Presentation draft

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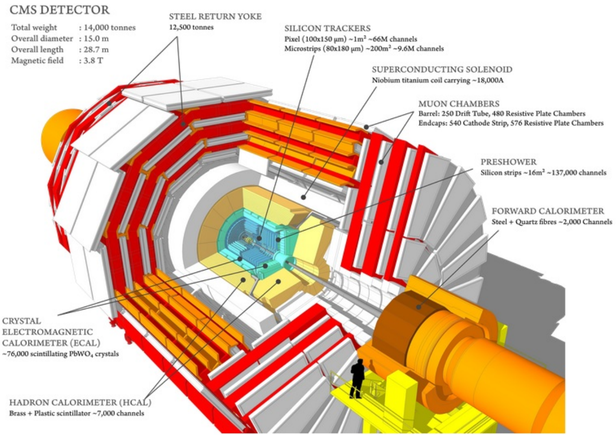
The CMS Experiment overview

The CMS detector at the LHC



Coordinates at the CMS

Given the solenoid geometry of the CMS detector, it is more convenient to use a spherical type of coordinates(r, ϕ, θ).

$$\begin{aligned} p_x &= P_T \cos\phi \\ p_y &= P_T \sin\phi \\ p_z &= P_T \sinh\eta \\ |\vec{P}| &= P_T \cosh\eta \end{aligned} \tag{1}$$

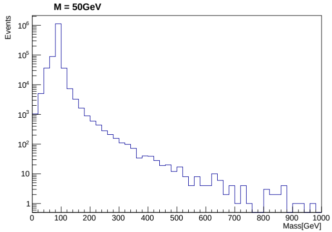
$\phi \in [0, 2\pi]$the azimuthal angle, and $\eta \in [-\infty, +\infty]$ is defined as:

$$\eta \equiv -\ln\left[\tan\left(\frac{\theta}{2}\right)\right] \tag{2}$$

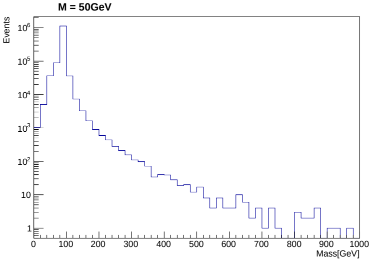
Decays & Resonances

Not every particle can be detected by the CMS detector(i.e neutrinos)

- Detectable Decay Products $\rightarrow$ Resonance



- Non Detectable Decay Products $\rightarrow$ Not a resonance



Calibration and energy scale uncertainties

- Calibration process adjusts energy scale and resolution to match well-known resonances (Z boson, J/psi meson) in data and simulation,
- Imperfect agreement due to subdetector complexities and nonlinear effects

How do analysis techniques respond to energy scale uncertainties ?

Our work will focus on the effects that energy scale uncertainties have, on a traditional fit-based analysis and a more modern Boosted Decision Tree-based analysis, using the generic diobject production process as the working example.

BDT 1: Supervised Learning

Supervised learning:

- The model is trained using training data
- The trained model is tested using testing data
- If we like the resulting model, we apply it!

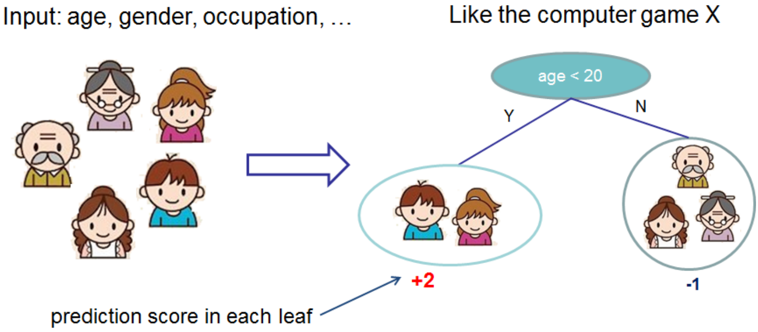
but what is this model?

- A function that given the input feautres x, it returns the probability x beeing class A
- The goal of the training is to minimize the difference between the predicted output $y_i \in [0, 1]$ and the real output $\hat{y}_i = 0$ class B, or $\hat{y}_i = 1$ class A

BDT 2a: Boosted decision trees

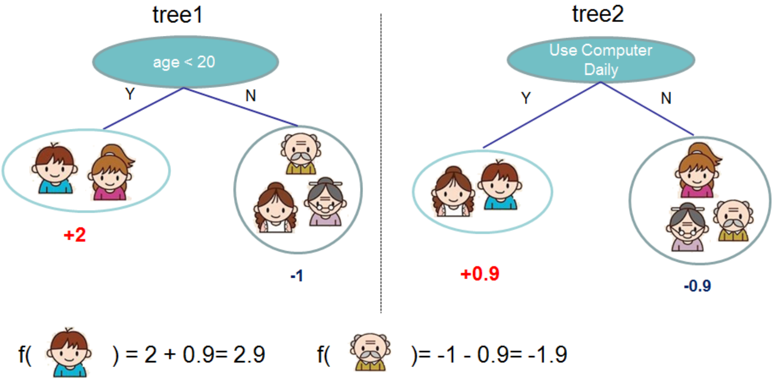
In this study the model of choice is Boosted Decision Trees(BDT).

