Improved $e^+e^- \to \Lambda\bar{\Lambda}$ Selection with Neural Networks

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Outline

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- **Motivation**
- Neural Network
- Consistency and Systematics Checks
- Prospects
- Summary

ElectroMagnetic Form Factors (EMFFs)

Spin $1/2$ **baryons:**

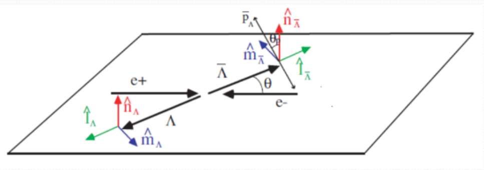
- Two independent EMFFs: $G_E(s)$, $G_M(s)$

  ($s = q^2$, four-momentum transfer)

- In time-like region: Complex, with rel. phase $\Delta\Phi(s)$

$$\frac{d\sigma_{Born}(q^2)}{d\cos\theta} = \frac{2\pi\alpha^2\beta}{4q^2}[(1+\cos^2\theta) + \frac{1}{\tau}R^2(\sin^2\theta)],$$

$$\cos\theta = \hat{p}\cdot\hat{k}$$



Aim of this Study

Study $e^+e^- \to \Lambda\bar{\Lambda}$ at 2.396-2.9 GeV and measure:

- Cross section
- $R = |G_E/G_M|$
- $\Delta\Phi$?

The Method:

- Select events with:
  - Exactly one Λ candidate
  - No $\bar{\Lambda}$ in acceptance.
- Can have three stat. independent samples:
  - Only Λ tagged
  - Only $\bar{\Lambda}$ tagged
  - Both Λ and $\bar{\Lambda}$ tagged (Done at 2.396 arXiv:1903.09421)
- Improve precision by combining samples

Data Sample

Highest statistics points of R-Scan sample:

E_{cm} [GeV]	Integrated Luminosity [pb^{-1}]
2.3864	$22.588 \pm 0.010 \pm 0.174$
2.396	$66.893 \pm 0.017 \pm 0.462$
2.6444	$33.650 \pm 0.013 \pm 0.209$
2.6464	$34.064 \pm 0.013 \pm 0.276$
2.9	$105.53 \pm 0.025 \pm 0.897$

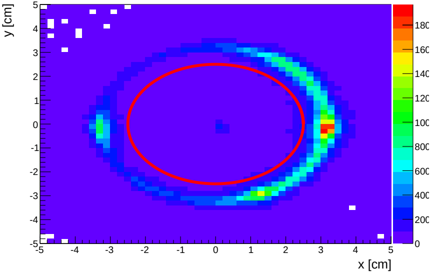
Two points at 2.64 GeV analysed together.

MC samples:

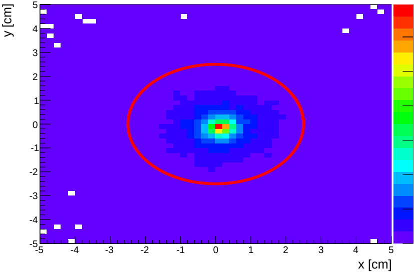
- 50M PHSP at each energy
- 1M ConExc (Angles+ISR) at each energy
- 10M "mDIY" (Angles) at each energy

Beam Pipe Background

- Λ-vertex distribution shows background from beam pipe.
- Background not described by MC
- Naive solution is a vertex cut (red circle)
  - → Risk losing signal. Can one do better?



(a) Data



(b) Signal MC

What can we do?

Typical Procedure:

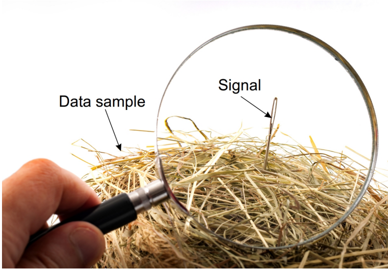
1. Model background
2. Find useful patterns "by eye"

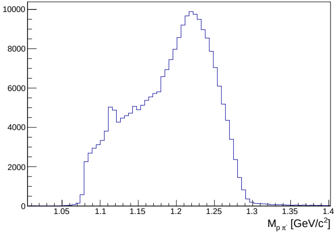
However:

- Background is right there in the data.

