COS 424 Final Project: Machine Learning in Physics

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Machine Learning in Statistical Physics

The Ising Model

- binary “spin” degrees of freedom on a 2-d square lattice
- two phases (ferro- and para-magnetic) and a critical point

$$H(\vec{s}) = -\sum_{\langle i_1 i_2 \rangle} s_{i_1} s_{i_2} \qquad p^{\text{Ising}}(\vec{s}) \propto \exp\left(-\frac{H(\vec{s})}{T}\right)$$

$$\begin{array}{cccc} \downarrow & \downarrow & \downarrow & \downarrow \\ \downarrow & \downarrow & \downarrow & \downarrow \\ \downarrow & \downarrow & \downarrow & \downarrow \\ \downarrow & \downarrow & \downarrow & \downarrow \end{array} \qquad\qquad \begin{array}{cccc} \uparrow & \downarrow & \uparrow & \downarrow \\ \downarrow & \downarrow & \uparrow & \downarrow \\ \uparrow & \downarrow & \downarrow & \uparrow \\ \uparrow & \uparrow & \downarrow & \downarrow \end{array}$$

Onsager (1944)

Sampling (S) and Phase-Discovery (P) Tasks

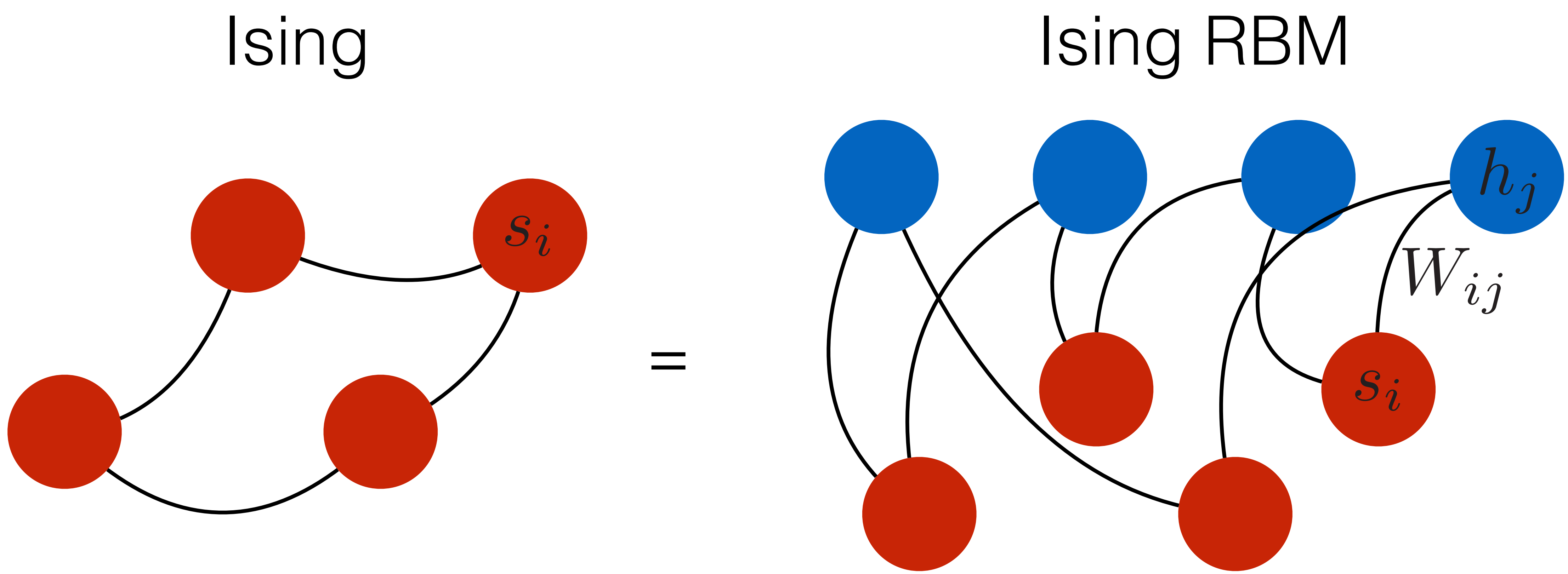
- physics problem: sample spin configurations from the thermal distribution
- machine learning method: find a generative model whose probability distribution is the thermal Ising distribution and sample that
- physics problem: identify phases and critical points from configurations
- machine learning method: unsupervised pattern recognition

Wang (2017)
van Nieuwenburg et al. (2017)

(S)

