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Research Statement

The standard model of particle physics has been an extremely successful tool, but we know that it remains incomplete. If new physics is discoverable at the LHC, then we will need to use the most sensitive tools and combine measurements from as many signatures as possible to find it. Possibly the most room for improvement can be gained from searches in the all hadronic final state due to the difficulty in reducing the QCD multijet background. These searches can greatly benefit from cutting-edge selection techniques, and of these, perhaps the most exciting is the tagging of merged heavy resonances. Merged heavy resonances arise in BSM physics searches for massive gauge bosons, heavy quark partners, SUSY partners, Kaluza-Klein excitations, and others. Classically, analyses that identify hadronic signatures (for example from a top decay) would not be as sensitive as the leptonic decay mode, due to the extremely difficult problem of reducing the hadronic backgrounds.

A boosted heavy resonance decay can be reconstructed as a single wide jet with a characteristic substructure, and heavy resonance tagging techniques use this substructure to reduce the hadronic background. Generally, tagging techniques discriminate boosted resonances using analytical variables such as the "groomed" mass of the jet which selects a jet mass consistent with the progenitor particle, a shape criterion that selects an energy deposition pattern consistent with the number or expected cores, and a selection of the heavy flavor content within the jet. These methods have had much success, but recent developments in machine-learned pattern recognition improve the sensitivity far beyond what is achieved by analytical variable selections. First, I will discuss my historical contributions to merged jet tagging, then my work in porting convolutional neural network (CNN) image recognition to jet tagging and the rich physics analysis program that these methods make possible, and finally my role in the outer tracker hardware program in preparation for the HL-LHC upgrade.

My introduction to LHC physics research was the application of the first tagging techniques for merged top jets. I applied the methods that were pioneered in the $\mathrm{Z}' \to \mathrm{t\bar{t}}$ all hadronic search [**?**], to the $\mathrm{W}' \to \mathrm{t\bar{b}}$ search [**?**] (see also the run 2 reboot in Ref. [**?**]). I was the first to use the N-subjettiness and subjet b-tagging algorithms for top-jet identification, which proved to be much more effective in reducing the QCD-multijet background than the methods used previously. I extracted the scale factor for this new top tagger by studying a highly pure sample of semileptonic $\mathrm{t\bar{t}}$ (leading to the JME-13-007 [**?**] analysis). I then applied this new top tagging method to the hadronic $\mathrm{b}^* \to \mathrm{tW}$ search [**?**], and then additionally to the $\mathrm{W}' \to \mathrm{qQ} \to \mathrm{tHb}$ search [**?**]. Motivated by extensive studies in the theoretical community [**?**, **?**], I employed the latest advances in machine learning to produce a CNN tagger for CMS, "$\mathrm{imageTop}$". The improvements that I made on top of the previous CNN studies include an adaptive zoom, particle flow identification "colors", flavor discrimination, and mass decorrelation. This tagger debuted in Ref. [**?**], and shows an improvement of nearly a **factor of ten** in background rejection compared to the standard CMS top-tagger, and is the most sensitive mass decorrelated tagger in CMS.

The $\mathrm{imageTop_{MD}}$ network offers a substantial improvement over other tagging methods, so I then expanded to include additional physics objects ($\mathrm{imageX_{MD}}$) and moved to the physics analysis implementation. I designed a data-driven background estimate that is capable of predicting a generic final state to create an "analysis factory", which takes advantage of the kinematic decorrelation of the $\mathrm{imageX_{MD}}$ network. In order to commission the $\mathrm{imageTop_{MD}}$ tagger and analysis factory, I rebooted the $\mathrm{W'} \rightarrow \mathrm{qQ} \rightarrow \mathrm{tHb}$ search using now the full CMS run 2 data. This analysis is now post-approval, and the next steps will involve multiple extensions of the tagger and analysis methods. We are investigating the sensitivity of the $\mathrm{image_{MD}}$ network when applied to several exotic jet signatures. In the case of a boosted resonance decaying to two bosons (For example a WED-motivated light radion), we expect a merged diboson jet (for example $\mathrm{WW} \rightarrow \mathrm{qqqq}$ or $\mathrm{Z}\gamma \rightarrow \mathrm{qq}\gamma$ within a single jet). In the WW case, we expect a dedicated neural network training to give a substantial improvement in such a feature-dense jet, and in the $\mathrm{Z}\gamma$ case, we expect the photon and neutral colors to improve signal efficiency in the case of a non-isolated photon. Additionally, there is room to expand the aforementioned $\mathrm{W'} \rightarrow \mathrm{qQ} \rightarrow \mathrm{tHb}$ search in interesting ways. The same final state here is reproduced by the $\mathrm{W'} \rightarrow \mathrm{HH^{\pm}} \rightarrow \mathrm{tHb}$ signature [**?**]. However, here there is the possibility of a boosted $\mathrm{H^{\pm}}$ which would produce a merged top jet with an additional hard b quark. Also, the same theoretical framework allows for a robust set of analyses the analysis with the inclusion of the additional $\mathrm{W'}$ decays $\mathrm{W'} \rightarrow \mathrm{H^0H^{\pm}} \rightarrow \mathrm{tttb}$ or tbbb, which would similarly cover an element of phase space that necessitates a dedicated boosted bb or tt jet tagger. These additional merged jets are prime candidates for the $\mathrm{imageX_{MD}}$ network. In preliminary studies, the exotic taggers show a large improvement over the conventional methods, and the analysis factory produces an impressive background closure with only minor tweaking.

