A Framework for Artificial Intelligence in the Perioperative Period

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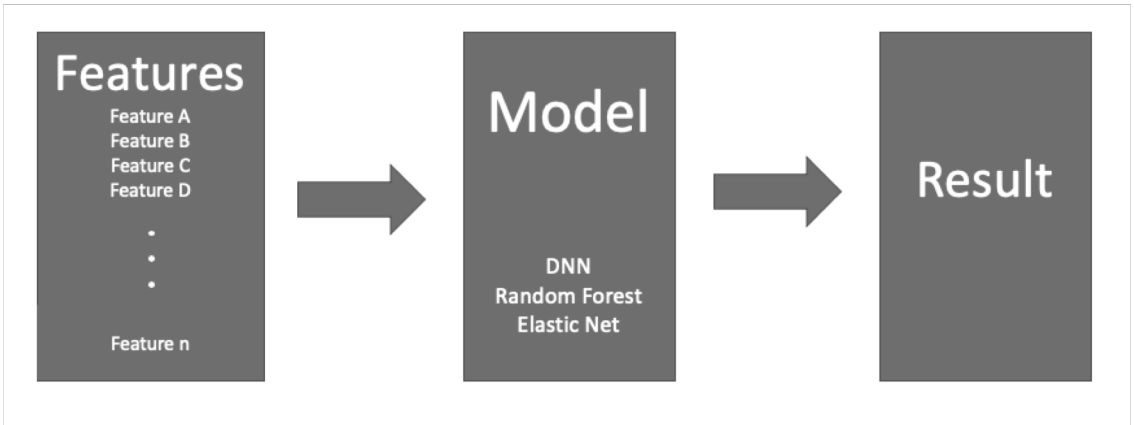
Personal Background

- Assistant Professor of Anesthesiology at UCLA
- Director, Division of Bioinformatics, Department of Anesthesiology
- 10 Years working in EMR Data
- Research Interest: Understanding, quantifying and mitigating perioperative risk
- Financial Disclosers: Copyright on software to extract data from EMR
- Funding: NIH 1R01AG059815-01 Co-I