- It classifies data using decision tree models



BDT 2b: Boosted Decision Trees

Usually only one tree is not power full enough –> Use more trees in additive manner(Boosting)



BDT 3a: Signal from Background Separation

In our case:

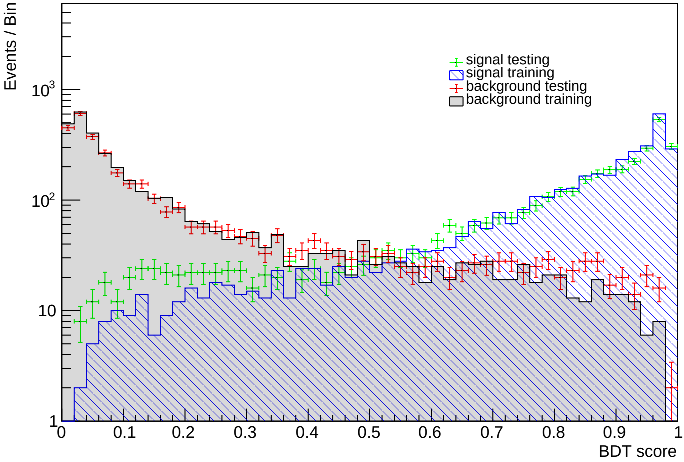
- Signal: a resonant decay Y->xx
- Background: a non resonant process

How to separate them?

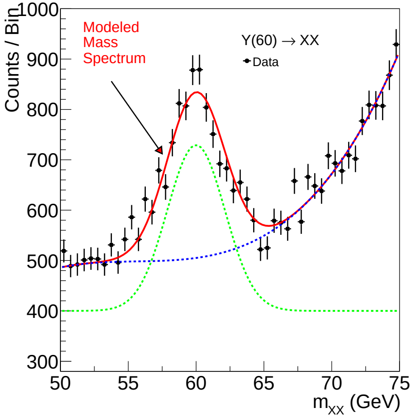
- Plot the number of Signal and Background events per BDT score –> BDT histogram

BDT 3b: Signal from background separation

Where should we place the cut in order to accpet most most of the signal while rejecting most of background?

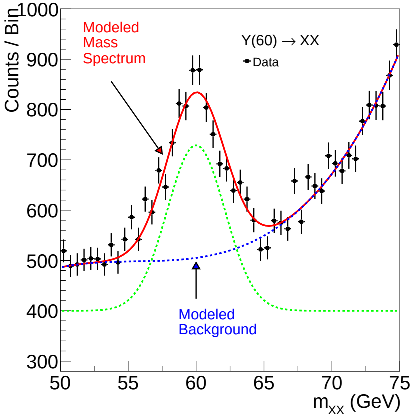


Fit the mass spectrum . . .



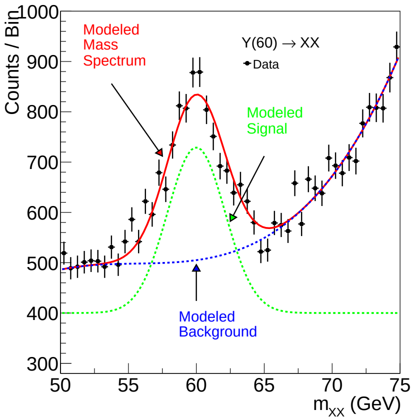
Fit based signal from background separation

. . . and decompose it to a background component . . .



Fit based signal from background separation

. . . and a signal component



Fit based signal from background separation

Then we can count the signal and background events, in a region of interest I:

$$O = \int_I observation(x)dx \tag{3}$$

$$B = \int_I bkg(x)dx \tag{4}$$

$$S = O - B \tag{5}$$

Statistical interpretation of results

Are the signal events we counted, statistically significant?

- We use the following metric:

$$\text{Significance} = \frac{Signal}{\sqrt{Background}} \tag{6}$$

- The selected regions of interest both in BDT and Fit based analysis, are those that maximize the significance.

Searches for $Y \to XX$

Search for heavy $Y \to XX$

- Mass range from 100GeV up to 300GeV

Search for light $Y \to XX$

- Mass range from 50GeV up to 70GeV

The $Y \to XX$ channel

The specific characteristics(mass etc.) of each dataset is different but the main idea is the same

- Use a non resonant process for background
- Use a resonant process for signal
- Separate signal from background
- Apply energy scale uncertainties to signal
- Separate again
- Compare the nominal case with the smeared cases

The $Y \to XX$ channel: Background

- Drell-Yan process

The $Y \to XX$ channel: Signal

- W Φ –> ll

Energy scale uncertainties

To smear the data by $x\%$,

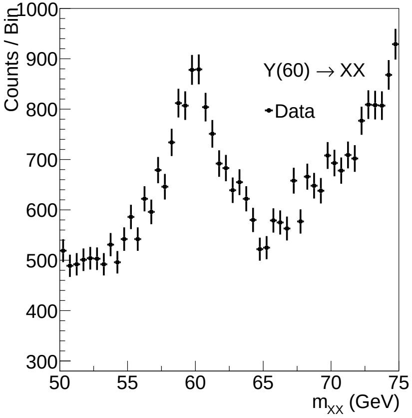
- iterate over every signal event
- multiply each P_T by a number sampled from a Gaussian distribution of $\mu = 1$ and $\sigma = x/100$

Search for light $Y \rightarrow XX$

We will study the following smearing cases:

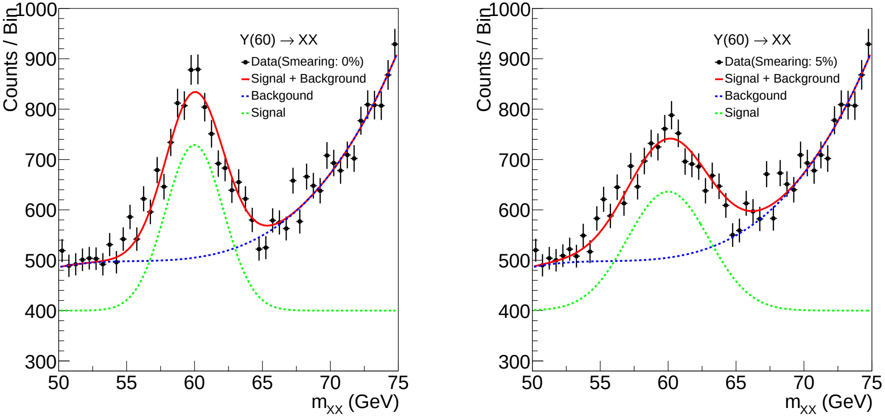
- 0%(Nominal case)
- 5%
- 7%
- 10%
- 12%

The working mass range is quite small –> smearing has a significant effect real quick



Fit based approach: Fitting

Then we proceed with the fits!



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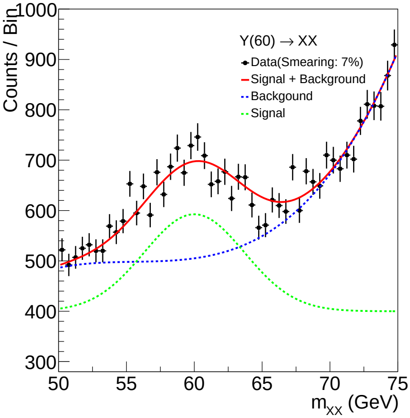
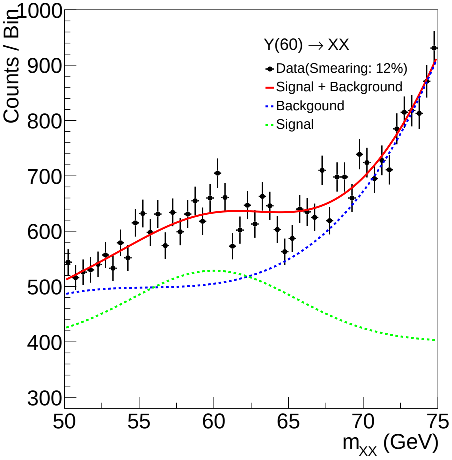


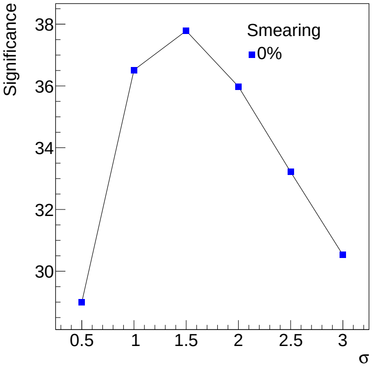
Fit based approach: Fitting

Any further smearing will make the signal indistiguishable!



Fit based approach: Signal from background separation

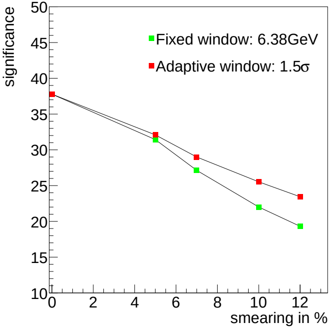
Working in the nominal case, we find the region that yields the best significance, by scanning the ranges $m = \pm\frac{n}{2}\sigma$, $n = 1, 2, 3, 4, 5, 6$



Fit based approach: Signal from background separation

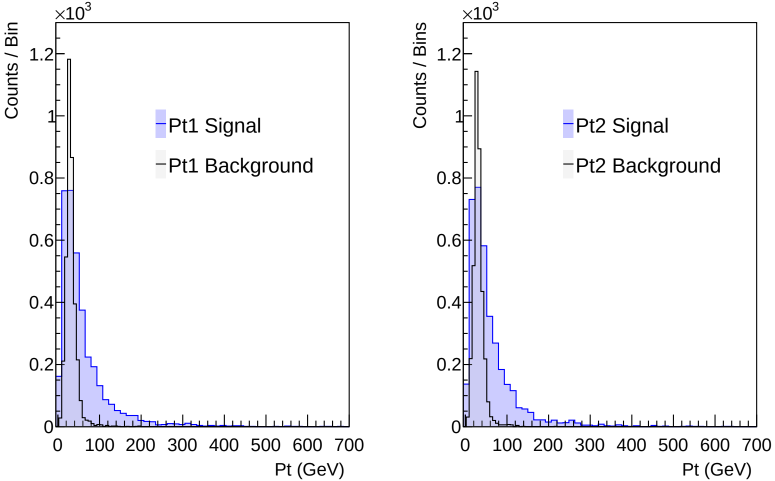
The region of interest that yields the best significance is the $\pm 1.5\sigma$. There are two ways to interpret this.

