

Motivation

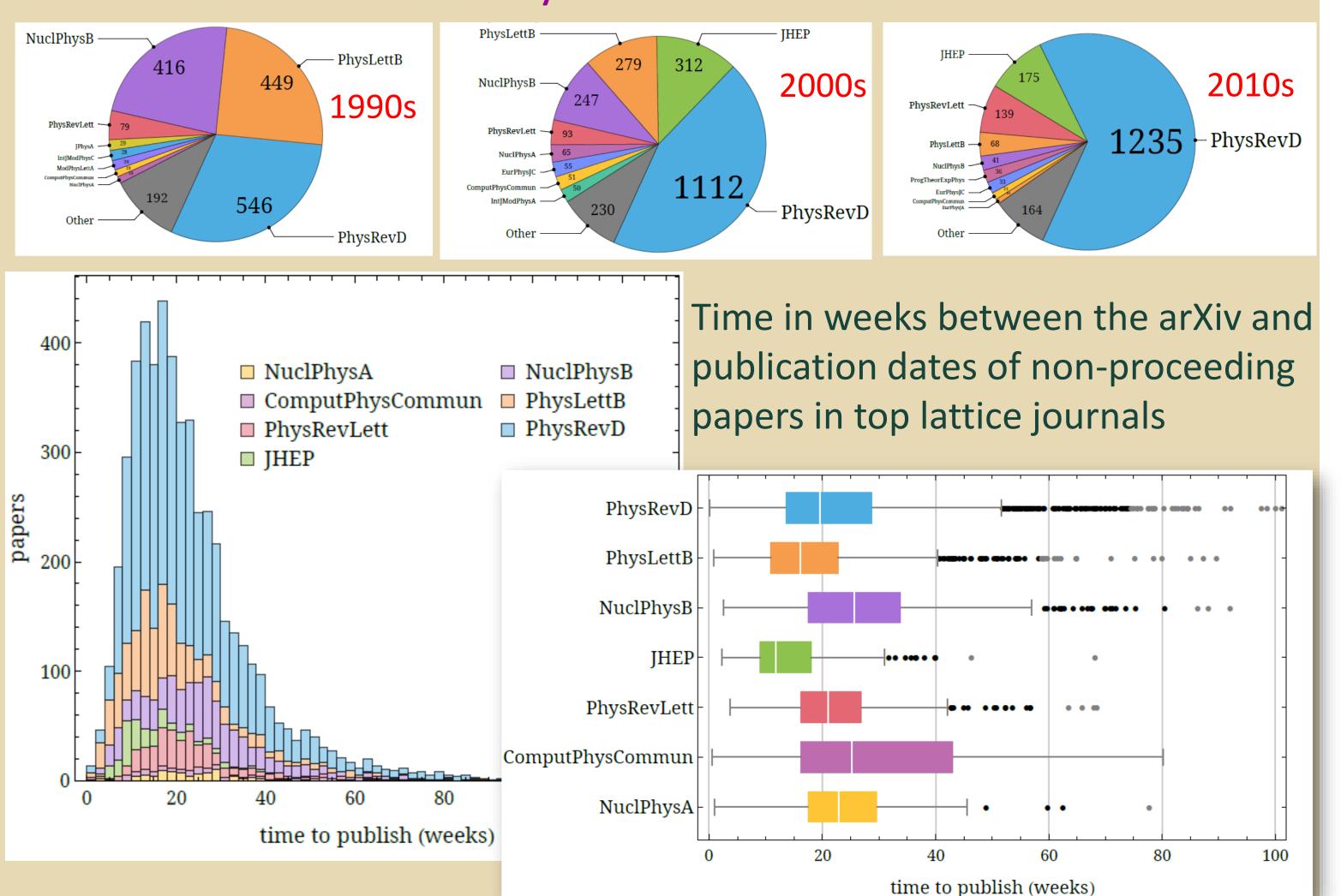
Nationwide growing effort to improve diversity in STEM