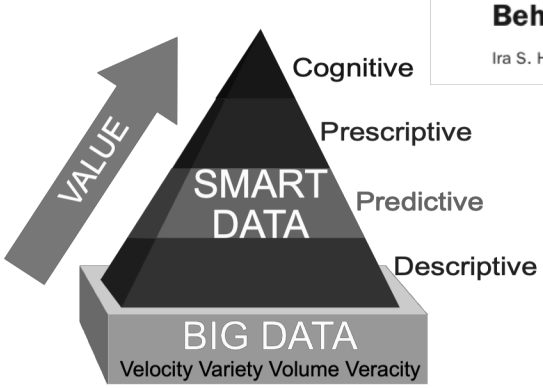
What is Machine Learning



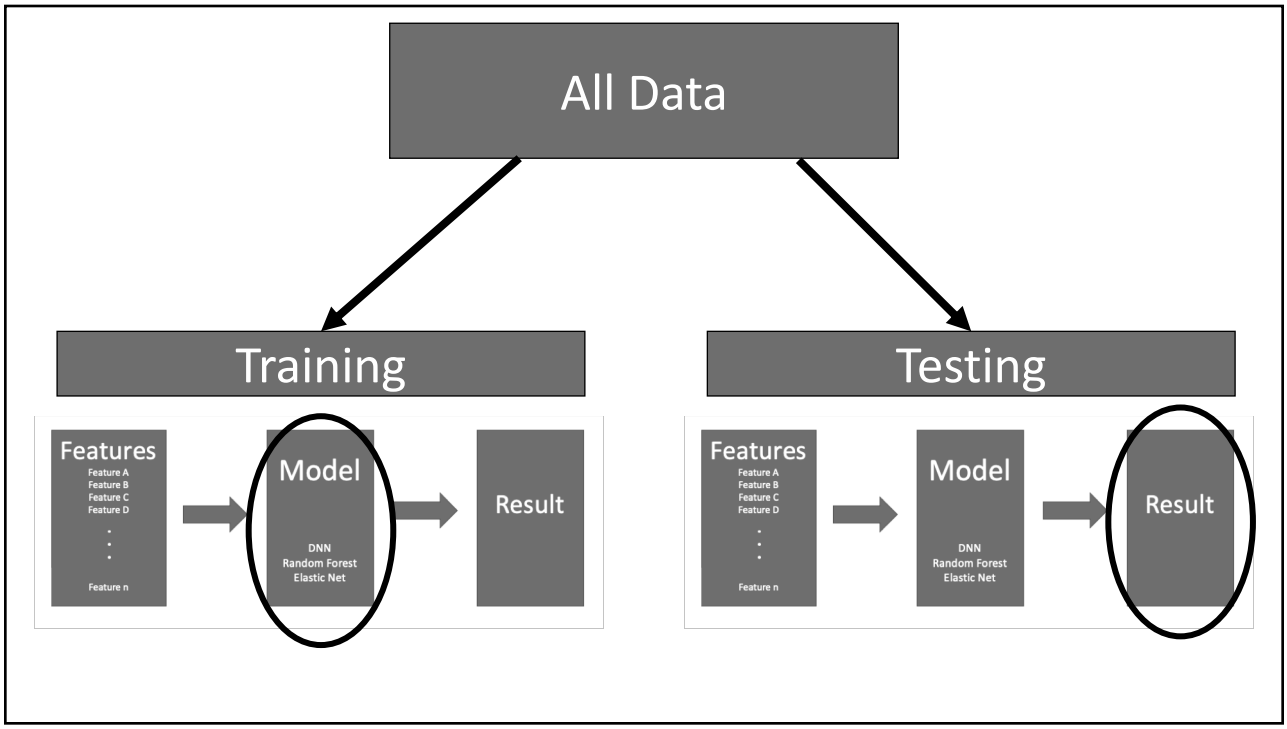
NARRATIVE REVIEW ARTICLE

Opening the Black Box: Understanding the Science Behind Big Data and Predictive Analytics

Ira S. Hofer, MD,* Eran Halperin, PhD,†‡ and Maxime Cannesson, MD, PhD*



Value Proposition of Smart Data



Triangulation: Using multiple data points to arrive a better definition

Creation and Validation of an Automated Algorithm to Determine Postoperative Ventilator Requirements After Cardiac Surgery

Eilon Gabel, MD, Ira S. Hofer, MD, Nancy Satou, RN, Tristan Grogan, MS, Richard Shemin, MD, Aman Mahajan, MD, PhD, and Maxime Cannesson, MD, PhD

May 2017 • Volume 124 • Number 5 www.anesthesia-analgesia.org 1

Algorithm: >99% Correct

Manual Review: ~70% Correct

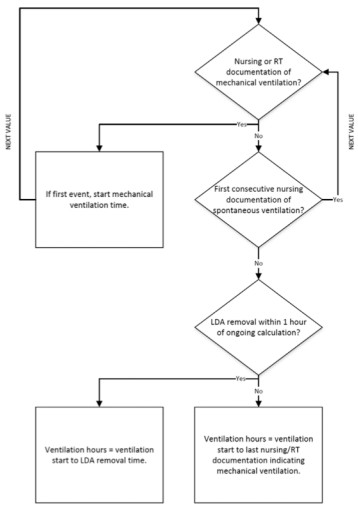
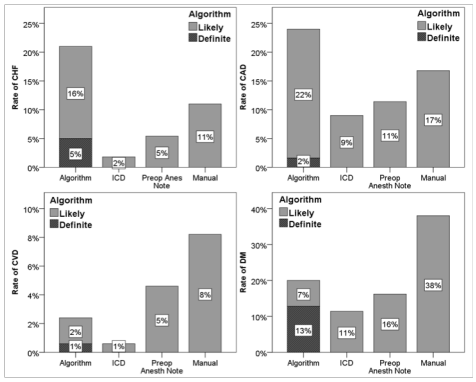


Figure 1. Graphical representation of the algorithm logic. Representation of the logic used by the algorithm to calculate the total postoperative ventilation hours. The algorithm incorporates logic from 3 data sources: nursing, LDA, and RT documentation. LDA indicates line drains and airway; RT, respiratory therapy.

Patient Phenotyping

- Phenotype patients based on RCRI
  - Diabetes, CAD, CHF, Cerebrovascular Disease
- Algorithms look at
  - Past medical history
  - Previous procedures
  - Previous coding
  - Lab results
  - Medication usage

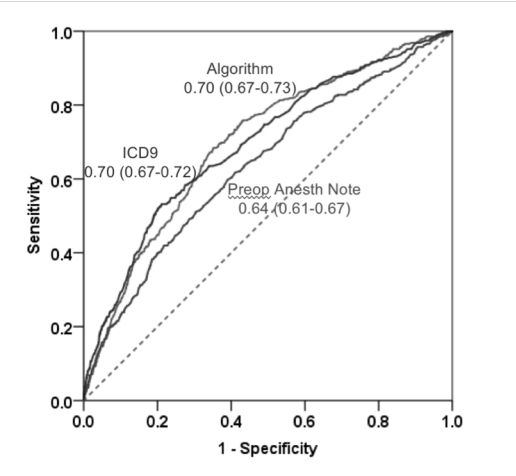


- Prevalence of each of the disease (A: CHF, B: CAD, C: CVD, D: DM) as determined by each of the four methods: diagnosis algorithms, ICD codes, Anesthesiologist preoperative note, and Manual review.