Ising RBM

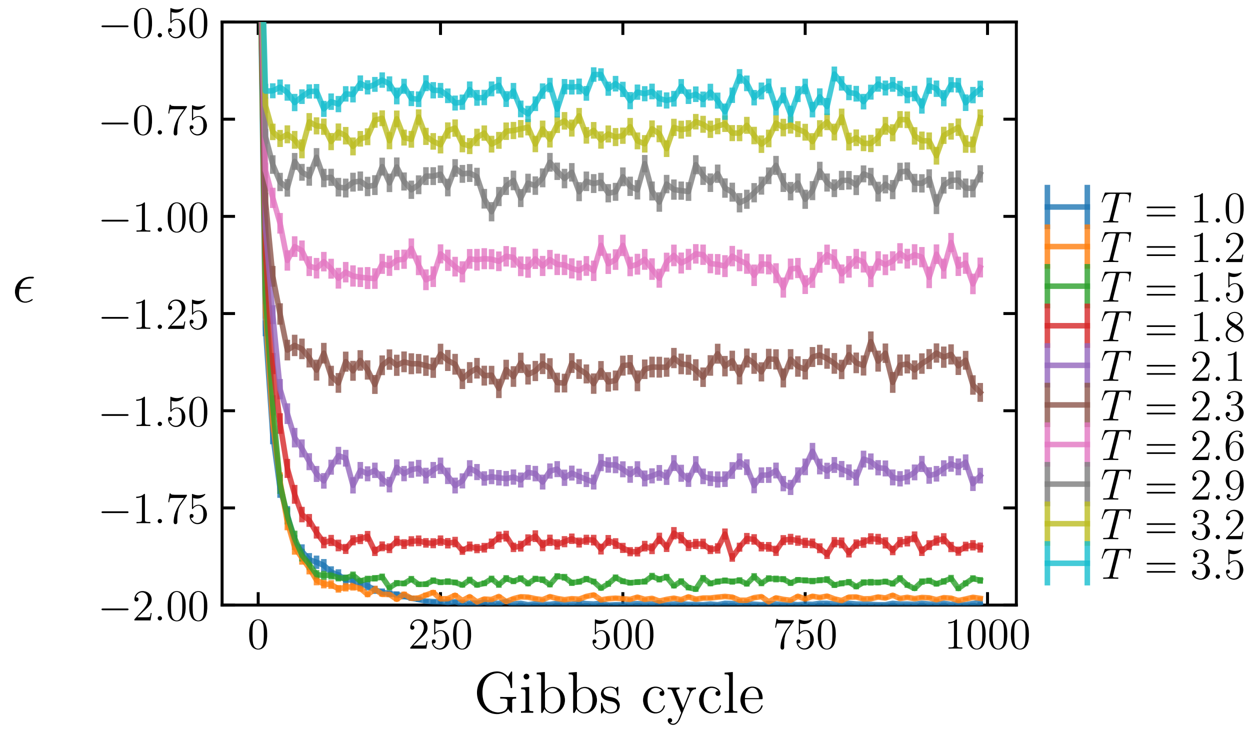
- an RBM is a bipartite undirected graphical model with hidden variables $$p_W^{RBM}(\vec{s},\vec{h}) \propto \exp\left(\vec{h}\cdot W\vec{s}\right)$$
- can solve for parameters in $$\sum_{\vec{h}} p_W^{\mathrm{RBM}}(\vec{s},\vec{h}) = p^{\mathrm{Ising}}(\vec{s})$$

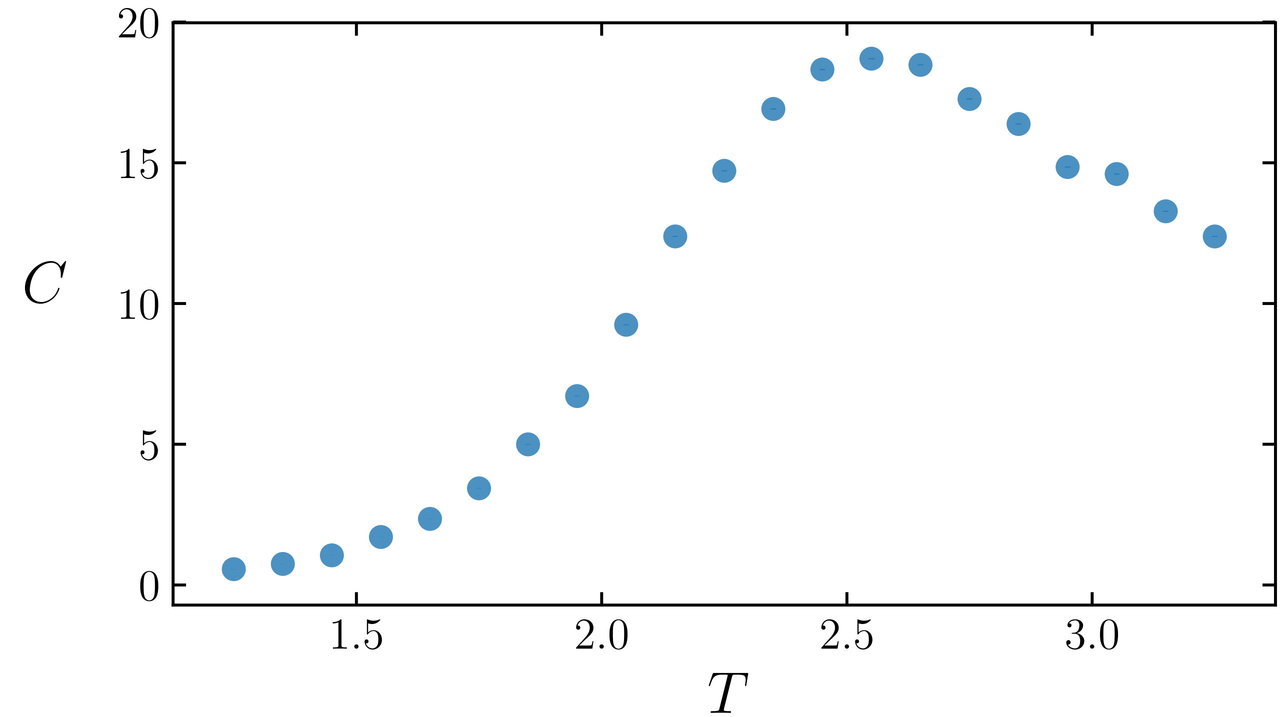


(S)