- interpret σ as the the spread of the nominal case –> fixed window
- interpret σ as the the spread of each cases –> adaptive window

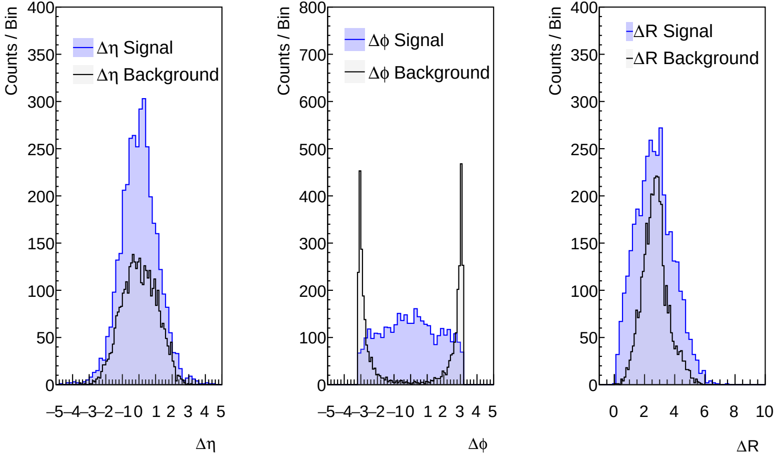


BDT approach: Feature space

What features of the dataset are best for the classification task?

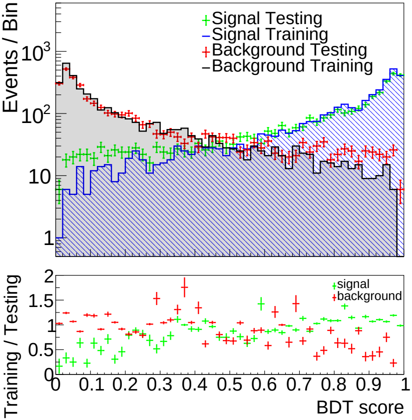


BDT approach: Feature space



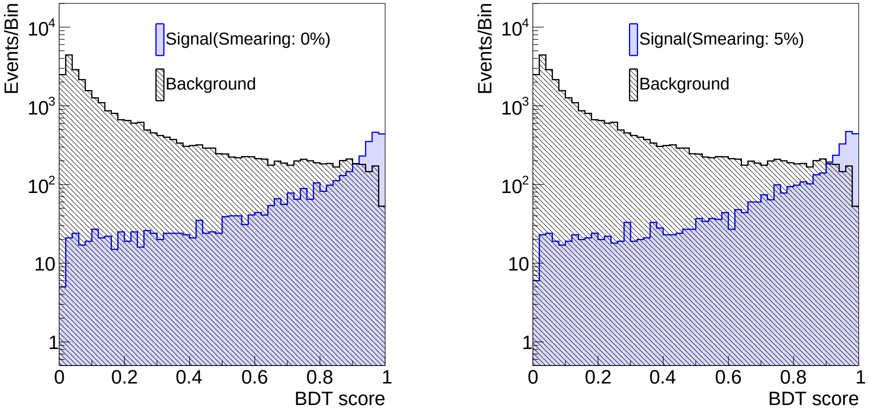
BDT approach: The model

- Trained with approximately 3K events
- To examine overfitting we compare the ratio of training events to testing for each bdt score



BDT approach: Application

Feed the application set to the BDT –> BDT plots



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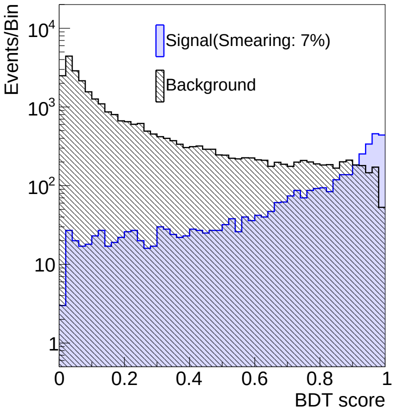

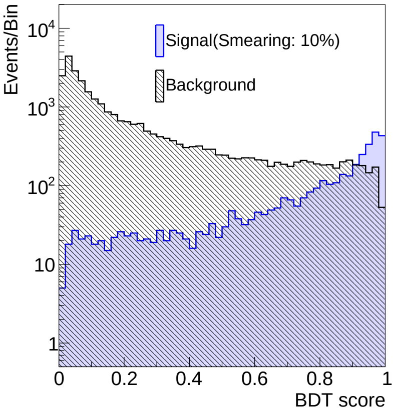

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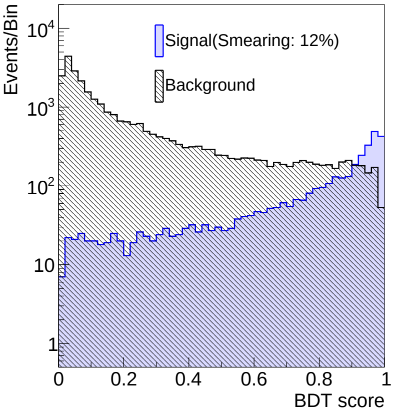
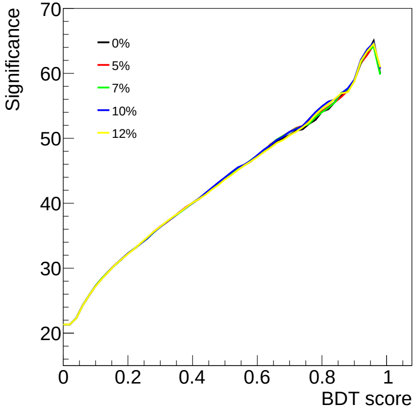


