Deep Learning Studies for the Measurement of the Top Quark Mass

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ATLAS EXPERIMENT

“Are you sitting comfortably?
Then we’ll begin...”

Measurement Idea - Baseline approach

- **Why the top quark mass matters**
- Heaviest known fundamental particle – $\mathbf{m_{top}}$ plays a key role in:
  - Electroweak precision tests
  - Stability of the SM vacuum
  - Connection to Higgs boson physics
- The goal is to measure m_{top} by reconstructing top decays in the **lepton + jets** channel.
- Using two kinematic observables:
  - $M_w^{reco} = m(q_1, q_2)$
  - $M_{lb}^{reco} = m(b_{lep}, lep)$
- **Baseline method: Kinematic Likelihood Fit (KLFitter)**
- Assigns jets to partons using likelihood maximization.
- Achieves ~**63% correct matching efficiency**.
- Provides a physics-motivated benchmark, but still limited by combinatorial background.

Why go beyond KLFitter?

- **Limitations of KLFitter**
  - Efficiency capped at ~63%
  - Sensitive to resolution effects and wrong jet assignments
  - Struggles with light-quark assignment from W decays (low-p_T jets often mis-assigned)

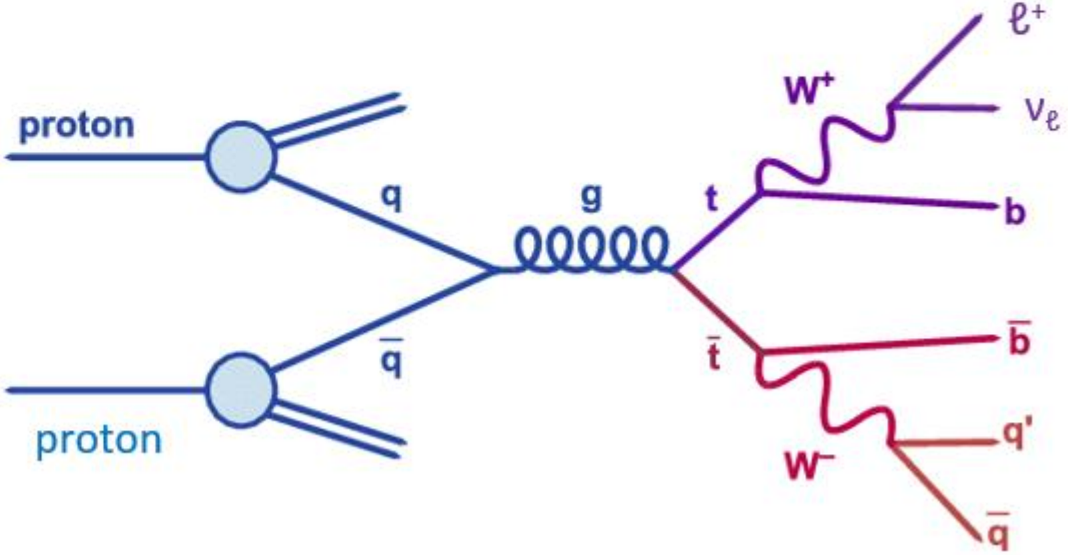
- **Impact of limitations**
  - Lower purity in reconstructed observables
  - Reduced statistical precision in mass measurement
  - Bias from incorrect jet-parton permutations

These limitations motivate more flexible, data-driven methods to capture complex correlations — leading to machine learning approaches (DNN).

Production & Decay

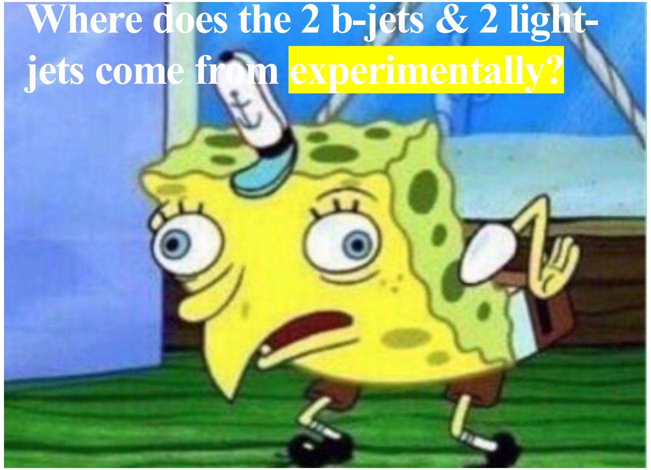
Production

Decay



- Top quark pair are produced in the largest cross-section of all top processes.
- We expect about 51 million ttbar events in the lepton+jets channel in the dataset (before selection)

- 4 Quarks → 4 Jets
- 4 quarks hadronize into **jets**:
  - 2 b-jets (tagged)
  - 2 light jets (from W decays)
- 1 lepton
- 1 neutrino inferred via missing E_T



Jet-Parton reconstruction

The Two Observables:

Option 1: $(M_t^{reco})^2 = | p_b + p_q + p_{q'} |^2$ → Direct sensitivity but high uncertainty

- Reconstruct the top mass from the **b-jet + two light jets**
- Uses 3 jets

❖ **Advantage** → Directly reconstruct hadronic top mass

Problem!