Burn-in and Heat Capacity

- can efficiently sample Ising RBM with block Gibbs sampling due to bipartite graph





Torlai et al. (2016)

(P)

“Learning by Confusion”

- $\vec{s}, T$ for various temperatures (generated by sampling Ising RBM)

- algorithm:

    1. choose T_p and set labels $y(T) = \mathrm{int}(T < T_p)$

    2. train classifier on $(\vec{s}, y)$

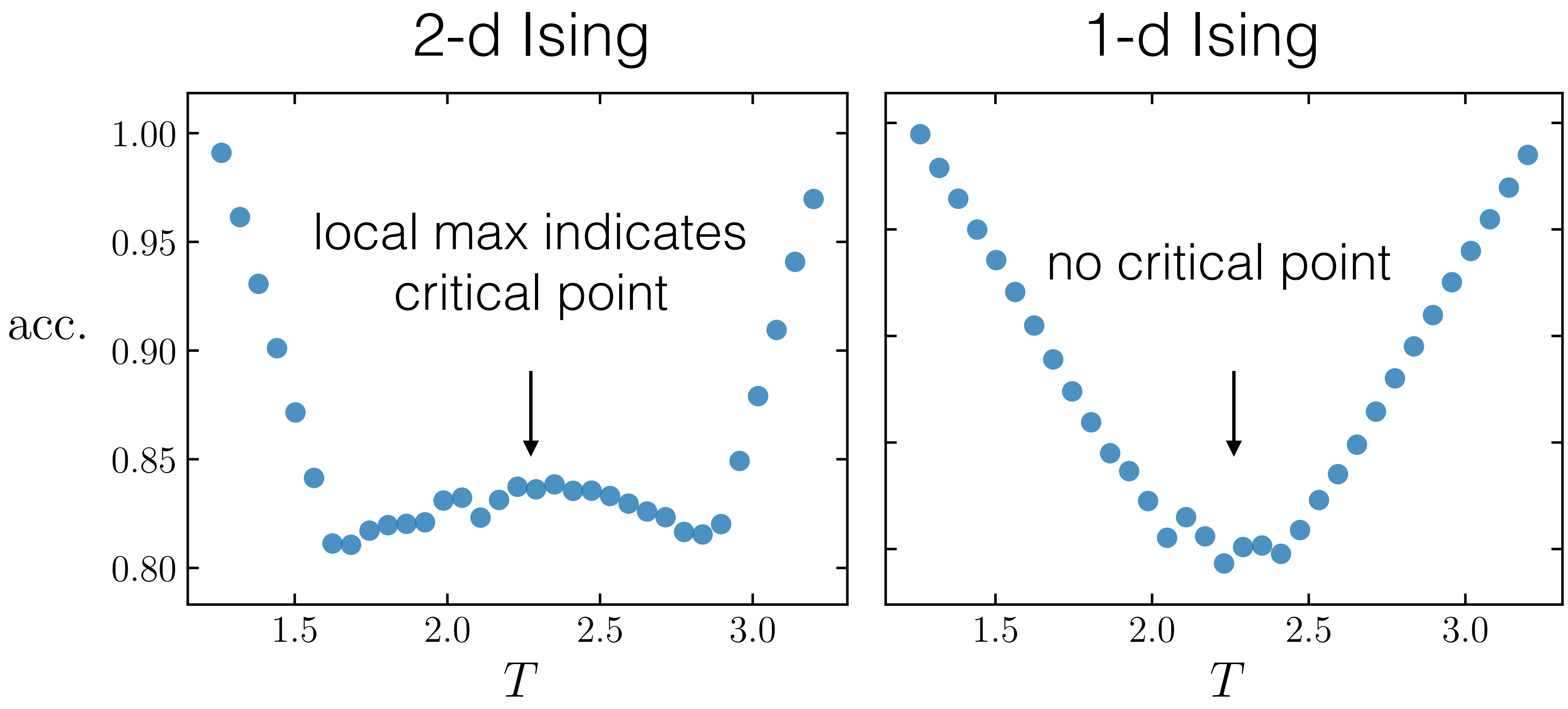
    3. compute accuracy measure of trained classifier

    4. repeat for a range of T_p and record accuracies

van Nieuwenburg et al. (2017)

(P)