The main challenge in producing BSM taggers is the data validation, given that there is usually no acceptable SM analogue, and a machine-learned tagger necessitates a high level of confidence, given the lack of physical intuition of the learned features. Therefore, I am investigating methods of validation through event superposition which can be used to create BSM jet analogues in CMS data. Although the network is very sensitive in its current form, there are potential future improvements. The $\mathrm{image_{MD}}$ network could be improved by expanding the inputs to include lower-level detector subsystems, and by converting to a particle-based GCN model instead of using pixelization. With my technical experience from implementing the $\mathrm{image_{MD}}$ network and leadership experience from my B2G:RES and JMAR subgroup convenerships, I am in a prime position to play a leading role in the field of hadronic searches, which will carry into the HL-LHC era.

Although these dedicated methods are extremely powerful, the network can also be used in a generic way. We are currently investigating the possibility of converting the network to an unsupervised anomaly detector. This can be accomplished by porting the architecture to an autoencoder or GAN. With this type of network, an anomaly would show up as a poorly reconstructed jet image. Additionally, the anomaly detection performance is bolstered by a careful determination of the latent space pdf by using autoregressive flows. The anomaly is then detected as an unlikely latent space configuration.

Looking towards the future, the HL-LHC offers benefits to analysis sensitivity but also unique challenges that need to be addressed with new analysis methods and detector hardware improvements. On the analysis side, the dense environment will certainly only make machine-learned methods like $\mathrm{image_{MD}}$ more relevant. From the hardware side, I am helping to prepare for the HL-LHC upgrade through the outer tracker silicon module prototyping. Specifically, characterizing the PS-module, which correlates hits from two closely spaced silicon layers such that a fast p_{T} measurement can be made. I contributed to this effort by characterizing the prototype assembly for the silicon pixel portion of the PS-module.

My work with the PS-module started from studying the first bare readout chip, the MPA-light. Here, I was in charge of wirebonding and software development. The task involved the initial testing with prototype PCBs and firmware, which offered a unique challenge. The bare readout chip allowed me to write the first functional DAQ system for data taking. The next step was to test the MaPSA-light, which consisted of eight MPA chips that have been bump bonded to a pixelized silicon sensor. I was in charge of the MaPSA-light testbeam campaign as the spokesperson for experiment T-1209, which was performed using the Fermilab Main Injector. I also added to the analysis effort through the unfolded time efficiency measurement using a convolved fit to the timing response spectrum. After the MaPSA-light, we created a "micro module" from two closely spaced MaPSA-light assemblies. This allows the correlation of hits from the two devices in an analogous way to the full PS-module. This lead to additional testbeam campaigns where the correlated hit pairs could be studied in real data. The data collected during the multiple testbeams were used in various analyses contributing to the Phase-II outer tracker TDR.

My experience contributing to the upgrade project has given me a better understanding of the breadth of a full physics analysis, from achieving the first readout on an experimental detector to a publishable result. My upgrade duties continue, leading toward the final MPA (and SSA) chip software integration with the full Phase-II outer tracker software framework. Currently, I am finalizing the software for the half PS-module at Fermilab, the latest evolution of the OT hardware. My work characterizing the very first prototype MPA modules has been an exciting introduction to HL-LHC upgrade hardware and the experience that I have gained will prove essential to future hardware contributions during my time at replace$_jobname$.

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