BDT approach: Signal from background separation

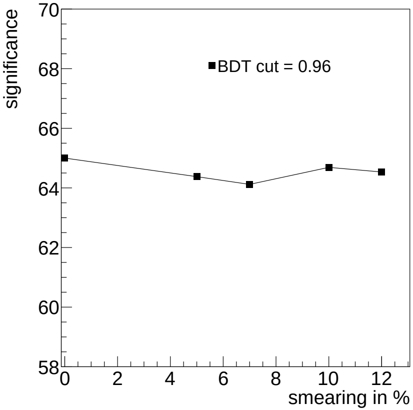
Where should we place the cut?

- Same philosophy as in the fit based search
- We scan the bdt range to find the best region of interest
- Best cut –> BDT score = 0.96.



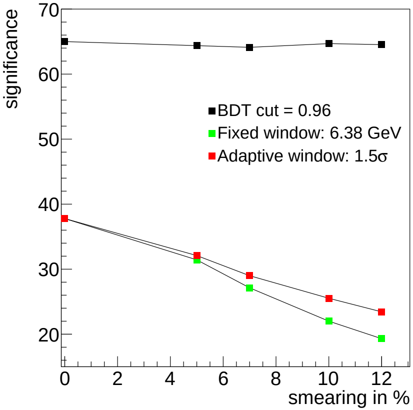
BDT approach: Signal from background separation

- The performance of the BDT remains invariant under energy scale uncertainties!



Synopsis

- BDT performs better than the fit based
- Remains invariant under smearing
- Performance of the fit drops



Search for heavy $Y \to XX$

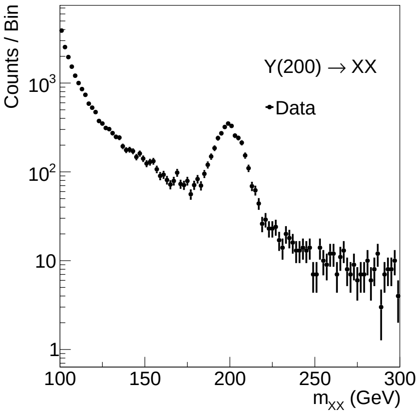
We will study the following smearing cases:

Medium to extreme cases

- 0%(Nominal case)
- 5%
- 10%
- 15%
- 20%

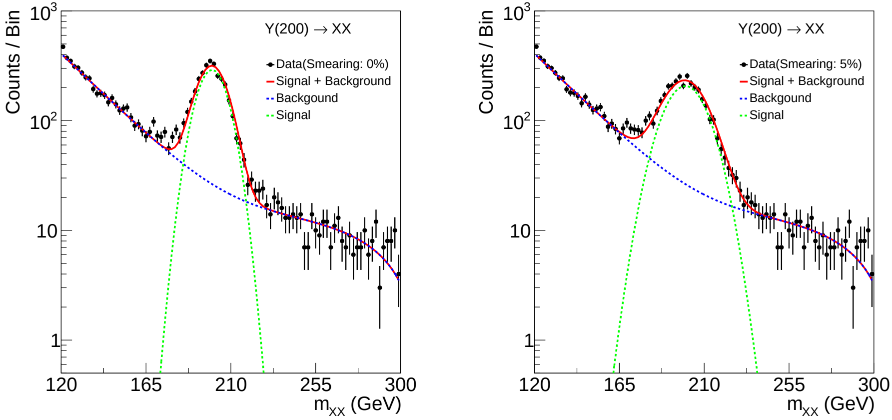
Plus some really extreme cases

- 30%
- 40%
- 50%



Fit based approach: Signal Fitting

Then we proceed and fit the signal



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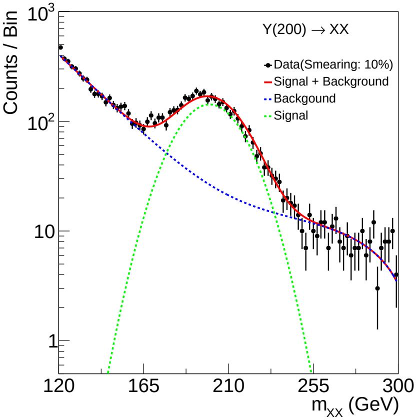

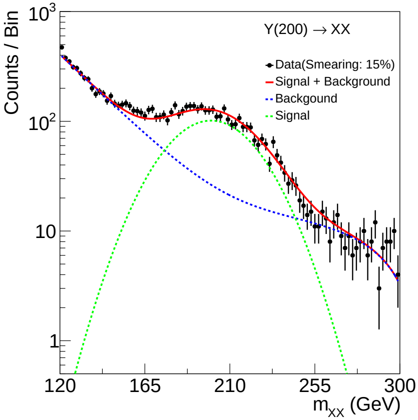

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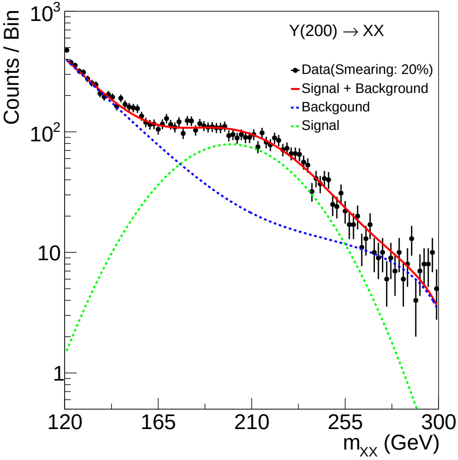

