­­OMB No. 0925-0001 and 0925-0002 (Rev. 09/17 Approved Through 03/31/2020)

BIOGRAPHICAL SKETCH

Provide the following information for the Senior/key personnel and other significant contributors.  
Follow this format for each person. **DO NOT EXCEED FIVE PAGES.**

NAME: Hughes, Michael C.

eRA COMMONS USER NAME (credential, e.g., agency login): not yet acquired

POSITION TITLE: Assistant Professor of Computer Science

EDUCATION/TRAINING (Begin with baccalaureate or other initial professional education, such as nursing, include postdoctoral training and residency training if applicable. Add/delete rows as necessary.)

| INSTITUTION AND LOCATION | DEGREE  (if applicable) | Completion Date  MM/YYYY | FIELD OF STUDY |
| --- | --- | --- | --- |
|  |  |  |  |
| Franklin W. Olin College of Engineering  Brown University  Brown University  Harvard University | B.S.  M.S.  Ph.D.  (post-doc) | 05/2010  05/2012  05/2016  08/2018 | Electrical & Computer Engineering  Computer Science  Computer Science  Computer Science |
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**A. Personal Statement**

**My research goal is to develop principled machine learning models that discover actionable knowledge from large, messy datasets. My applied focus is healthcare, where novel probabilistic models and optimization algorithms are needed to learn from big, noisy, unlabeled electronic health records to produce recommendations clinicians can trust to improve patient care. My research provides better methods to the machine learning community, patient-specific treatment advice to doctors, and scientific insight into possible subtypes or trajectories of targeted diseases. I strive to deliver top-tier publications in both computational and clinical venues, as well as reproducible open-source software and (eventually) deployed clinical decision support systems.**

**My background in statistical machine learning, optimization algorithms, clinical informatics, and open-source software engineering makes me uniquely positioned to achieve these goals. Through my postdoctoral training, I have experience in 3 distinct clinical informatics projects: modeling vital sign trajectories in the Intensive Care Unit across 36,000 patients to predict the need for mechanical ventilators over time; modeling coded EHR histories from over 50,000 patients with major depression disorder to improve recommendations for antidepressants (with Dr. Roy Perlis and Dr. Tom McCoy at Mass. General Hospital); and modeling patient histories to improve treatments for infertility (with Boston IVF). Armed with this background, as a new faculty PI I am excited to pursue deep informatics collaborations with clinicians at Tufts School of Medicine, seek funding for such projects, and train computing students to produce strong interdisciplinary research.**

**B. Positions and Honors**

**Employment**

2016-2018 Postdoctoral Fellow, School of Engineering and Applied Sciences, Harvard University

2018- Assistant Professor, Department of Computer Science, Tufts University

Honors

2018 Best Paper Award, SoCal Natural Language Processing (NLP) Symposium

2017 Nominee for AMIA Clinical Informatics Research Award (1 of 7)

2011 NSF Graduate Research Fellowship Award

**C. Contributions to Science**

1. Semi-supervised models for personalized medicine from large observational EHR data

Observational medical datasets contain orders of magnitude more data than the largest randomized controled trials and thus offer promise as a source of information about why drugs might be effective for some patients but not others or finding useful subgroups of patients with similar symptoms, responses, or trajectories. However, there exist many challenges in using such data to draw meaningful conclusions, including learning from many sources of data that are often noisy and high-dimensional and determining clinically-useful outcomes (which drugs were successful, not just attempted) when manual annotation is unavailable or too expensive. My postdoc work at the intersection of machine learning and clinical informatics tries to overcome these barriers.

For predicting needed interventions in the intensive care unit (ICU), our AMIA CRI 2017 paper applied switching-state models to time-series data from 36,000 ICU patients. Although trained in an unsupervised way (discovering common patient states without labels), our learned representations improved 4-hour look-ahead predictions of need for me- chanical ventilation. Such models can improve personalized care and smooth logistics in the busy ICU, but to reach higher accuracies we must supervise training by including labels.

For our work on antidepressant recommendation for 50,000+ patients in Boston-area hospitals, we have developed a semi-supervised dimensionality reduction approach that learns from few labeled examples and many unlabeled ones. Supervised topic models which explain both the data and predict the labels can achieve two needed goals: good generative models of data (scientific insight on possible patient subgroups or important variable interactions) and good prediction of labels from data (effective personalized treatment recommendations). We have shown these methods offer competitive predictions that generalize well to new hospital systems.

**M. C. Hughes,** L. Weiner, G. Hope, T. H. McCoy Jr, R. H. Perlis, E. B. Sudderth, and F. Doshi-Velez

Semi-supervised prediction-constrained topic models.

In Artificial Intelligence and Statistics (AISTATS), 2018.

<https://www.michaelchughes.com/papers/HughesEtAl_AISTATS_2018.pdf>

M. Ghassemi\*, M. Wu\*, **M. C. Hughes\***, P. Szolovits, and F. Doshi-Velez

Predicting intervention onset in the ICU with switching state space models.