Rediscovering the Ising Critical Point



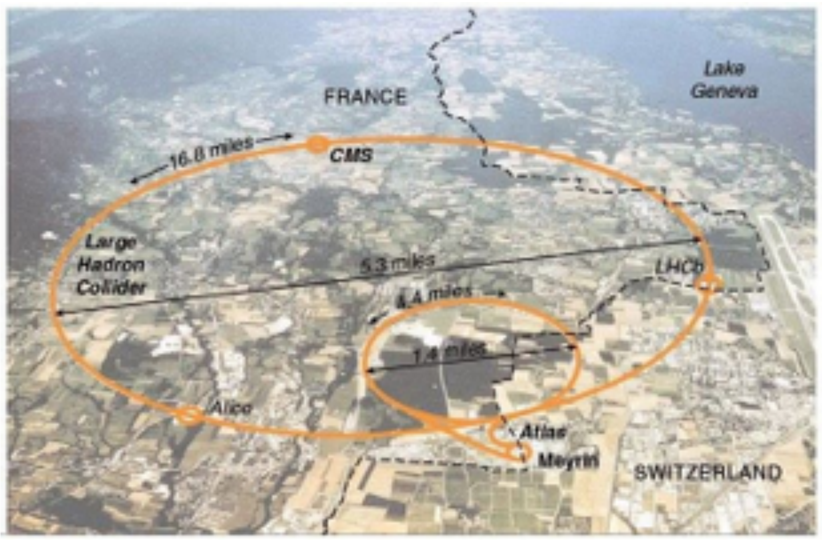
Machine Learning in Particle Physics

Overview

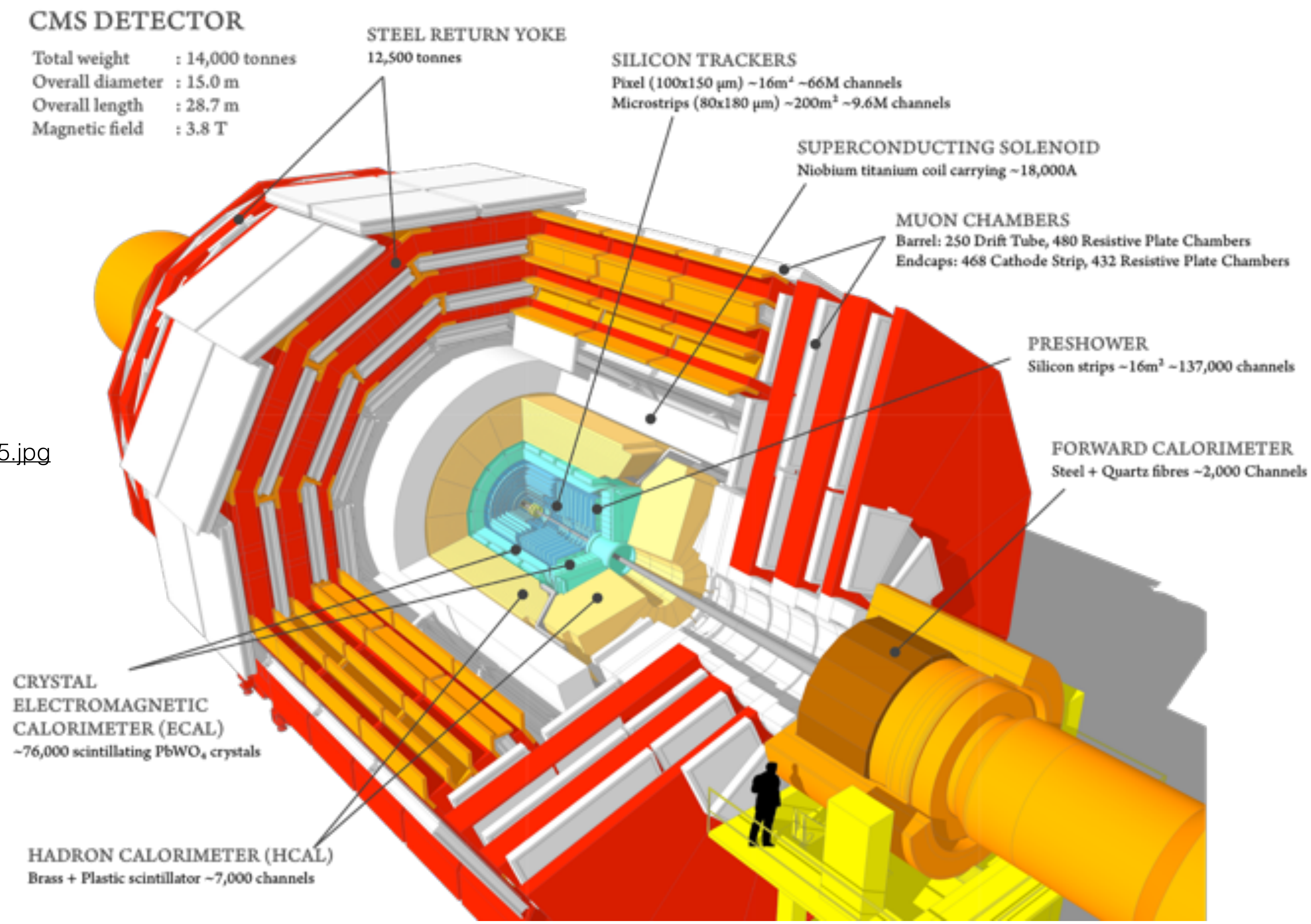
- Goal: Use supervised machine learning to classify particle collisions at the LHC
- Discriminate proposed signal events from background events using Monte Carlo data from the Compact Muon Solenoid Experiment
- Signal: $h \rightarrow aa \rightarrow 4b$, hypothetical 'a' has 60 GeV mass
- Background: Anything that produces 4 b-like particles
- Construct helpful discriminating features via physical principles
- Evaluate neural nets with ROC curve and search significance

Curtin et al. (2014)