Automated Assessment of Existing Patient's Revised Cardiac Risk Index Using Algorithmic Software

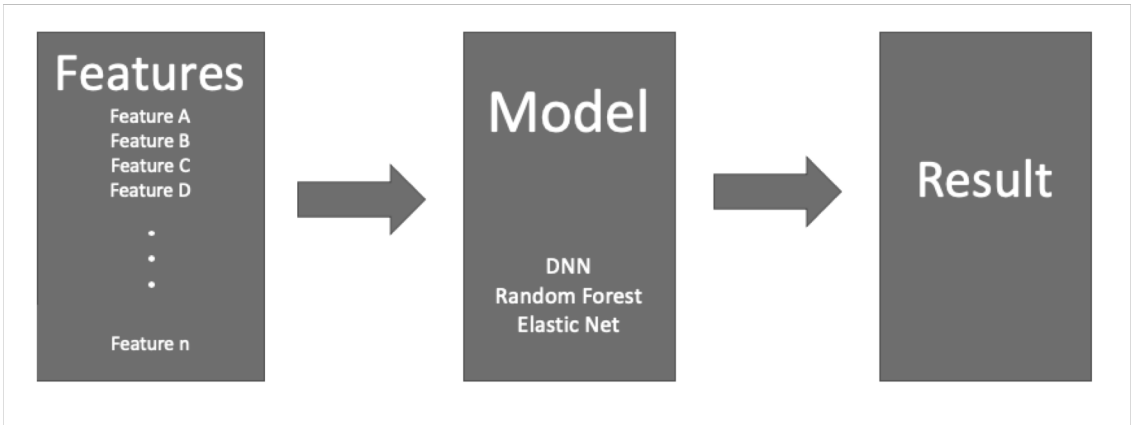
Ira S. Hofer, MD,* Drew Cheng, MD,* Tristan Grogan, MS,* Yohei Fujimoto, MD, PhD,† Takashige Yamada, MD, PhD,‡ Lauren Beck, MD,* Maxime Cannesson, MD, PhD,* and Aman Mahajan, MD, PhD*

AUC plots for predicting in hospital mortality



Single data points are never sufficient to classify a patient

What is Machine Learning



The right intervention for the right patient at the right time – ***every*** time

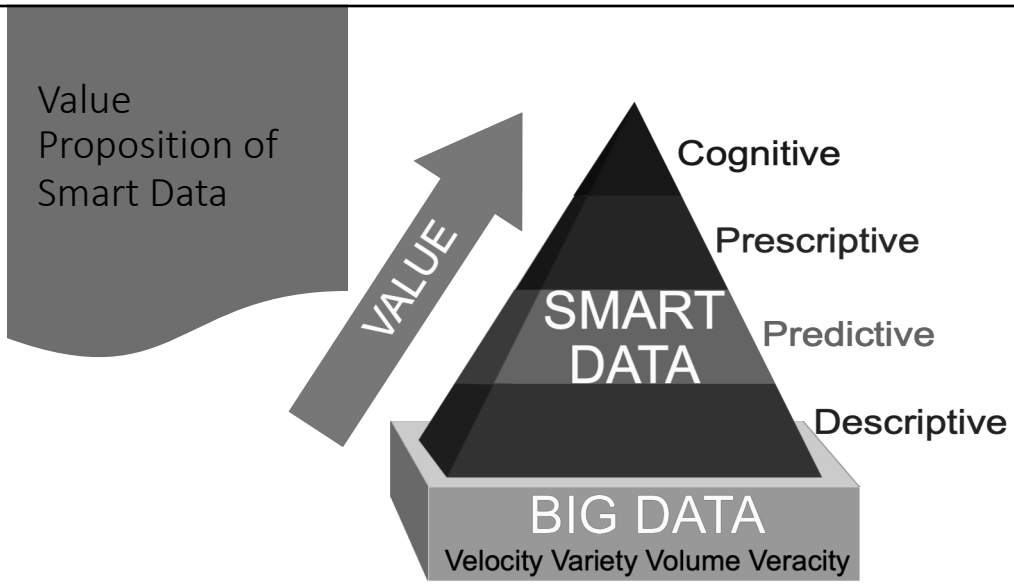


Figure 2: Progressive Value of Smart Data

Sobol and Wunsch *Critical Care* 2011, **15**:217
http://ccforum.com/content/15/2/217