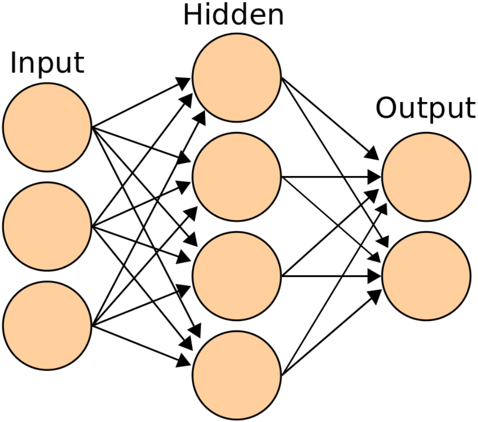
→ Not necessary to model it!

→ Find patterns with machine learning





Artifical Neural Networks



Hidden layer: $H = \mathbf{W}\bar{y} + \bar{b}$,

Activation Function: $f(H) = max(0, H)$

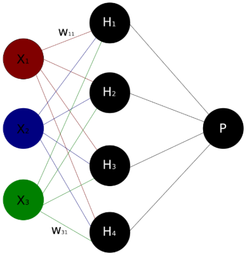
Bayesian Neural Networks

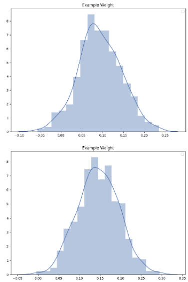
How are they different?

- Approximate posterior distribution of weights given data
  - $\rightarrow$ Weights are distributions, not fixed numbers
  - $\rightarrow$ Sample from distributions to evaluate model

Advantages:

- Ensemble model. Combats overfitting
- Can assign uncertainties to predictions





Neural Network: Implementation, Training and Input

Software: (Originally by project students T. Littau and T. Nordahl)

- TensorFlow with Keras in Python
- pyROOT

Training:

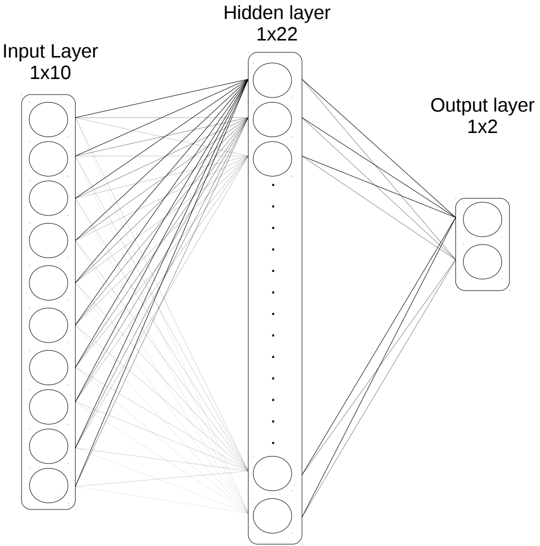
- Signal represented by ConExc MC sample
- Background represented by data.

Architecture: (see also next slide)

- 8 input features

  [Decay Length, LambdaVertexX, LambdaVertexY, LambdaVertexZ, mdcStartpionX, mdcStartpionY, mdcStartpionZ, mdcStartprotonX, mdcStartprotonY, mdcStartprotonZ]
- 1 Hidden Layers, 22 neurons
- Output layer, 2 classes

Network Architecture



Training the Network

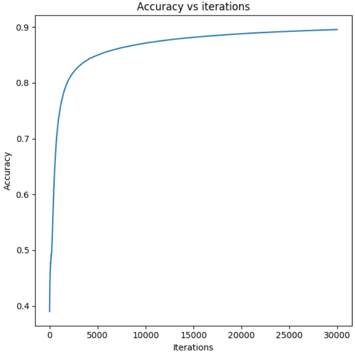
1. Label events: '0' for background. '1' for signal
2. Create training dataset
3. Process data in batches of 100. Average 'loss function' over batch
   - Processing one batch = one **iteration**
   - Reading through the whole dataset one time = one **epoch**
4. Update weights
5. When accuracy on validation data converges, apply on full data set.