LHC and CMS Detector



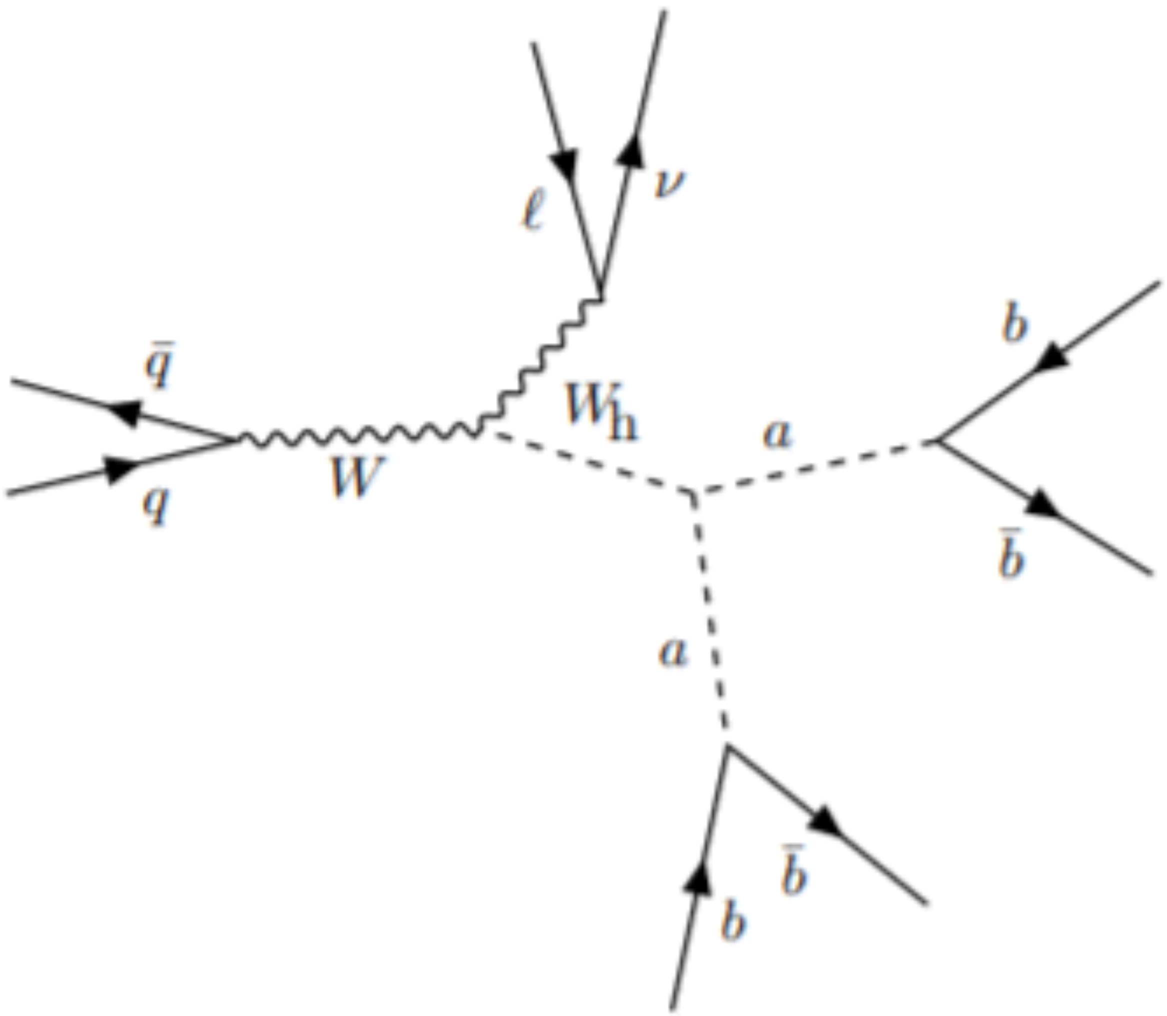
http://www.extremetech.com/wp-content/uploads/2015/07/lhc-5.jpg