CRITICAL CARE

REVIEW

Triage of high-risk surgical patients for intensive care

Julia B Sobol and Hannah Wunsch*

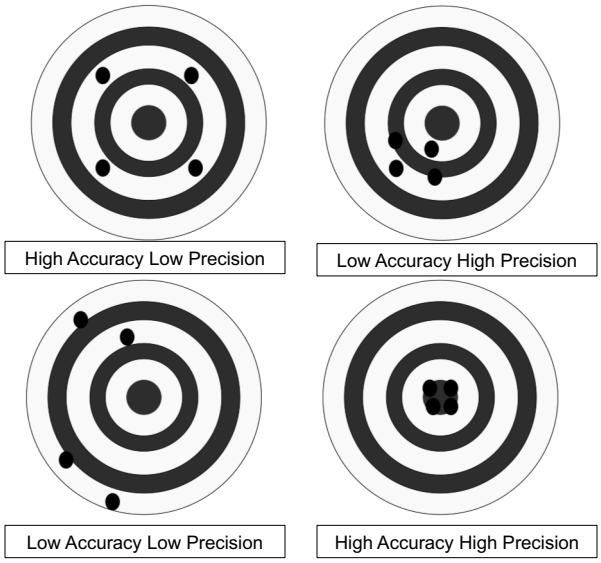
This article is one of eleven reviews selected from the *Annual Update in Intensive Care and Emergency Medicine 2011* (Springer Verlag) and co-published as a series in *Critical Care*. Other articles in the series can be found online at http://ccforum.com/series/annual. Further information about the *Annual Update in Intensive Care and Emergency Medicine* is available from http://www.springer.com/series/8901

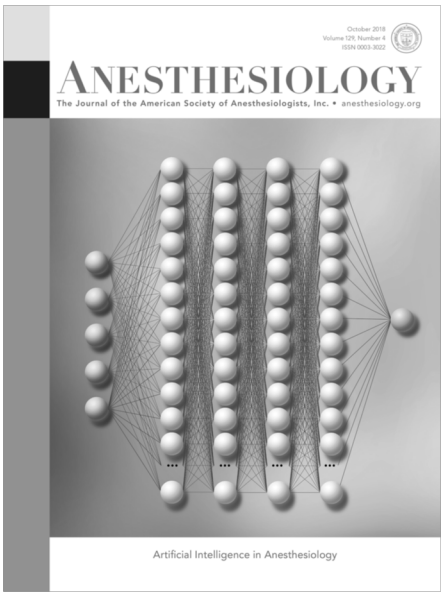
Table 1. Select scoring systems available for assessment of postoperative risk

Scoring system	Year	Number of variables	Inclusion of intraoperative variables	Outcomes predicted	Simplicity	Objectivity
Preoperative						
ASA	1941	Unlimited	No	None	Simple	Subjective
Charlson Comorbidity Index	1987	19	No	Mortality	Mildly complex	Objective
RCRI	1999	6	No	Major cardiac complication	Simple	Objective
Postoperative						
P-POSSUM	1998	12 physiologic, 6 operative	Yes	Morbidity & mortality	Complex	Objective
E-PASS	2001	6 preoperative, 3 operative	Yes	Morbidity & mortality	Complex	Subjective (includes ASA)
NSQIP	1997	57 preoperative, 15 operative	Yes	Morbidity & mortality	Complex	Subjective (includes ASA)
SAS	2007	3 operative	Yes	Morbidity & mortality	Simple	Objective
Intensive care						
APACHE I-IV*	1981–2006	> 10*	No	Mortality	Complex	Objective
SAPS I-III*	1983–2005	> 10*	No	Mortality	Complex	Objective
MPM I-III*	1985–2007	> 10*	No	Mortality	Complex	Objective
SOFA	1994	6	No	None	Mildly complex	Objective
MODS	1995	6	No	None	Mildly complex	Objective

* Dependent on the version of the scoring system used
ASA: American Society of Anesthesiologists' physical status; RCRI: Revised Cardiac Risk Index; APACHE: Acute Physiology and Chronic Health Evaluation; SAPS: Simplified Acute Physiology Score; MPM: Mortality Probability Model; SOFA: Sequential Organ Failure Assessment; MODS: Multiple Organ Dysfunction Score; P-POSSUM: Portsmouth Physiological and Operative Severity Score for the enUmeration of Mortality and morbidity; E-PASS: Estimation of Physiologic Ability and Surgical Stress; NSQIP: National Surgical Quality Improvement Program; SAS: Surgical Apgar Score.