Convergence: When is the training done?

$$\text{Acc.} = \frac{f\big(\big(\text{true labels}\big) - \big(\text{predicted labels}\big)\big)}{N_{events}},$$

where

$$f(x) = \begin{cases} 1, & \text{if } x = 0 \\ 0, & \text{else} \end{cases},$$

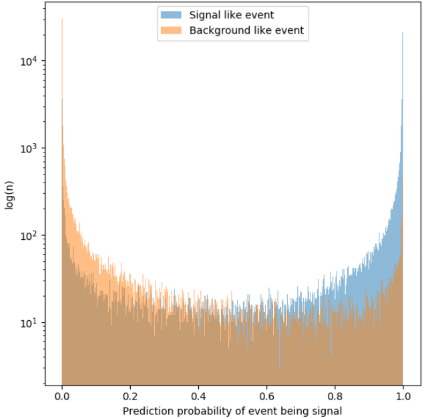


Applying a Trained Network

1. Sample model weights from trained distributions
2. Compute model output
3. Repeat (1) and (2) a large number of times
4. Average over all samples to get final result

Output

- Degree of belief that event belongs to class 1
- Obtain final sample by cut
  - → Threshold be optimized on case-by-case basis



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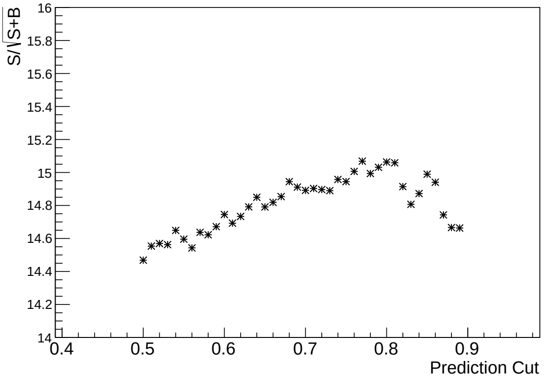
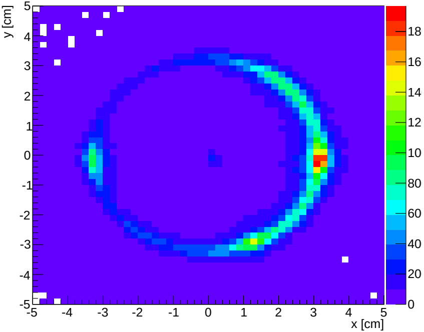
Decision Cut

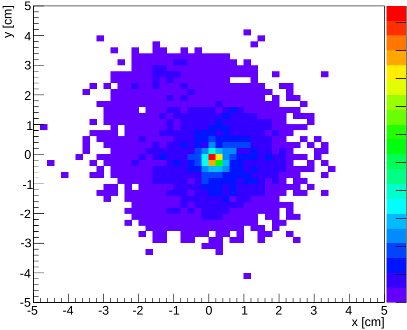
Typical cut optimization plot:



Effect on Beam Pipe Background

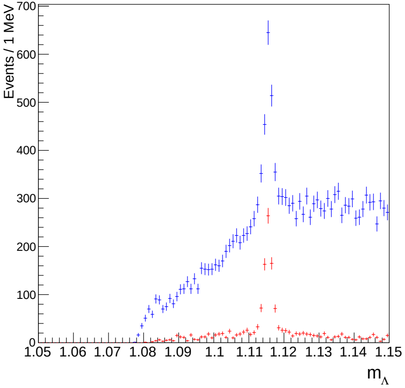


(a) Before



(b) After

Effect on m_Λ



Efficiencies

- Estimated with ConExc MC
- We select two types of signal events:
  - Type 1: $\Lambda \to p\pi^-$, $\bar{\Lambda} \to \bar{p}\pi^+$
  - Type 2: $\Lambda \to p\pi^-$, $\bar{\Lambda} \to \bar{n}\pi^0$
- For brevity we identify:
  - $\epsilon_1 = \epsilon_{\Lambda\to p\pi^-, \bar{\Lambda}\to\bar{p}\pi^+}$
  - $\epsilon_2 = \epsilon_{\Lambda\to p\pi^-, \bar{\Lambda}\to\bar{n}\pi^0}$

