Example: analyzing observational data of 1,000's Parkinson's disease patients based on 10,000's signature biomarkers derived from multi-source **imaging, genetics, clinical, physiologic, phenomics and demographic** data elements.

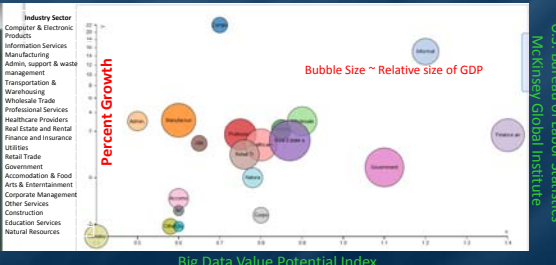
Software developments, student training, service platforms and methodological advances associated with the Big Data Discovery Science all present existing opportunities for learners, educators, researchers, practitioners and policy makers

Mixture of quantitative & qualitative estimates Dinov, et al. (2014)




Availability, Sharing, Aggregation & Services

- There will be over 10 billion mobile-connected devices in 2016; i.e., there will be 1.3 mobile devices per capita





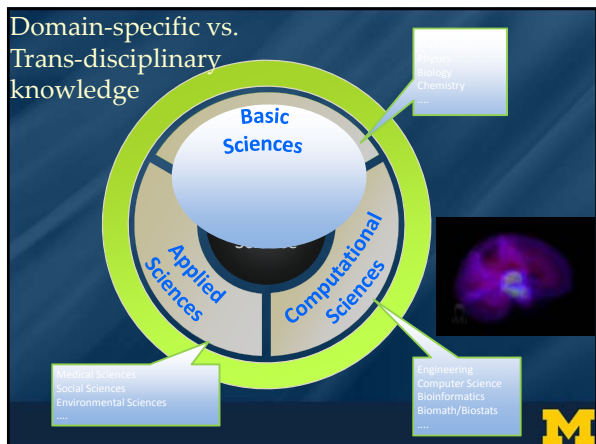
U.S. Bureau of Labor Statistics
McKinsey Global Institute



Democratization of Big Data Science

- Doctorate training is not mandatory nor does it guarantee appropriate Big Data expertise
- Lower barriers of entry
- Demand for constant "Continuing Education" and self-training
- Dichotomy between theoretical and empirical sciences
- Differences between fundamental knowledge and experimental skills (big data properties closely approximate core scientific principles)



Big Data Resourceome

- There is an explosion of open-data-science resources
 - www.data.gov
 - www.ncbi.nlm.nih.gov/gap
- Spawning of a number of industries and enterprises blending proprietary and open-source data, code, documentation, expert-support, infrastructure and services
- Big Data to Knowledge Initiative: www.BD2K.org
- Google Cloud Platform (GCP)
- Amazon Web Services (AWS)