Precision vs Accuracy





PERIOPERATIVE MEDICINE

Development and Validation of a Deep Neural Network Model for Prediction of Postoperative In-hospital Mortality

Christine K. Lee, M.S., Ph.D., Ira Hofer, M.D., Eilon Gabel, M.D., Pierre Baldi, Ph.D., Maxime Cannesson, M.D., Ph.D.

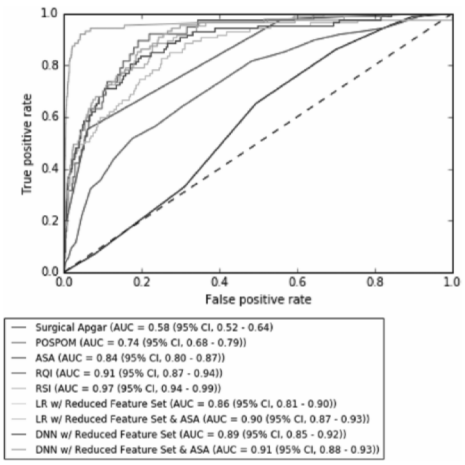


Fig. 2. Receiver operating characteristic curves to predict postoperative in-hospital mortality.

Preoperative predictions of in-hospital mortality using electronic medical record data

Brian Hill[1‡], Robert Brown[1‡], Eilon Gabel[2], Christine Lee[3,4], Maxime Cannesson[2], Loes Olde Loohuis[5], Ruth Johnson[1], Brandon Jew[6], Uri Maoz[2,9,10,11,12,13] Aman Mahajan[2], Sriram Sankararaman[1,7†], Ira Hofer[2*†], Eran Halperin[1,2,7,8†]

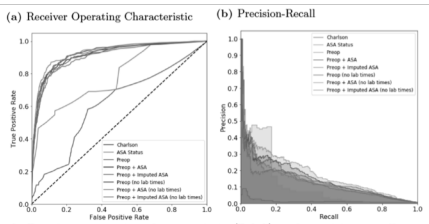


Fig 2. Receiver operating characteristic (ROC) and precision recall curves for the random forest model Plots were generated using cross-validated predictions on the entire dataset. ROC curves (a) show the false positive rate on the x-axis and the true positive rate on the y-axis. The optimal point is the upper-left corner. Precision-recall curves (b) show the recall on the x-axis and precision on the y-axis. The optimal point is in the upper-right corner.

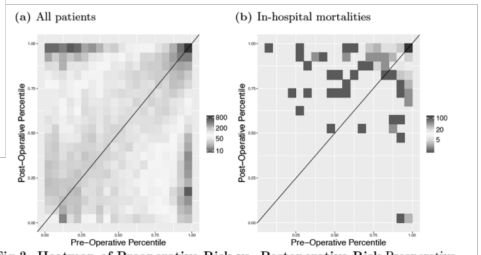


Fig 3. Heatmap of Preoperative Risk vs. Postoperative Risk Preoperative (x-axis) and postoperative (y-axis) risk scores were binned by percentile, and the counts per bin visualized as a heatmap in log scale. In (a) all patients are displayed, and in (b) only the in-hospital mortalities are shown. 78% of patients who die and have a pre-operative risk percentile below 95% have an increased postoperative risk percentile.

PERIOPERATIVE MEDICINE

Machine-learning Algorithm to Predict Hypotension Based on High-fidelity Arterial Pressure Waveform Analysis

Feras Hatib, Ph.D., Zhongping Jian, Ph.D., Sai Buddi, Ph.D., Christine Lee, M.S., Jos Settels, Karen Sibert, M.D., F.A.S.A., Joseph Rinehart, M.D., Maxime Cannesson, M.D., Ph.D.