- Both NSF and DOE had grant opportunities in 2020 Improve diversity and retention at the doctoral level
- Many higher-education institutions and labs are also investing in outreach efforts targeting the pipeline issue in STEM > Funding K-12 activities locally throughout the year REU programs
 - Summer internships
- One can expect a wave of new-generation diverse scientists with unique ways of thinking and problem-solving abilities
- In the late stages of the pipeline within academic jobs, scientists are subject to evaluation based on their publications Affects students getting postdocs; postdocs to faculty Faculty to get grants and achieve tenure, and so on
- Any significant gender or racial could cause years of effort bringing up a diverse workforce to be in vain > We must study and monitor any potential bias and make sure that there is no bottleneck in these final stages > In this poster, we focus on hep-lat primary publication only

Data Collection and Processing

Starting with hep-lat arXiv metadata using API

- Removed all papers cross-listed to other fields
- Removed proceedings (Nucl. Phys. Proc. Suppl., PoS, J of Phys Conf. Series, etc.).
- Results below sorted by decade



Machine-Learning Evaluation of Author Ethnicity in Lattice Publications

Department of Physics and Astronomy & Computational Mathematics, Science and Engineering Michigan State University, East Lansing, MI 48824 Contact: Prof. Huey-Wen Lin (hwlin@pa.msu.edu)



Author Ethnicity via Machine Learning

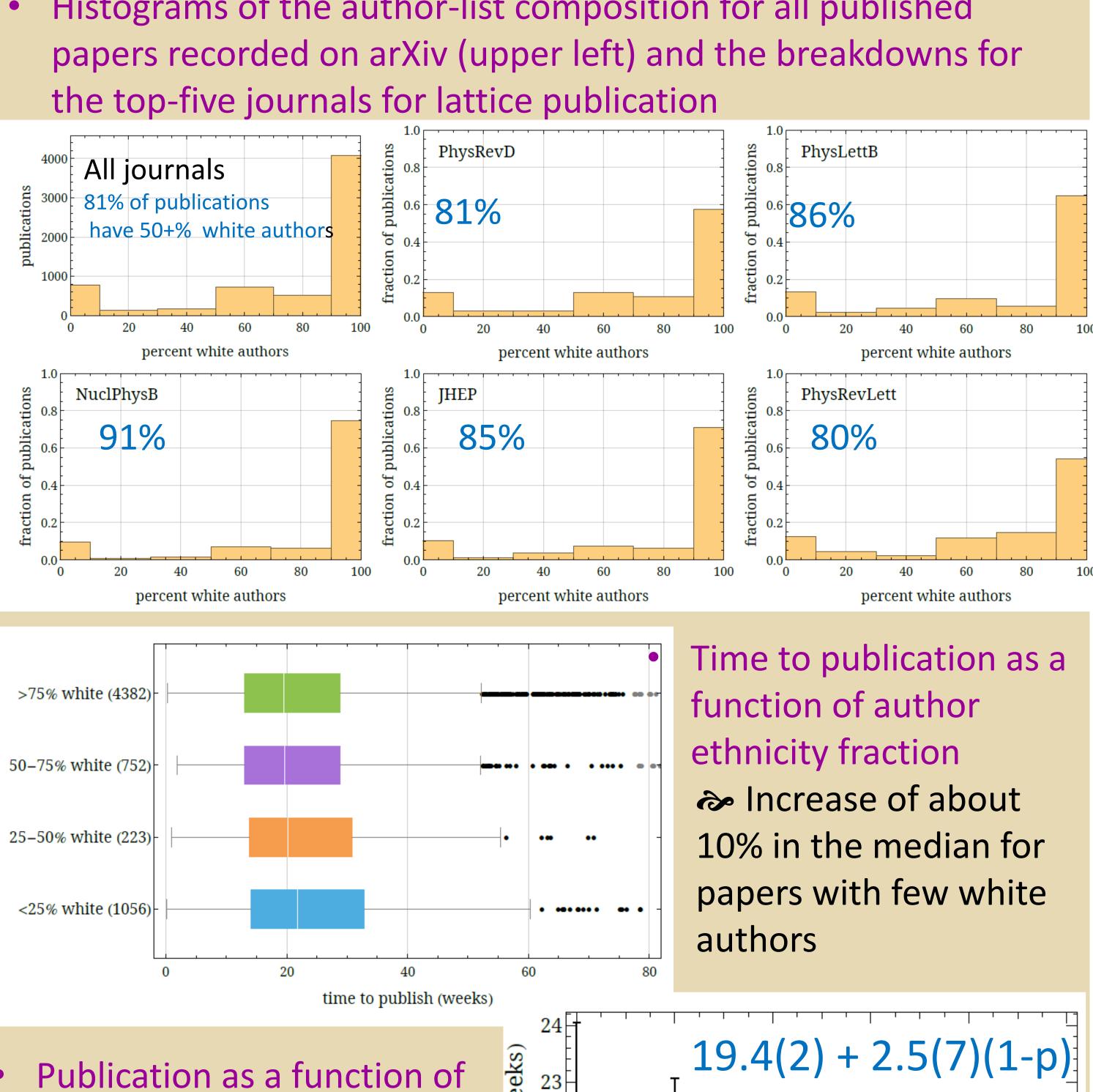
Use TensorFlow to perform the NN training with GPU acceleration via NVIDIA's cuDNN deep-neural-network library.