Big Data Analytics Resourceome

<http://bd2k.org/BigDataResourceome.html>

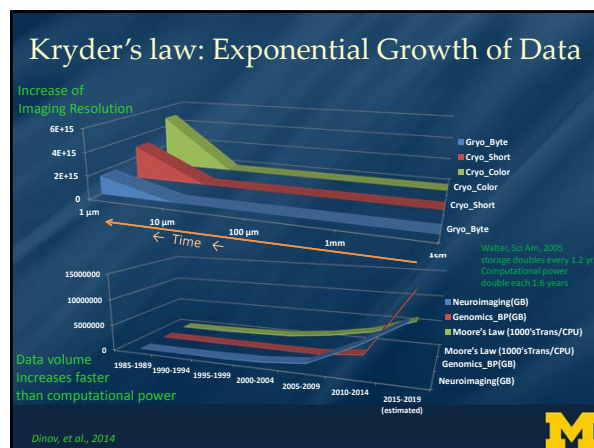
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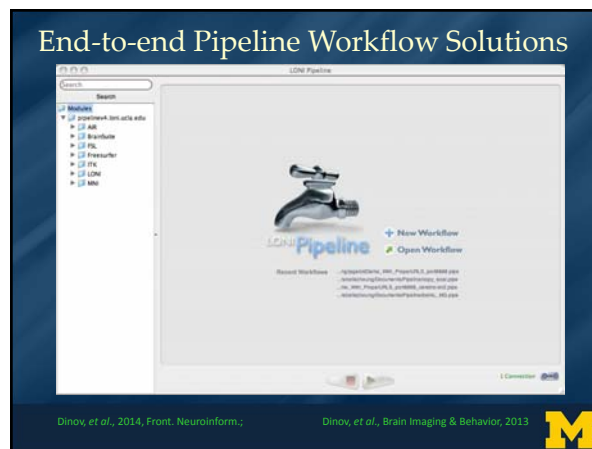
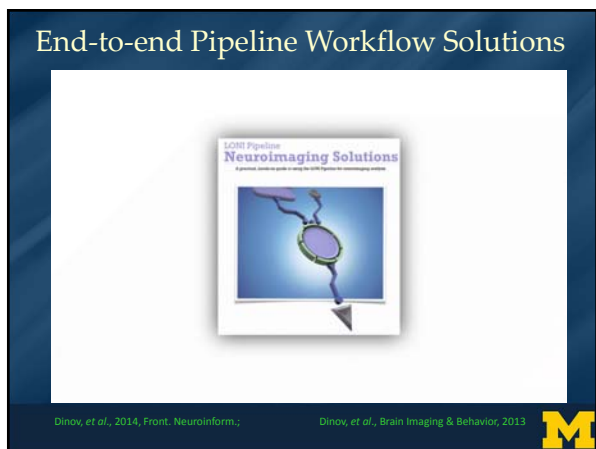
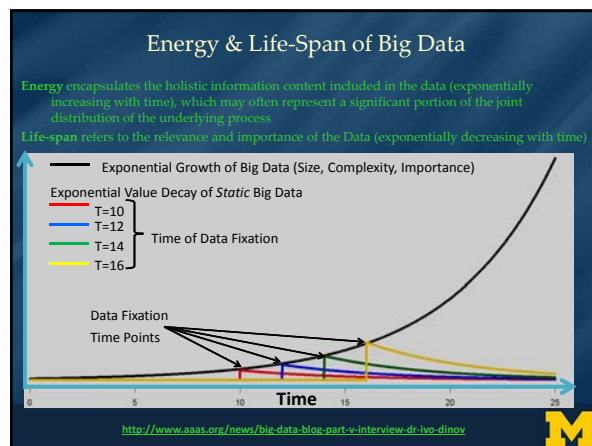
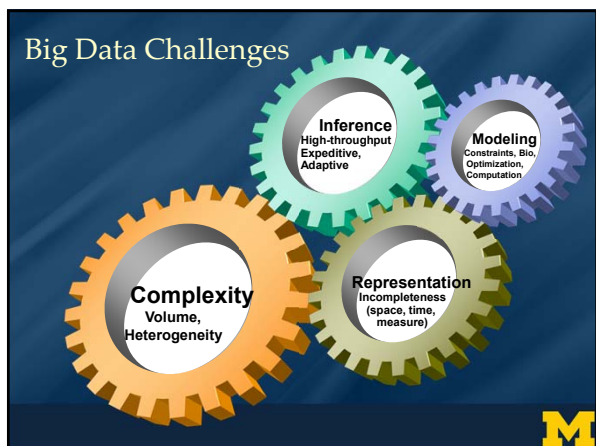
Big Data	Information	Knowledge	Action
Raw Observations	Processed Data	Maps, Models	Actionable Decisions
Data Aggregation	Data Fusion	Causal Inference	Treatment Regimens
Data Scrubbing	Summary Stats	Networks, Analytics	Forecasts, Predictions
Semantic-Mapping	Derived Biomarkers	Linkages, Associations	Healthcare Outcomes

National Big Data to Knowledge (BD2K) Centers

- Center for Causal Modeling and Discovery of Biomedical Knowledge from Big Data (U Pitt, Cooper, Bahar, Berg)
- Center for Predictive Computational Phenotyping (U Wisconsin, Craven)
- National Center for Mobility Data Integration to Insight (The Mobilize Center) (Stanford, Delp)
- KnowEng, a Scalable Knowledge Engine for Large-Scale Genomic Data The (U Illinois Urbana-Champaign, Han, Sinha, Sorg, Weinsilboum)
- Center for Big Data in Translational Genomics (UC Santa Cruz, Haussler, Patterson)
- Patient-Centered Information Commons (Harvard, Kohane)
- Center of Excellence for Mobile Sensor Data-to-Knowledge (MD2K) (U Memphis, Kumar)
- Center for Expanded Data Annotation and Retrieval (CEDAR) (Stanford, Musen)
- A Community Effort to Translate Protein Data to Knowledge: An Integrated Platform (UCLA, Ping, Lindsey, Su, Watson)
- ENIGMA Center for Worldwide Medicine, Imaging, and Genomics (USC, Thompson)
- Big Data for Discovery Science (USC, Toga)

www.BD2K.org





Neurodegenerative Disease Applications: Imaging-Genetic Biomarker Interactions in Alzheimer's Disease