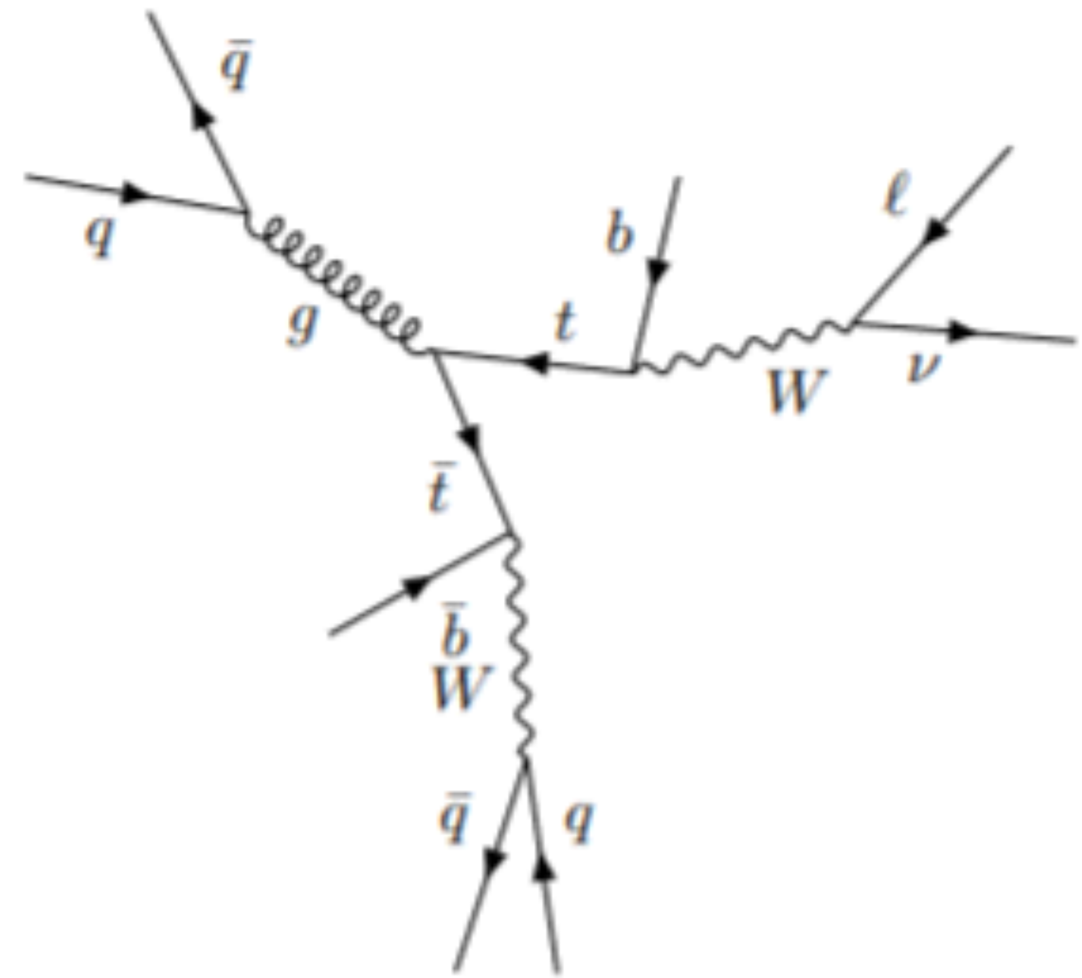
https://cms.cern/news/cms-detector-design

Chatrchyan et al. (2008)