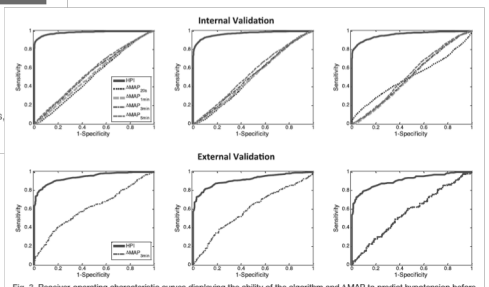


Fig. 3. Receiver-operating characteristic curves displaying the ability of the algorithm and ΔMAP to predict hypotension before its occurrence in the internal and external validation cohorts. Receiver-operating characteristic curves displaying the ability of the algorithm and ΔMAP to predict hypotension 5, 10, and 15 min (*left*, *center*, and *right*, respectively) before its occurrence in the internal validation cohort (*upper*) and in the external validation cohort (*bottom*). HPI = Hypotension Prediction Index; ΔMAP_{20s}, ΔMAP_{1min}, ΔMAP_{3min}, and ΔMAP_{5min} = the absolute changes in mean arterial pressure more than 20 s, 1 min, 3 min, and 5 min, respectively.

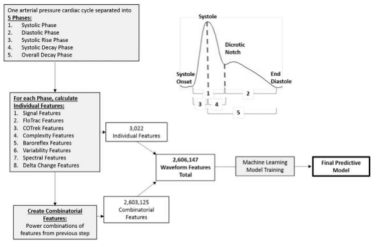


Fig. 2. Summarizing arterial pressure waveform featurization and model training. Higher-level overview of the predictive model development.

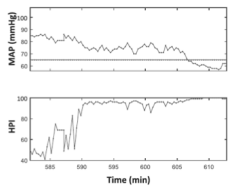


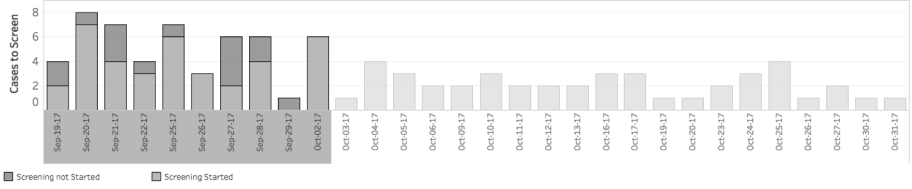
Fig. 5. One illustrative patient record showing the association between the algorithm output (Hypotension Prediction Index [HPI]) and the evolution of mean arterial pressure (MAP) over time.

SMART Screen

UCLA Health

Center of Excellence: Perioperative Analytics

Click On The Dates Below To Show Details



Day of Last Sched..	MRN	Asa Score	Num Primary Visits	Last Bmi	Reason For Screening
Sep-19-2017	[redacted]		32	28	DM
			9	16.4	DM
			2	32.6	DM, CAD, New Patient
		3	32	23.6	CHF, ASA Score
Sep-20-2017		3	7	22.1	ASA Score
		2	123	22.8	DM
			16	23.5	DM
		3	59	27.6	DM, ASA Score
		3	33	37.4	CAD, ASA Score
			1	Null	New Patient
		3	6	34.1	DM, ASA Score
		2	12	40.2	BMI
Sep-21-2017		3	124	21.1	CHF, DM, ASA Score
			61	33.4	DM
		3	135	20.5	CAD, ASA Score
			19	29.9	DM
		3	38	28.2	CHF, ASA Score
			1	20.6	New Patient
		3	14	39.5	ASA Score