In AMIA Summit on Clinical Research Informatics, 2017

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5543372/pdf/2611344.pdf>

2. Reliable inference for Bayesian nonparametric unsupervised learning

During my Ph.D. thesis, I made core contributions to statistical machine learning by inventing new algorithms to train a broad class of Bayesian nonparametric (BNP) models for unsupervised structure discovery, including mixture models, topic models for grouped data, and hidden Markov models for sequential data. While well-known parametric methods like k-means require an a priori specification of the exact number of clusters, BNP models, such as the Dirichlet process mixture model, can manage uncertainty in the number of clusters needed to explain a dataset and let the data determine model complexity without restrictive assumptions.

While this class of models is promising for many real datasets, before our work standard inference methods such as sampling or variational optimization did not live up to this promise. Such methods optimize non-convex objective functions via iterative updates to subsets of parameters. Even on small data, random initializations become stuck at poor local optima and fail to reach even the best single mode, let alone explore the real posterior. Scaling to millions of examples only exaggerates this problem. My Ph.D. work on reliable BNP suggests that these standard updates should be interleaved with data-driven proposals that create new clusters to better explain some examples or remove irrelevant clusters. Our proposal-driven algorithms reach qualitatively better solutions without expensive restarts or cross-validation. Experiments demonstrate the usefulness of our approach in discovering clusters from large collections of news articles (every New York Times article in last 20 years) and discovering recurring patterns of epigenetic modifications to the human genome. My collaborators and I released an open-source Python package called BNPy (Bayesian Nonparametrics for Python, [https://bnpy.readthedocs.io](https://bnpy.readthedocs.io/)) to make these techniques broadly available.

M. C. Hughes and E. B. Sudderth.

Memoized online variational inference for Dirichlet process mixture models.

In Neural Information Processing Systems (NIPS), 2013.

<https://www.michaelchughes.com/papers/HughesSudderth_NIPS_2013.pdf>

M. C. Hughes, D. I. Kim, and E. B. Sudderth.

Reliable and scalable variational inference for the hierarchical Dirichlet process.

In Artificial Intelligence and Statistics (AISTATS), 2015.

<https://www.michaelchughes.com/papers/HughesKimSudderth_AISTATS_2015.pdf>

M. C. Hughes, W. Stephenson and E. B. Sudderth.

Scalable adaptation of state complexity for nonparametric hidden Markov

models.

In Neural Information Processing Systems (NIPS), 2015.

<https://www.michaelchughes.com/papers/HughesStephensonSudderth_NIPS_2015.pdf>

3. Optimizing deep neural network classifiers for interpretability

While deep learning has made impressive strides on image and language tasks, many clinical practitioners are reluctant to adopt deep models because their predictions are difficult to interpret, explain, and trust. During my postdoc, I’ve pursued new machine learning methods to close this trust gap.

First, our IJCAI 2017 paper shows how to train models to respect expert annotations of features relevant to specific examples. Furthermore, even without expert annotations our method can actively discover models with different per-example decision rationales via the same regularization process. This gives practitioners valuable tools to debug pretrained models or discover confounding features hiding in their datasets.

Second, our AAAI 2018 paper introduces "tree regularization", a method to directly train deep models to be human-simulatable. Small decision trees with only a few nodes make it easy for humans to step through the entire prediction process, and thus enjoy widespread use in manual medical diagnosis. In contrast, feed-forward networks with a dozen hidden units can have far too many parameters and connections for a human to simulate. Deep models for sequential data are even more challenging. Simulatability allows clinicians to audit predictions easily. They can manually inspect how outputs change under slightly-perturbed inputs or identify when predictions are made due to systemic bias or confounders rather than real causes. Our work shows that recurrent neural networks for predicting treatments for patients with sepsis or HIV can be trained to have simpler, tree-like decision boundaries with fewer than 25 nodes, while still predicting better than standalone trees.

A. S. Ross, **M. C. Hughes**, and F. Doshi-Velez.

Right for the right reasons: Training differentiable models by constraining their explanations.

In International Joint Conference on Artificial Intelligence, 2017.

<https://www.michaelchughes.com/papers/RossHughesDoshiVelez_IJCAI_2017.pdf>

M. Wu, **M. C. Hughes**, S. Parbhoo, M. Zazzi, V. Roth, and F. Doshi-Velez.

Beyond sparsity: Tree regularization of deep models for interpretability.

In AAAI Conference on Artificial Intelligence, 2018*.*

[*https://arxiv.org/pdf/1711.06178.pdf*](https://arxiv.org/pdf/1711.06178.pdf)

**D. Additional Information: Research Support and/or Scholastic Performance**

**As a new faculty member (starting August 2018), I have no external funding to date, but I plan to seek NIH grants for extensive projects at the intersection of machine learning and healthcare.**

**My postdoctoral work was funded by Oracle Labs.**