Final efficiencies: $\epsilon_1 = 9.8$ %, $\epsilon_2 = 21.8$ %

(From Vertex cut: $\epsilon_1 = 10.5\%$, $\epsilon_2 = 23.6\%$)

	Vertex Cut	Bayesian Neural Network
Background in sample	34 %	19 %
Signal Efficiency ϵ_1	10.5 %	9.8 %
Signal Efficiency ϵ_2	23.6 %	21.8 %

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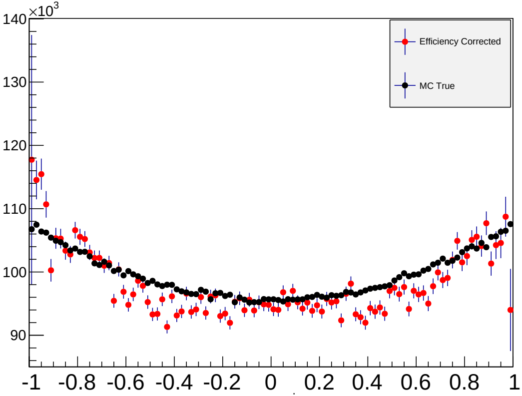
Efficiency Correction

1. Analyse 50M PHSP events
2. Form 1D histogram of correction factors. 1000 bins.
3. Get factor and correct data event-by-event

Consistency Check: Compare eff. corr. and true MC



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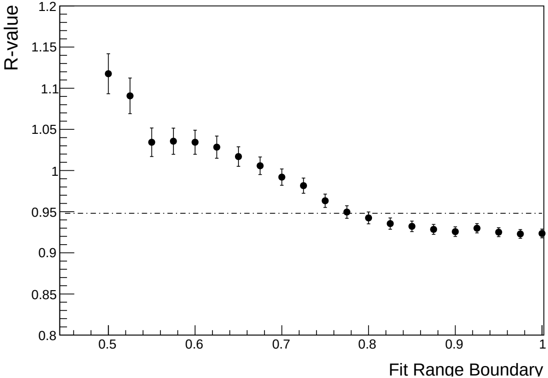
Input/Output Check

Fit rec. and corr. 10M MC events generated with R=0.948

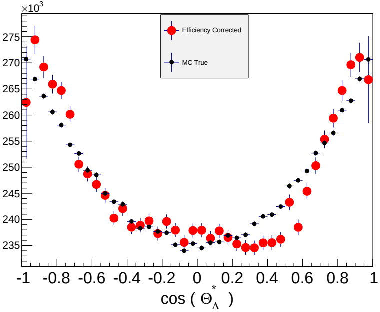
Fit function: $N \times (1 + \cos^2\theta_\Lambda + (\frac{R^2}{\tau})(1 - \cos^2\theta_\Lambda))$