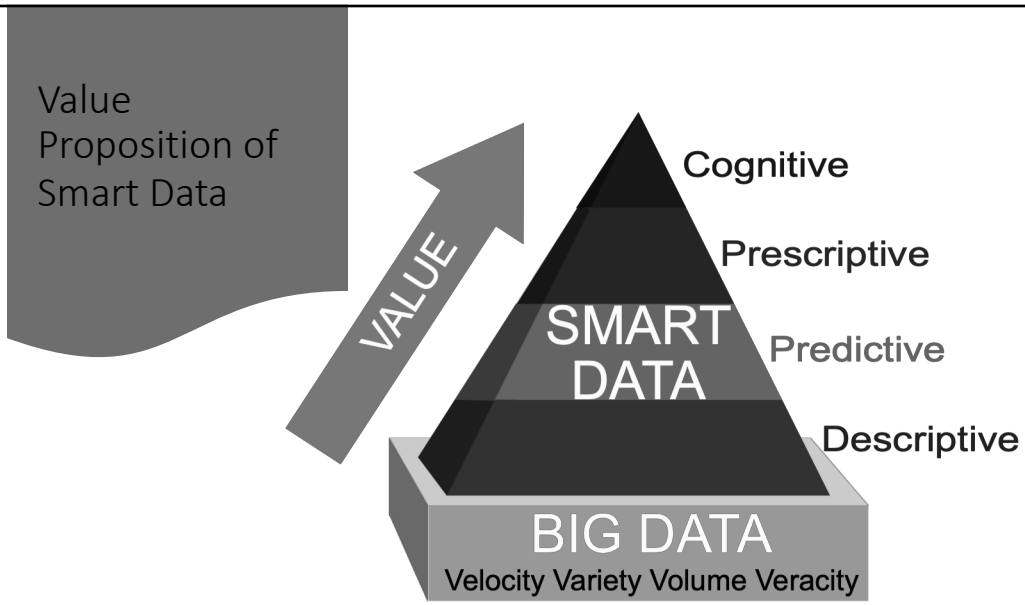
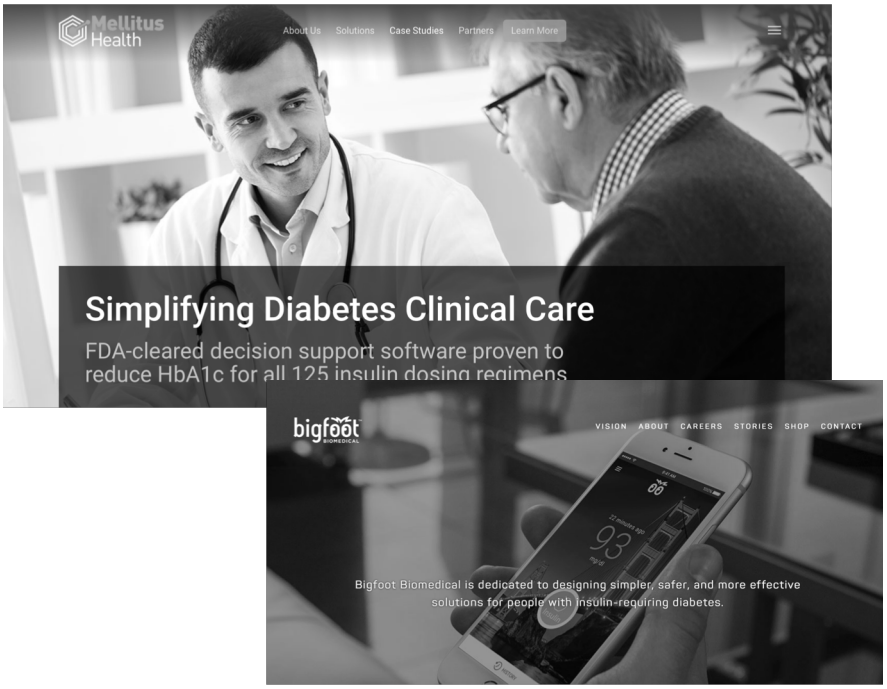


Figure 2: Progressive Value of Smart Data



Predicting Blood Pressure Response to Fluid Bolus Therapy Using Attention-Based Neural Networks for Clinical Interpretability

Uma M. Girkar[1], Ryo Uchimido[2], Li-wei H. Lehman[3]
Peter Szolovits[1], Leo Celi[3], and Wei-Hung Weng[1]
[1]Computer Science and Artificial Intelligence Laboratory, MIT, Cambridge, MA, USA
[2]Emergency Department, Beth Israel Deaconess Medical Center, Boston, MA, USA
[3]Laboratory for Computational Physiology, MIT, Cambridge,
ruchimido@bidmc.harvard.edu
{umag, lilehman, psz, lceli, ckbjimmy}@mit

Algorithm	Timesteps	Accuracy		AUC	
		Raw features	Distributed	Raw features	Distributed
L1-regularized logistic regression	-	0.706	0.688	0.680	0.659
L2-regularized logistic regression	-	0.699	0.695	0.679	0.664
Multiple layer perceptron	-	**0.712**	0.688	**0.690**	0.642
LSTM	12	0.751	0.705	0.818	0.718
GRU	12	0.748	0.721	0.813	0.770
LSTM + Attention	12	0.747	0.727	0.822	0.795
GRU + Attention	12	0.747	0.716	0.818	0.786
LSTM	36	0.814	0.827	0.899	0.899
GRU	36	0.820	0.794	0.898	0.869
LSTM + Attention	36	0.819	0.820	0.902	0.895
GRU + Attention	36	0.812	0.777	0.893	0.858
LSTM	72	0.843	0.834	**0.926**	0.915
GRU	72	0.848	0.836	0.922	0.904
LSTM + Attention	72	**0.852**	0.831	0.925	0.920
GRU + Attention	72	0.841	0.803	0.917	0.882

Table 1: Model performance in accuracy and AUC between different experimental settings. **Boldface** denotes the best performance in each group.