Signal and Background



h→aa→4b

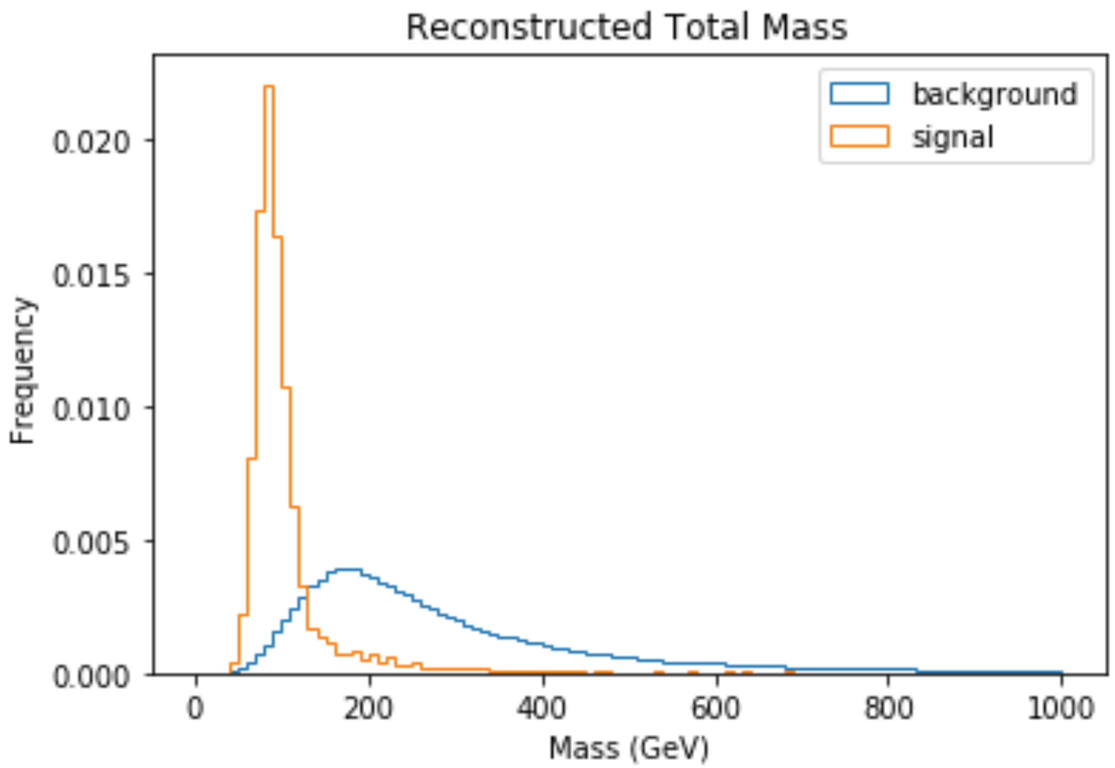


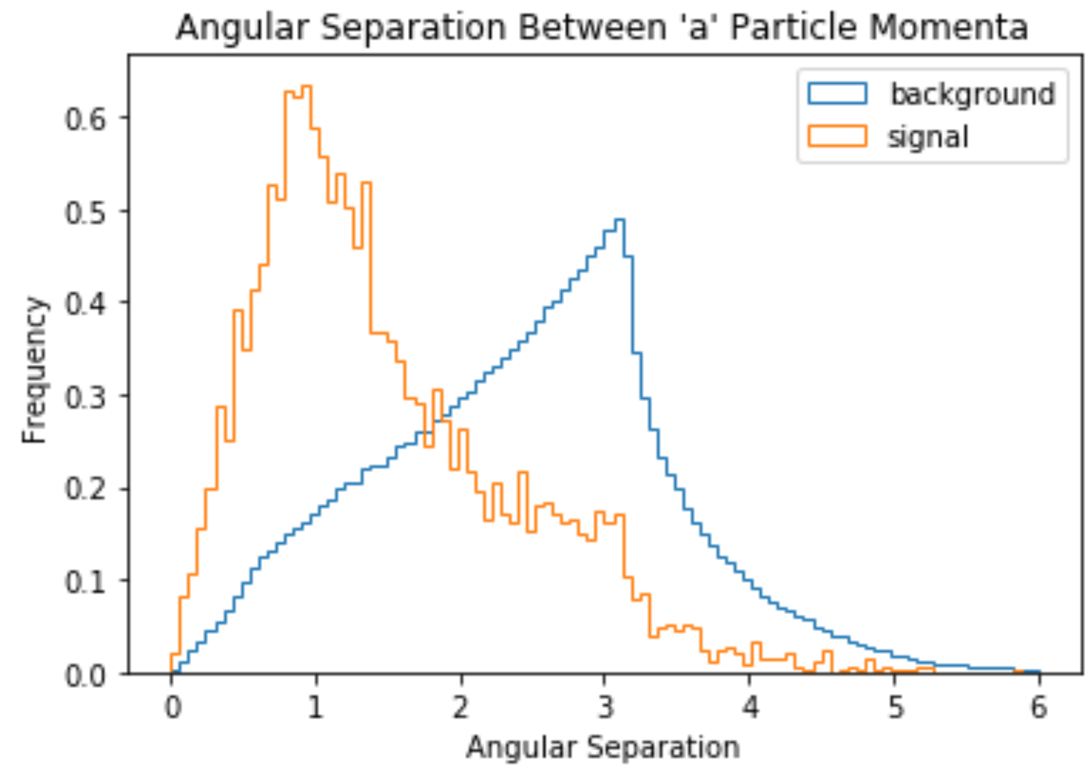
tt background

Data

- Training on 770,000 Monte Carlo Events with 20 features
- Four jets, each with:
    - Momentum
    - Angular Location (eta,phi)
    - mass
    - b-tag
- Evaluating performance on equal-sized dataset
    - Plenty of training data, good convergence, accurate evaluation important