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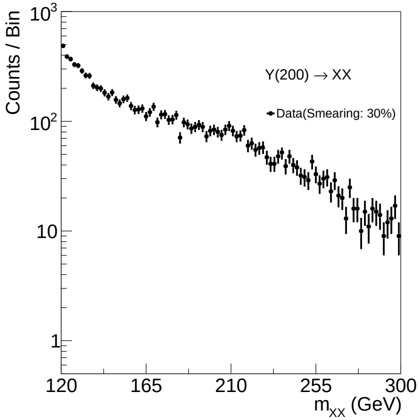

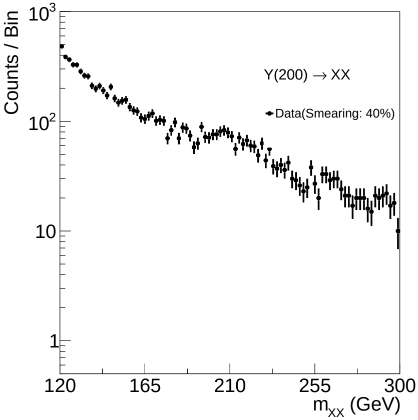

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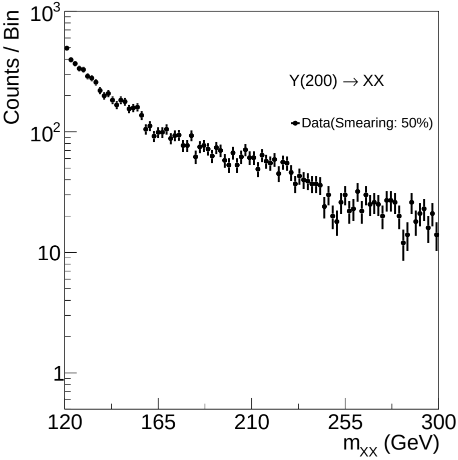

Fit based approach: Signal from background separation

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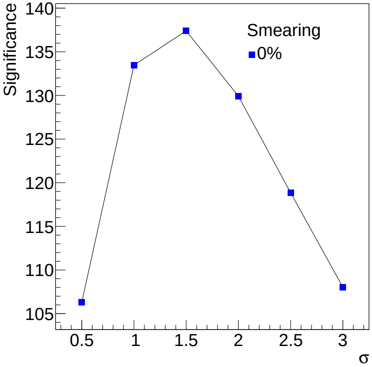
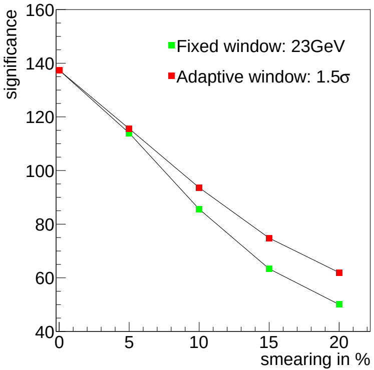


Fit based approach: Signal from background separation

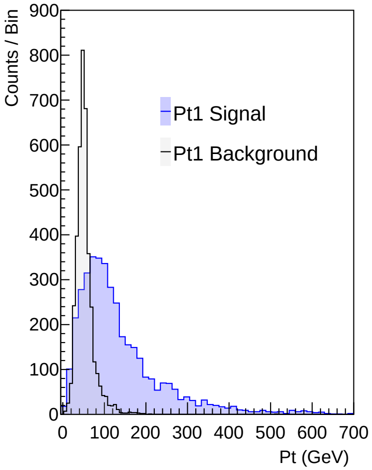
The best significance is in the $\pm 1.5\sigma$ range.