Goals
Investigate AD subjects (age 55 – 65) using Neuroimaging Initiative (ADNI) database to understand early-onset (EO) cognitive impairment using neuroimaging and genetics biomarkers

Data
9 EO-AD and 27 EO-MCI
Derived 15 most impactful neuroimaging markers (out of 336 morphometry measures)
Obtained 20 most significant single nucleotide polymorphisms (SNPs) associated with specific neuroimaging biomarkers (out of 620K SNPs)

Approach
Global Shape Analysis (GSA) Pipeline workflow

Moon, Dinov et al., 2015, Psych. Investig.
Moon, Dinov et al., 2015, J Neuroimaging

Results: AD Imaging-Genetic Biomarker Interactions

- Identified associations between neuroimaging phenotypes and genotypes for the cohort of 36 EO subjects
- Overall most significant associations:
 - rs7718456 (Chr 15) and L_hippocampus (volume)
 - rs7718456 and R_hippocampus (volume)
- For the 27 EO-MCI's, most significant associations
 - rs6446443 (Chr 4, JAKMIP1 janus kinase and microtubule interacting protein 1 gene) and R_superior_frontal_gyrus (volume)
 - rs17029131 (Chr 2) and L_Precuneus (volume)

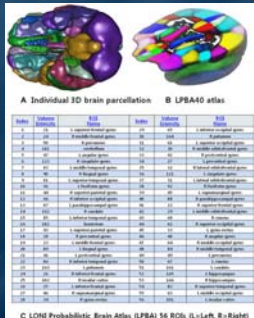
Moon, Dinov et al., 2015, Psych. Investig.

Neurodegenerative Disease Applications: Imaging-Genetic Biomarker Interactions in Alzheimer's Disease

Goals
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Results
Generated mean geometric models of the left and right hippocampi, middle frontal gyri, and the middle temporal gyri.
Linear model statistical maps, at each vertex on the triangulated shapes. **Dependent variable** was the radial distance morphometry measure (deviation of individual shape model from mean shape atlas) and **independent regressors** including diagnosis, age, education years, APOE (ε4), MMSE, visiting times, and logical memory (immediate and delayed recall).

Approach
Local Shape Analysis (LSA) Pipeline workflow



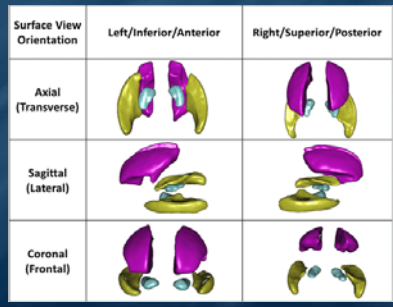
A Individual 3D brain parcellation **B LPSA40 atlas**

ROI	Volume	Area	Mean	Median	Max	Min	StDev	Skewness	Kurtosis	Label
1	10000	10000	10000	10000	10000	10000	10000	10000	10000	Left Hippocampus
2	10000	10000	10000	10000	10000	10000	10000	10000	10000	Right Hippocampus
3	10000	10000	10000	10000	10000	10000	10000	10000	10000	Middle Frontal Gyrus
4	10000	10000	10000	10000	10000	10000	10000	10000	10000	Middle Temporal Gyrus

C LONI Probabilistic Brain Atlas (LPSA) 54 ROIs (L=Left, R=Right)

Moon, Dinov et al., 2015, J Neuroimaging

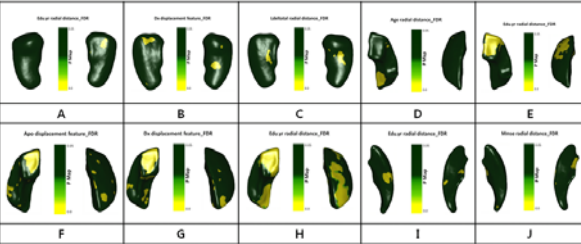
Neurodegenerative Disease Applications: Imaging-Genetic Biomarker Interactions in Alzheimer's Disease



Surface View Orientation	Left/Inferior/Anterior	Right/Superior/Posterior
Axial (Transverse)	[Image]	[Image]
Sagittal (Lateral)	[Image]	[Image]
Coronal (Frontal)	[Image]	[Image]

Moon, Dinov et al., 2015, Neuroimaging

Neurodegenerative Disease Applications: Imaging-Genetic Biomarker Interactions in Alzheimer's Disease



P-maps (A) for Lt. hippocampus, P-maps (B,C) for Rt. hippocampus, P-maps (D,E) for Lt. middle frontal gyrus, P-maps (F,G,H) for Rt. middle frontal gyrus, P-maps (I, J) for Lt. middle temporal gyrus.