US Census Training Data

- Known for high accuracy and amount of data: 162k surnames Breaks down surnames by race categories: "white", "black", "Hispanic", "Asian/Pacific islander", "American Indian", "mixed race"
- Prepare the surnames for input into the DNN > Convert each name into a vector of reals in the range [0,1] with uniform length, padded to the left to width 20 by zeros ➢ Model uses 4 dense layers with widths 200, 64, 32 and 4 trained with a *mean-squared* loss function and the *Adadelta* optimizer over 300 epochs
- Predictions of "white", "black", "Asian" and "Hispanic" Recognizes "AOKI", "LIU" and "HASHIMOTO" as "Asian", and "JANSEN", "LEINWEBER" and "HELLER" as "white" ➢ Predicts "LIN" as "white", possibly due to the fact that "-LIN" is a common ending in surnames such as "FRANKLIN" > Far more authors in this data tagged as "black" than our field has This can be understood due to American history; black and white Americans simply share many surnames, and there is a mixture of surnames in the training data. For example, "SMITH" is about 50% white and black according to the census data. These American trends do not well match the demographics of the lattice authors data set.

Identifying the ethnic origin of the surnames

- Training a network with the most common surnames from a diverse selection of countries
- ➢ Most common 1000 surnames from 27 countries: Spain, Mexico, Brazil, Argentina, Italy, France, England, Scotland, Ireland, Germany, Greece, Sweden, Russia, Poland, Hungary, Turkey, Israel, Egypt, Syria, Iran, Pakistan, India, Vietnam, China, Taiwan, Japan and South Korea Expanded our alphabet to 42 characters and padded length to 21, yielding an input dimension of 882
- Four-layer model with different widths (1764, 441, 216 and 27) > Final layer has sigmoid activation to constrain it to [0,1] > The output should be a unit vector (left it unnormalized) > Loss function to *categorical cross-entropy*; optimizer: *Adam* New model has 2.4M parameters • Final results
 - > Output the top-3 predictions for each last name Resolved many previously problematic surnames; it identified "JANSEN" as Swedish, "HELLER" as German, and "LIN" as Taiwanese. > Hand-checked the top-323 surnames, covering all authors with 20 or more lattice papers, and found 77% accuracy at the country level and 92% accuracy discerning white versus Asian





author ethnicity fraction fit to a linear trend An all-nonwhite authored paper expects to be tied up in the editorial process for 2.5 weeks longer percent white authors (**P**) than all-white author group

Conclusion & Outlook

- The machine-learning evaluation of the author ethnicity suggests a 10% extra time for non-white authors to get their hep-lat papers published
- Big Caveat: Survivor bias These public data are for all published papers. People may have some difficulties, but they make it. > We cannot measure how many papers are blocked from the publication system entirely
- We should minimize the (un)conscious bias > Double blind system? Unified referee data base to keep track of the unconscious bias training? Other suggestions?



Results and Discussion

Histograms of the author-list composition for all published