Value Proposition of Smart Data

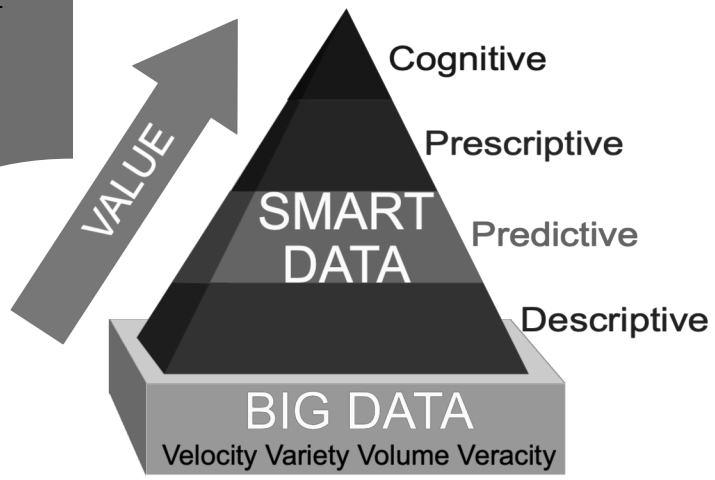


Figure 2: Progressive Value of Smart Data

Cognitive

Thank you

- UCLA PDW Team
  - Eilon Gabel MD
  - Theodora Wingert MD
  - Vali Salari PhD
  - Drew Cheng MD
  - Johnny Quach
  - Olivia Vallejo
  - Evan Moh
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  - Eran Halperin, PhD
  - Sriram Sankararaman, PhD
  - Eleazar Eskin, PhD
  - Christine Lee
  - Brian Hill
  - Nadav Rakocz
  - Robert Brown

- Mentors
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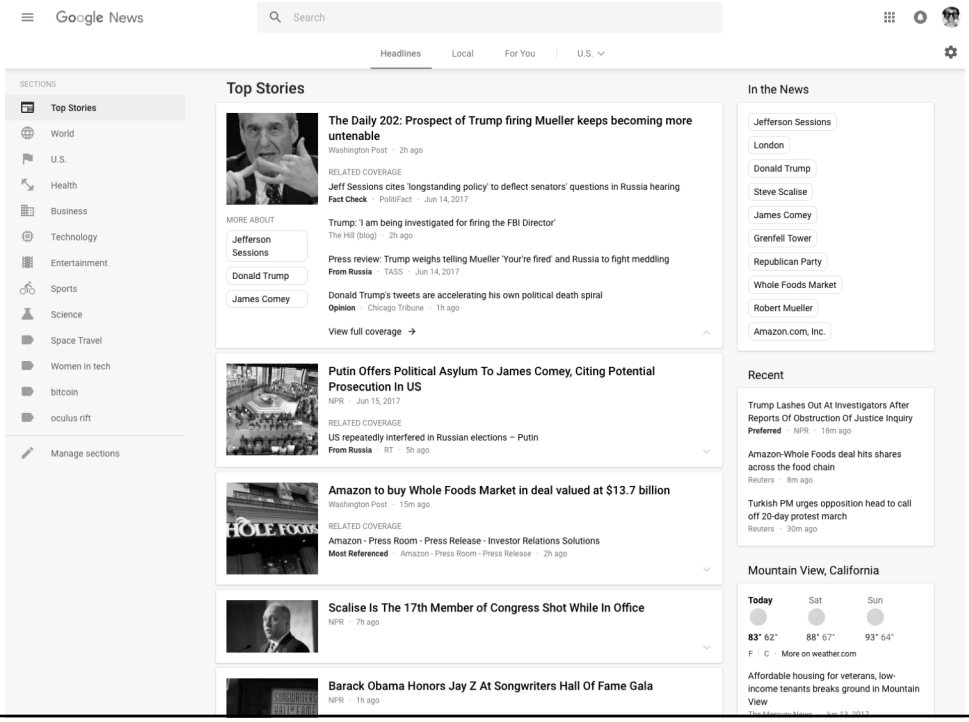
  - Adam Levine MD
  - Maxime Cannesson MD, PhD
  - Barbara Van de Wiele, MD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Use Clustering to group patients