- fixed window
- adaptive window

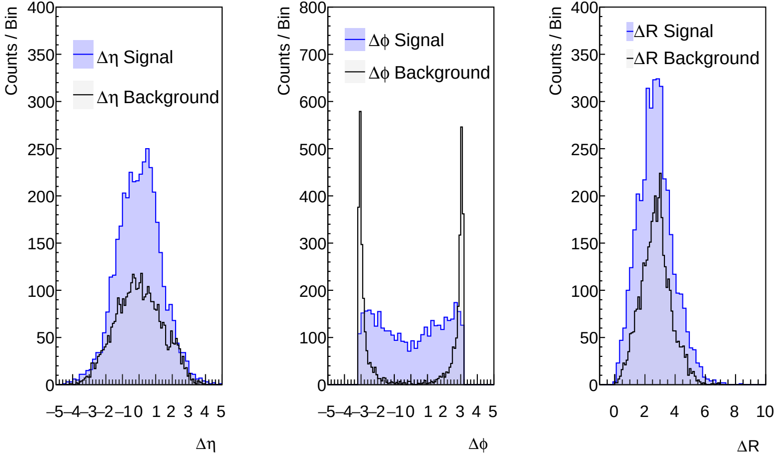


BDT approach: Feature space

We use the same feature space as with the light mass search



BDT approach: Feature space



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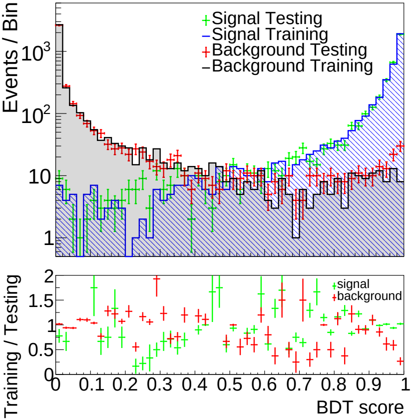
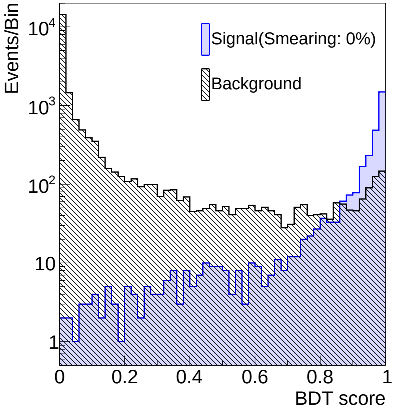
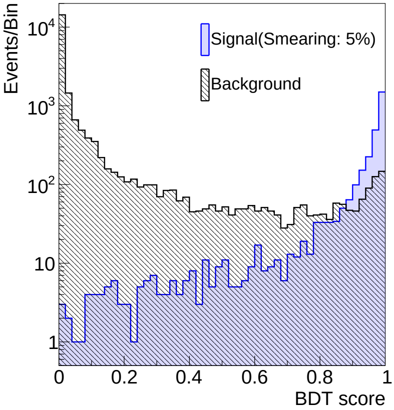


BDT approach: Application

Feed the application set to the BDT –> BDT plots





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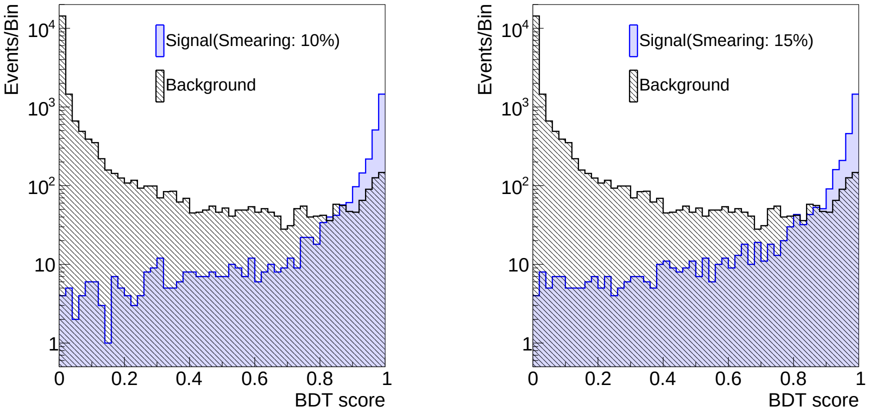

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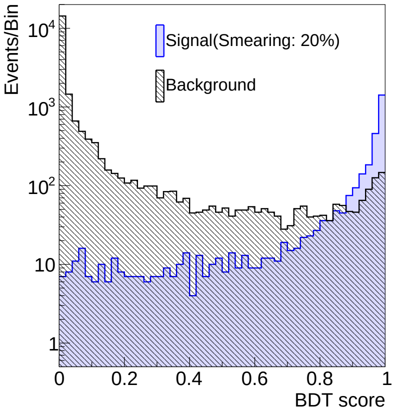
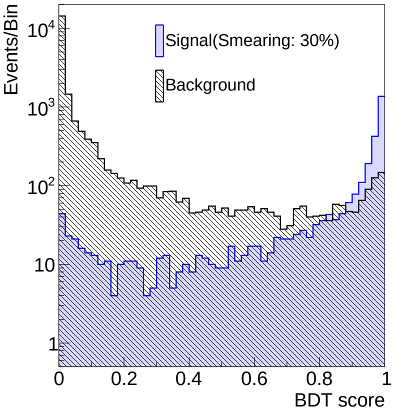
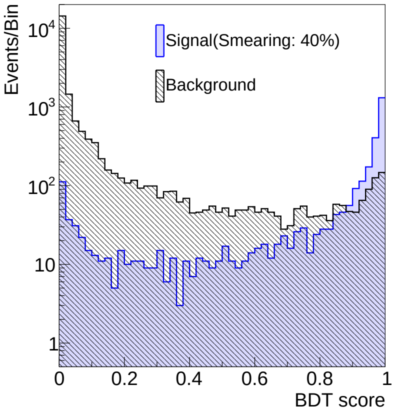
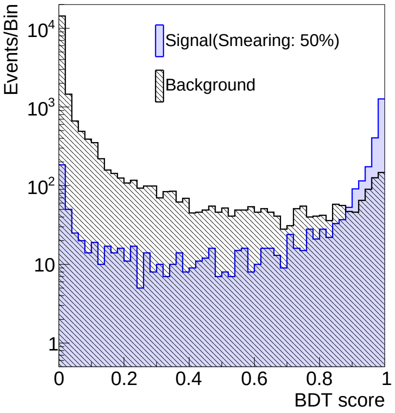