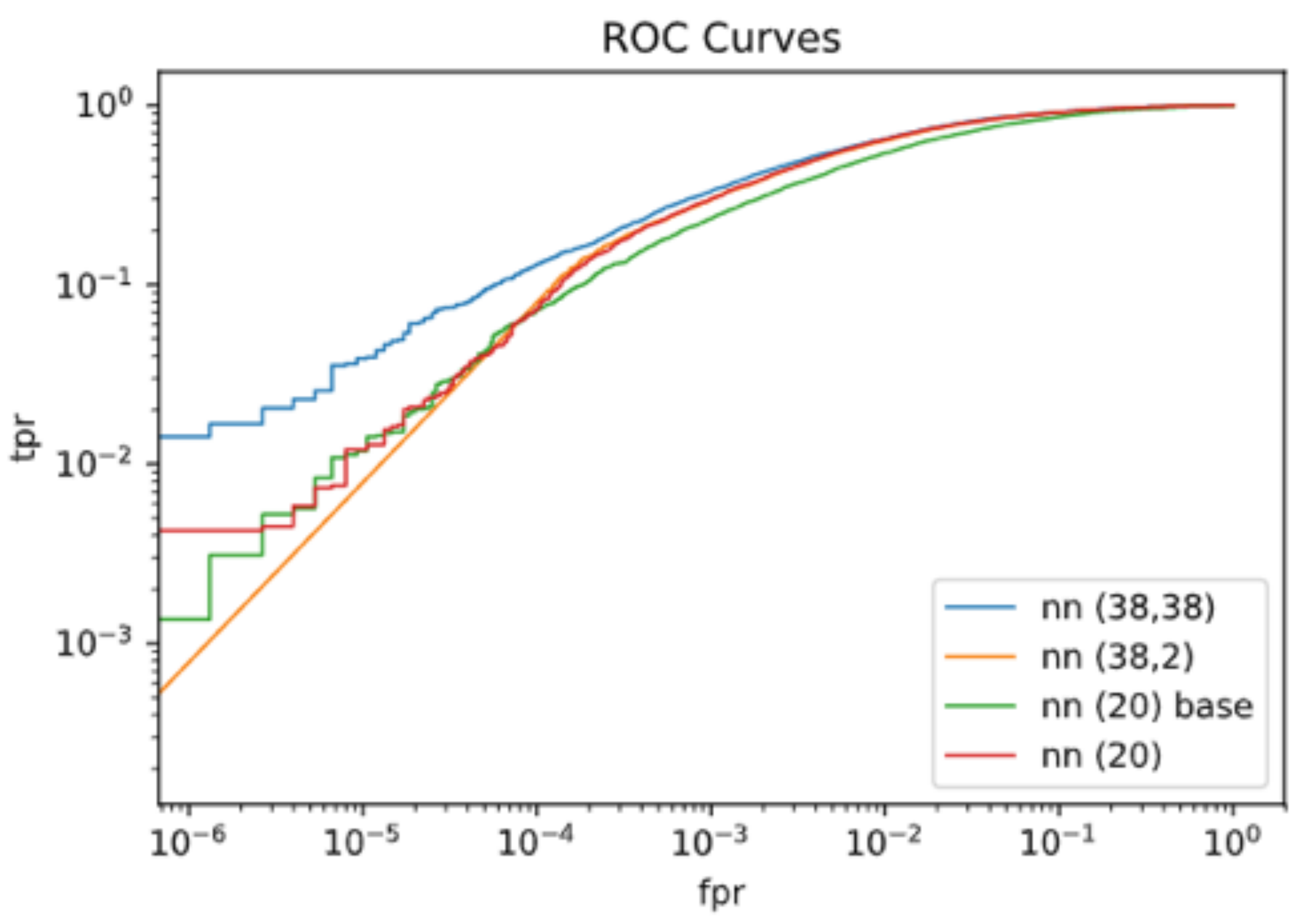
Constructing Discriminating Features

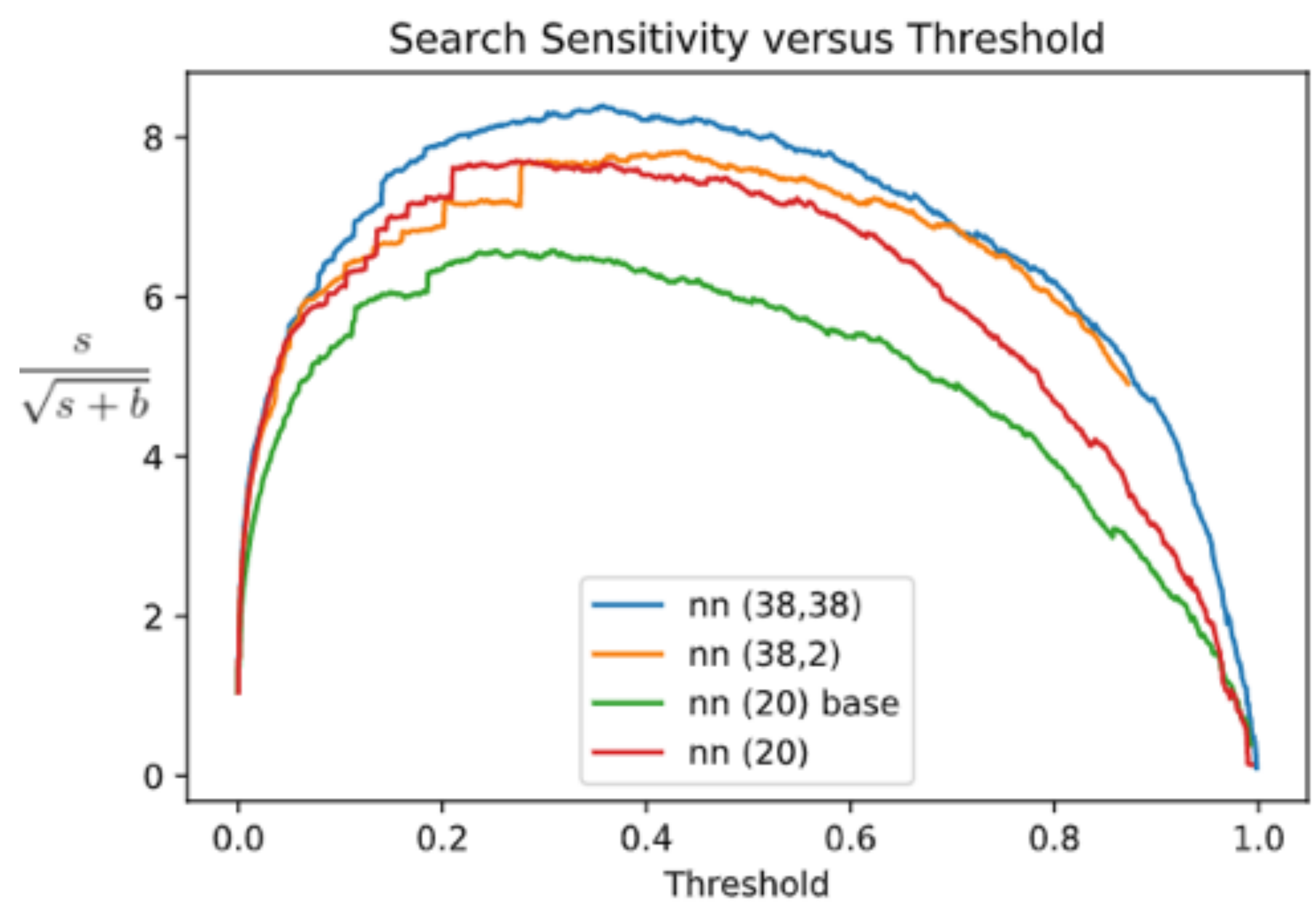




- Other constructed features: Higgs momentum, position, ‘a’ momentum, angular position, mass, b jet angular separation, scalar momentum sum, top mass: now 37 features

Evaluation





Read (2000)