Recent Progress in Jet Substructure

Andrew Larkoski
Reed College

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Jet Substructure at the Large Hadron Collider:
A Review of Recent Advances in Theory and Machine Learning

Andrew J. Larkoski
Physics Department, Reed College, Portland, OR 97202, USA

Ian Mout†
Berkeley Center for Theoretical Physics, University of California, Berkeley, CA 94720, USA

Benjamin Nachman†
Physics Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

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Jet substructure has emerged to play a central role at the Large Hadron Collider (LHC), where it has provided numerous innovative new ways to search for new physics and to probe the Standard Model in extreme regions of phase space. In this article we provide a comprehensive review of state of the art theoretical and machine learning developments in jet substructure. This article is meant both as a pedagogical introduction, covering the key physical principles underlying the calculation of jet substructure observables, the development of new observables, and cutting edge machine learning techniques for jet substructure, as well as a comprehensive reference for experts. We hope that it will provide a useful introduction to the exciting and rapidly developing field of jet substructure at the LHC.

This constitutes the theory and machine learning sections of a review on jet substructure at the LHC for Reviews of Modern Physics. An overview of recent experimental progress in jet substructure will appear separately, and the complete review will be submitted to Reviews of Modern Physics.

arXiv:1709.04464

Jet Substructure at the Large Hadron Collider: Experimental Review

Lily Asquith†, Mario Campanelli†, Chris Delitzsch†, Andreas Hinzmann†, Deepak Kar†, Roman Kogler†, Christine McLean†, Benjamin Nachman†, Justin Pilot†, Alexander Schmidt†, Nhan Tran†, Caterina Vernieri†, Marcel Vos†, and Emma Winkels†

†University of Sussex, UK
‡University College London, UK
§University of Arizona, USA
¶University Hamburg, Germany
University of Witwatersrand, South Africa
*University of California, Davis, USA
University of California, Lawrence Berkeley National Laboratory, USA
**RWTH Aachen University, Germany
††Fermilab, USA
‡‡IFIC Valencia, Spain

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Abstract

Jet substructure has emerged to play a central role at the Large Hadron Collider (LHC), where it has provided numerous innovative new ways to search for new physics and to probe the Standard Model, particularly in extreme regions of phase space. In this article we focus on a review of the development and use of state-of-the-art jet substructure techniques by the ATLAS and CMS experiments. ALICE and LHCb have been probing fragmentation functions since the start of the LHC [1, 2] and have also recently started studying other jet substructure techniques [3]. It is likely that in the near future all LHC collaborations will make significant use of jet substructure and grooming techniques. Much of the work in this field in recent years has been galvanized by the Boost Workshop Series [4, 5, 6], which continues to inspire fruitful collaborations between experimentalists and theorists. We hope that this review will prove a useful introduction and reference to experimental aspects of jet substructure at the LHC. A companion overview of recent progress in theory and machine learning approaches is given in [7]; the complete review will be submitted to Reviews of Modern Physics.

arXiv:1803.06991

For much more detail about recent advances
Revolts and Revolutions of Jet Substructure

**Big Bang**
c. 2008 BDRS

**Enlightenment**
c. 2012: Boosted measurements and calculations

**Deus Ex Machina**
c. 2016: Machine Learning
obtained with MCFM \[29, 30\] and found to be about 1
minosity times the LO values for the two signal and the
WW, ZZ, Z

Compute jet substructure well in a wide variety of pro-

some \(\hat{R}\) around

the underlying event model was chosen in line with the

yling event, which has been used throughout the sub-

The candidate Higgs jet should have a

order corrections, though further detailed NLO studies

comparing the HERWIG total cross section to \[32\]). This

CTEQ6L \[22\] PDFs.

\[\text{The above results were obtained with HER-}\]

\[\text{leading logarithms.}\]

\[\text{The}\]

\[\text{Jet definition}\]

\[\text{Feasible H \rightarrow bb observation}\]

\[\text{Jets are not monolithic!}\]

\[\text{First modern grooming}\]
The Other Big Bang: c. 2008 CERN

September 19, 2008

Gave experiments one more year to implement analyses

A year of fertile ideas!

arXiv:0912.0033, 0912.1342, 1011.2268, …
of Y-pruning, namely that at high Sudakov suppression. Despite this apparent advantage, one exploits the same double-logarithmic background suppress mass and the resulting pruning radius. It remains of interest.

It would also, of course, be interesting to extend our analysis to other types of method such as template flows, such as pull.

New techniques from theoretical properties

Explicit elimination of non-global logarithms
Explosion of Jet Substructure Calculations!
Deus Ex Machina: c. 2016 Machine Learning

CNN: image recognition

Beats “standard observables”

But not by much…

RNN: natural language processing
What is Machine Learning for Jet Physics?

Canonical problem: Binary Discrimination

Optimal discriminator is likelihood, by Neyman-Pearson lemma

Machine is just a tool to estimate likelihood
What is Machine Learning for Jet Physics?

Why machine learning in jet substructure?

Clear discrimination problems

Well-defined and studied benchmarks

Lots of automated jet tools

Pythia, Herwig, FastJet, …

List of plug-ins to FastJet
What is Machine Learning for Jet Physics?

What is the research strategy?

Find “best” inputs to the machine

What $f$ gives the best approximation of likelihood?
What is Machine Learning for Jet Physics?

What is the research strategy?

Find “best” inputs to the machine

Calo Pixels

Clustering Tree

IRC safe basis

Four-Vectors

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arXiv:1407.5675, 1511.05190, 1603.09349, 1701.08784, 1803.00107, 1501.05968, 1704.02124, 1812.09722, 1702.00748, 1704.08249, 1710.01305, 1712.07124, 1707.08966, 1810.05165, 1807.04769, 1808.08992, 1804.09720, 1808.08979, ...
What is Machine Learning for Jet Physics?

NB: if the function is invertible, all methods must agree

\[
L(p_1, p_2, \ldots, p_n)
\]

\[
\mathcal{L}(p_1, p_2, \ldots, p_n)
\]

**Universal Approximation Theorem:**
A “good” machine can output any function of the input
Machine Learning Interface to Theory

What is the machine learning that we didn’t know?

ML top tagger comparison
Machine Learning Interface to Theory

What is the machine learning that we didn’t know?

Theory-motivated observable benchmark

ML top tagger comparison
Machine Learning Interface to Theory

What is the machine learning that we didn’t know?

Theory-motivated observable benchmark

Gap in performance

Can we understand this?

How much information are we missing?

ML top tagger comparison
What’s Needed for Learning from a Machine

Contributions from many communities:

More theoretical predictions
What performance should we expect?
Does the theoretical likelihood inform the dominant physics for discrimination?

Careful Monte Carlo tuning
Is the machine just learning idiosyncrasies of the simulation?
What is responsible for disagreements between Monte Carlos?

Unsupervised learning
What if we don’t know what each event/jet is?
Can we directly machine learn on data, with no simulation?

Do we have a theoretical model of a neural network?

arXiv:1702.00414, 1708.02949, 1804.09720, …
arXiv:1710.06570, …