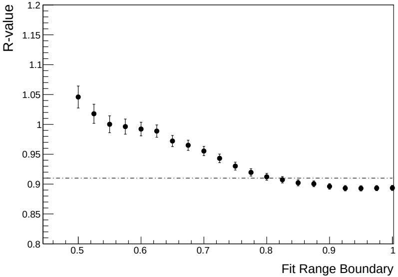
$\tau = \frac{q^2}{4m_\Lambda} = 1.15$



Efficiency Correction: 2.3864

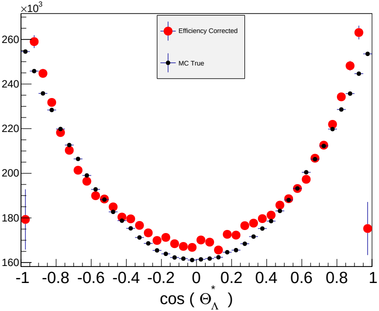
10 MC Events generated with R = 0.91

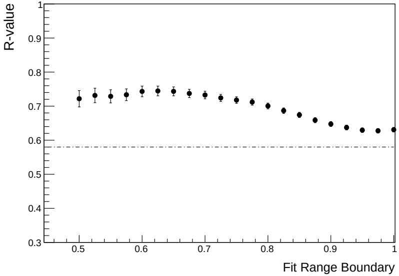




Efficiency Correction: 2.64

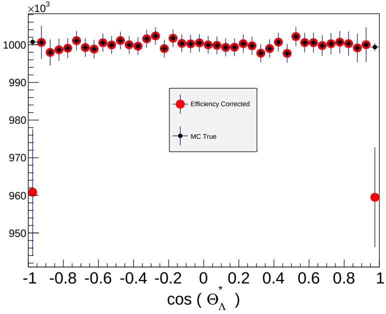
10 MC Events generated with R = 0.58



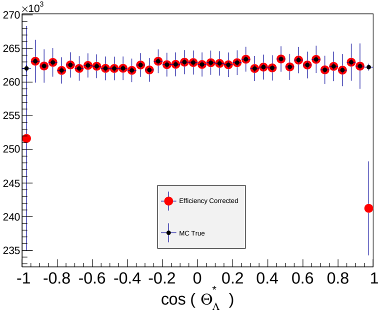


Consistency Checks

PHSP correction factors applied to PHSP sample



2.3864



2.396

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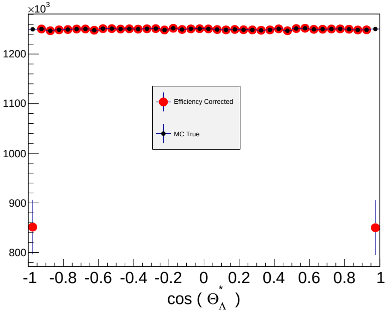
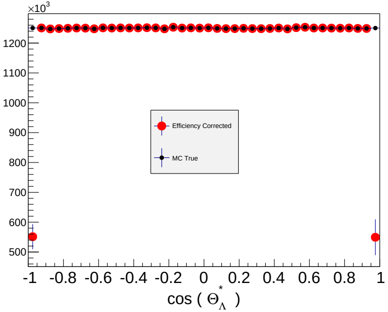
Consistency Checks

PHSP correction factors applied to PHSP sample

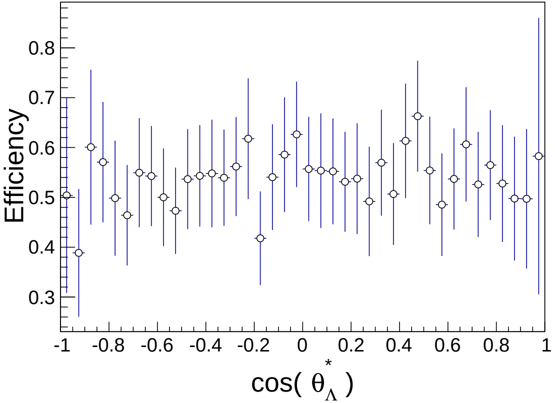


2.64



2.9

Relative Efficiency of NN Cut



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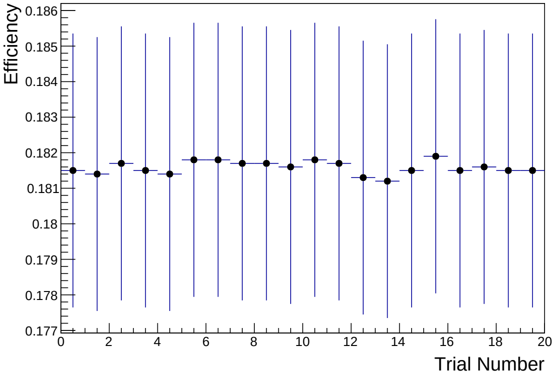
Check: Effect of Weight Sampling

Apply network 20 times to the same sample



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Future Prospects

How can the method evolve?