BDT approach: Application

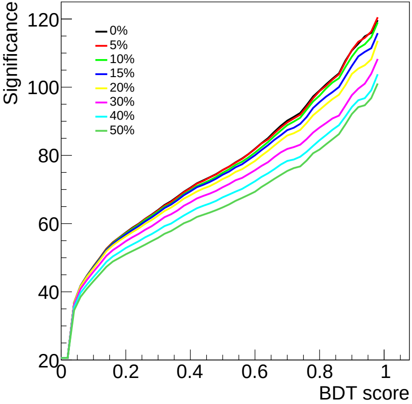




BDT approach: Signal from background separation

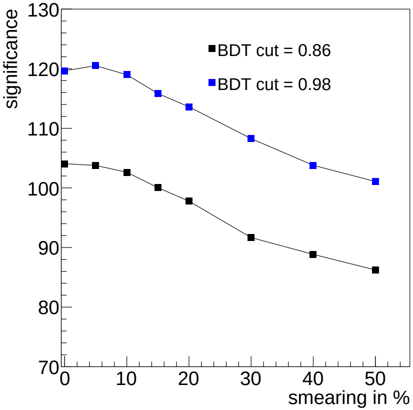
Where should we place the cut?

- We scan the whole bdt range to find the best region of interest
- Best cut –> BDT score = 0.98.
- This is rather tight, lets see what happens if we place a more relaxed cut at 0.86



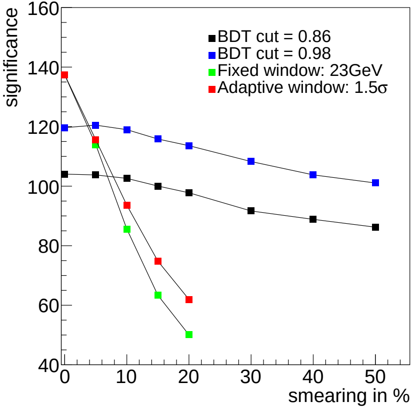
BDT approach: Signal from background separation

- The performance of the more relaxed cut is not as good as the best cut
- The bdt model is rather robust



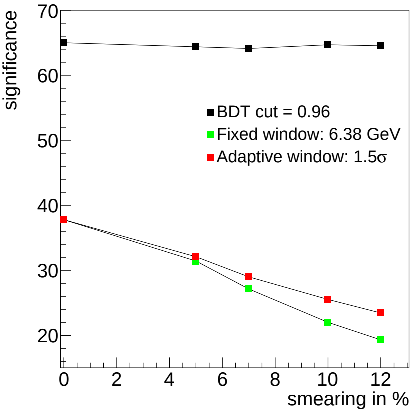
Synopsis

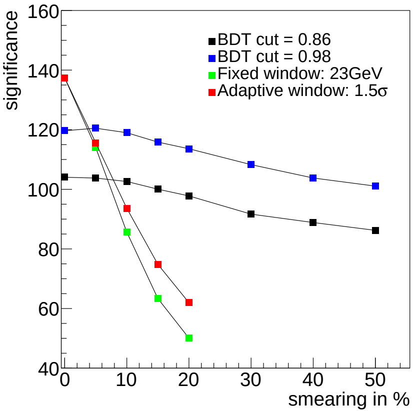
- The perfomance of the BDT and Fit are comparable when smeaing is mild
- Fit perfomance drops dramatically
- BDT is more robust



Results

- Light $Y \to XX$
- Heavy $Y \to XX$





Results

Overall, the BDT is more robust as it learns features that do not get affected by energy scale uncertainties

So is the BDT better?

- No: A more carefull event selection can improve the performance of the fit based analysis
- yes: In the presence of energy scale uncertainties, the fit based analysis reaches a "breaking point"

Unused stuff

Welcome to the backup slides!

Search for light $Y \to XX$

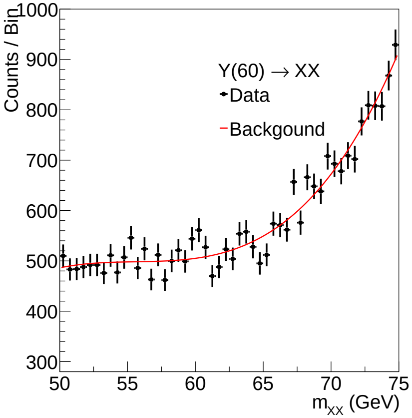
We will study the following smearing cases:

- 0%(Nominal case)
- 5%
- 7%
- 10%
- 12%

The working mass range is quite small –> smearing has a significant effect real quick

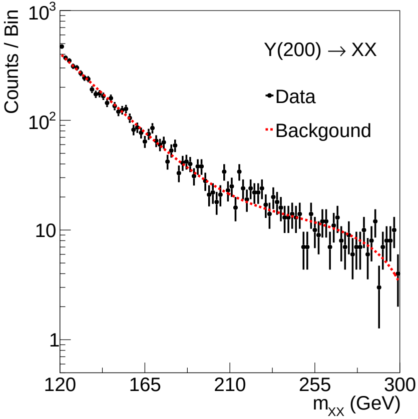
Fit based approach: Background Fitting light

- To simplify things a bit, we fit the background sepratelly
- The background shape is kept constant throughout the fits
- Shape: $\alpha + \beta x + \gamma x^2 + \delta x^3$



Fit based approach: Background Fitting

- The background shape is kept constant
- Shape: $\alpha + \beta x^{-1/2} + \gamma x^{-1} + \delta x^{3/2}$



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