Moon, Dinov et al., 2015, J Neuroimaging

SOCR Big Data Dashboard

<http://socr.umich.edu/HTML5/Dashboard>

- Web-service combining and integrating multi-source socioeconomic and medical datasets
- Big data analytic processing
- Interface for exploratory navigation, manipulation and visualization
- Adding/removing of visual queries and interactive exploration of multivariate associations
- Powerful HTML5 technology enabling mobile on-demand computing

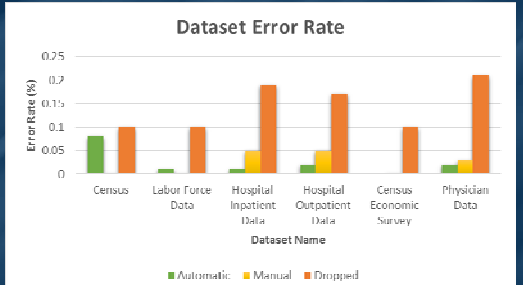
Husain, et al., 2015, J Big Data

SOCR Dashboard (Exploratory Big Data Analytics): Data Fusion



<http://socr.umich.edu/HTML5/Dashboard>

SOCR Dashboard (Exploratory Big Data Analytics): Data_QC



Dataset Name	Automatic (%)	Manual (%)	Dropped (%)
Census	~0.08	~0.02	~0.02
Labor Force Data	~0.01	~0.01	~0.08
Hospital Inpatient Data	~0.02	~0.02	~0.15
Hospital Outpatient Data	~0.02	~0.02	~0.15
Census Economic Survey	~0.01	~0.01	~0.08
Physician Data	~0.01	~0.01	~0.18

<http://socr-dev.nursing.umich.edu:8080>

Training: Big Data Skills


- 1) **Listening:** streams, information and language, analyzing sentiment, intent and trends;
- 2) **Looking:** searching, indexing and memory management of heterogeneous datasets; **Loading:** Raw, derived or indexed data as well as meta-data;
- 3) **Programming:** Handling Map-Reduce/HDFS, No-SQL DB, protocol provenance, pipeline workflows;
- 4) **Inferring:** Principals of data analyses, Bayesian modeling, inference, uncertainty and quantification of likelihoods; **Connecting:** Reasoning, logic and its limits, dealing with uncertainty; **Analytics:** Regression, feature selection, dimensionality reduction, temporal patterns;
- 5) **Learning:** Classification, clustering, mining, information extraction, knowledge retrieval, decision making;
- 6) **Predicting:** Forecasting, neural models, deep learning, and research topics;
- 7) **Summarizing:** Presentation of data, processing protocol, analytics provenance, visualization



Training: Core Proficiencies

The Data Science Certificate program aims to ensure that students awarded this certificate would have the following experiences:

- 1) **(Modeling)** Understanding of core Data Science principles, assumptions and applications
- 2) **(Technology)** Knowledge of basic protocols for data management, processing, computation, information extraction & visualization
- 3) **(Practice)** Hands-on experience with modeling tools and technology resources in a real project setting




University of Michigan Data Science Training

MIDAS MICHIGAN INSTITUTE FOR DATA SCIENCE UNIVERSITY OF MICHIGAN

Graduate Data Science (DS) Certificate Program

The overarching goal of the Graduate Data Science Certificate Program is to train a cadre of skilled data scientists with significant multidisciplinary knowledge, broad analytical skills and agile technological abilities. The program emphasizes the practice of modeling using modern technology to handle large, incongruent, and heterogeneous collections of data. The Graduate Certificate for Data Science is approved by the Rackham School for Graduate Studies. The Program provides interactive data-centered training and involves 9 credits of courses and 3 credits of experiential training that require a written report on data analytics. MIDAS faculty from different disciplines provide mentorship and advising and the Institute offers merit-based top-off scholarships for graduate students enrolled in the Certificate program. The Data Science Certificate Program is now open for Fall 2015 enrollment. U-M graduate students from any field are eligible to enroll. Merit-based Graduate Data Science top-off fellowships may be provided. Minority and underrepresented students are strongly encouraged to enroll and complete the Data Science training program. The 6 course credits must be outside the student's regular degree program/department. Completion of the program is expected in 3-4 semesters. The Data Science Certificate program aims to provide core experiences in:

- (Modeling) Understanding of core Data Science principles, assumptions & applications;

<http://midas.umich.edu/training>




Acknowledgments

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