- Use more information
  - Add *e.g.* "raw" detector output
- Modify architecture
  - Activation function, loss function, number of nodes, *etc.*
- Constructs new "features"
  - Physics based: *e.g.* Lorentz Boost Network

    arXiv:1812.09722v1 [hep-ex]
  - Arbitrary: *e.g.*
- Use unsupervised algorithms
  - Find anomalies: *e.g.* autoencoders

    arXiv:1812.09722v1 [hep-ex]
  - Identify Patterns: *e.g.* Self-organizing maps

Summary & Outlook

Summary

- BNN improves signal to background ratio over vertex cut
- Edge effects limit fit range for R-determination
- New systematics arise from BNN method
  - Effect from no. of training iterations, weight sampling is small
  - Impact of decision cut non-negligible

Outlook

- Systematics to be quantified, *e.g.* due to bias in fit
- Software is straightforward to use and can be applied to other reactions with minimal modifications

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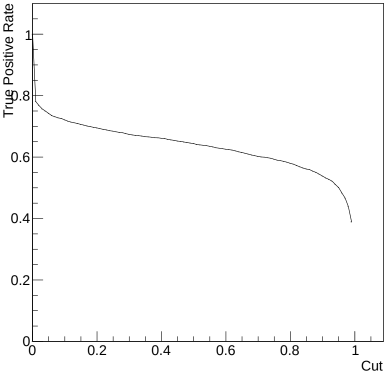
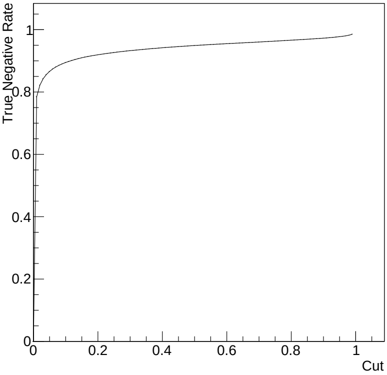
Backup: Decision Cut

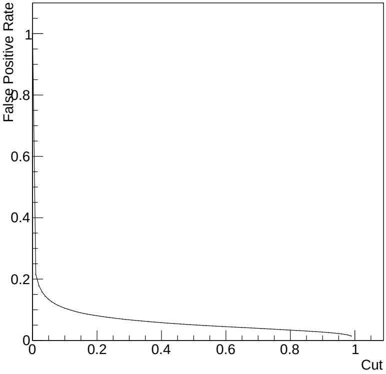


True Positive Rate

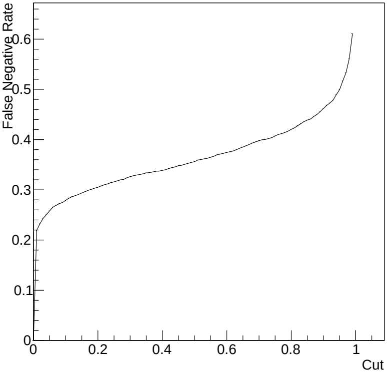


True Negative Rate

Backup: Decision Cut

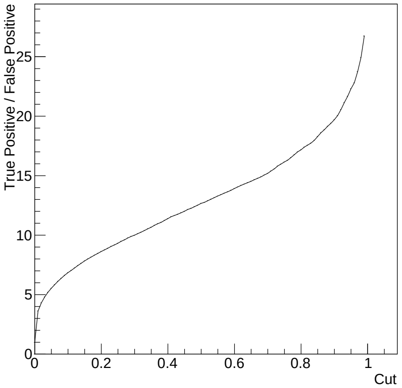


False Positive Rate



False Negative Rate

Backup: Decision Cut



True Positive rate/False Positive rate

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Backup: Cut Flow (2.3864)

Cut	Signal Remaining Ch. 1 [%]	Signal Remaining Ch 2. [%
Decay Length	15.79 ± 0.04	32.89 ± 0.04
Momentum window	13.73 ± 0.03	29.09 ± 0.03
Inv. Mass window	12.75 ± 0.03	27.10 ± 0.03
NN. Prediction ≥ 0.95	7.81 ± 0.03	19.96 ± 0.03

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Backup:Cut Flow (2.64)

Cut	Signal Remaining Ch. 1 [%]	Signal Remaining Ch 2. [%
Decay Length	11.38 ± 0.04	22.7 ± 0.04
Momentum window	10.62 ± 0.03	21.45 ± 0.03
Inv. Mass window	9.83 ± 0.03	19.94 ± 0.03
NN. Prediction ≥ 0.95	4.20 ± 0.03	12.58 ± 0.03

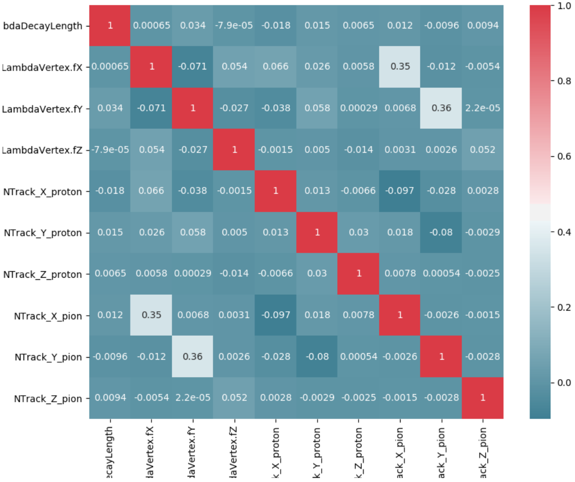
Backup:Cut Flow (2.9)

Cut	Signal Remaining Ch. 1 [%]	Signal Remaining Ch 2. [%
Decay Length	10.00 ± 0.03	18.78 ± 0.04
Momentum window	9.33 ± 0.03	17.71 ± 0.04
Inv. Mass window	8.67 ± 0.03	16.52 ± 0.04
NN. Prediction ≥ 0.71	5.79 ± 0.02	14.74 ± 0.04

Backup: All Efficiencies

Energy [GeV]	ϵ_1 [%]	ϵ_2 [%]
2.3864	7.81 ± 0.03	19.96 ± 0.03
2.396	9.8 ± 0.03	21.8 ± 0.04
2.64	4.2 ± 0.03	12.58 ± 0.03
2.9	5.79 ± 0.02	14.74 ± 0.04

Backup: Signal Correlations



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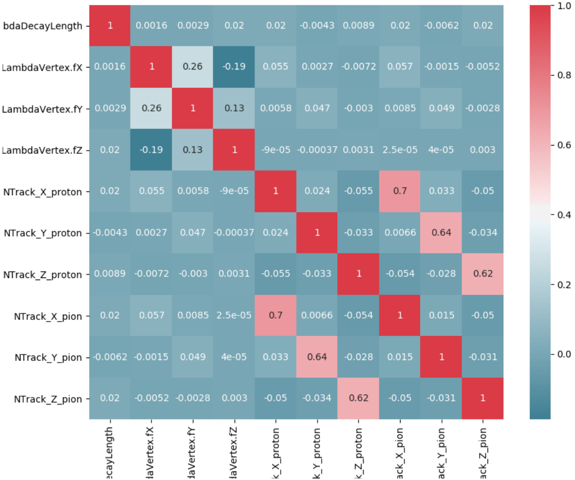
Backup: Background Correlations



Backup: Comparison with Vertex Cut

Comparable Efficiencies:

- $\epsilon_1 = 10.5\%$, $\epsilon_2 = 23.6\%$ from Vertex cut
- $\epsilon_1 = 10.\%$, $\epsilon_2 = 23.6\%$ from Vertex cut

But lowered background:

- 34 % After vertex cut
- 20 % After NN