- Jets have large experimental uncertainties:
  - Jet energy scale uncertainty
  - Jet energy resolution
- M_{top} measurement has larger uncertainty

Option 2: $(M_{b\ell}^{reco})^2 = | p_b + p_\ell |^2$ → Indirect sensitivity but lower uncertainty

- Reconstruct the top mass from the **b-jet + lepton**
- Uses 1 jet

❖ **Advantage** → lepton momentum has much smaller uncertainty than jets
→ m_{top} measurement has smaller uncertainty

Problem!

- Also depends on correctly assigning the **b-jet and lepton pair** (combinatorial problem).

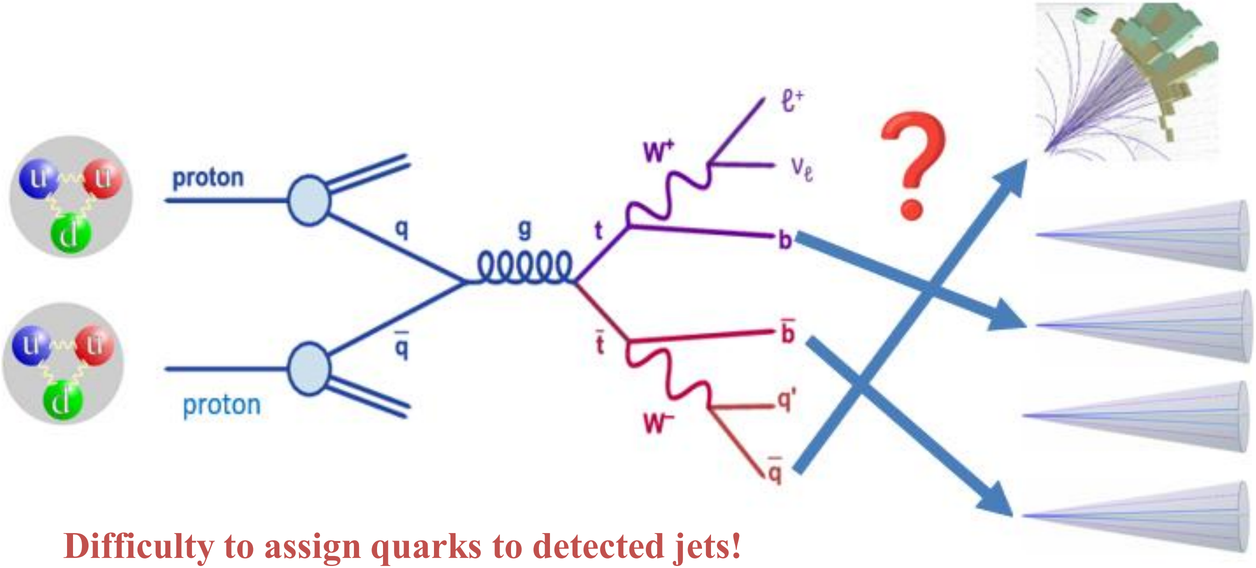
Jet-To-Quark Assignment Classes (Jet mapping)

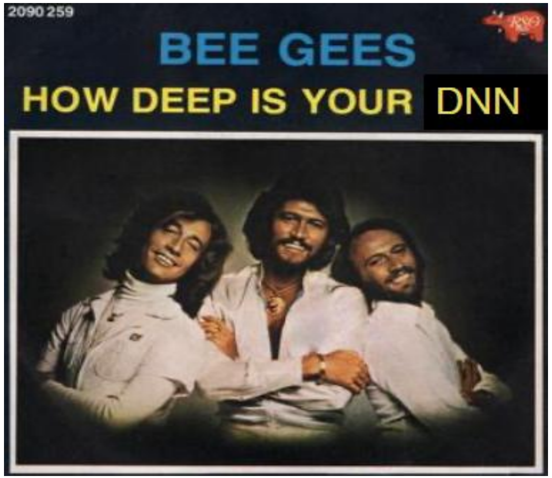
S/N	b_{had}	q_1	q_2	b_{lep}
1	Jet1	Jet2	Jet3	Jet4
2	Jet1	Jet2	Jet4	Jet3
3	Jet1	Jet3	Jet4	Jet2
4	Jet2	Jet1	Jet3	Jet4

Output Y:

- 24 possible permutations
- 12 valid permutations of 4 jets assigned to 4 quarks (after W jet symmetry)
- In reality, we have less than 12 permutations if only b-jets are allowed in the position of b-quarks.

Combinatorial background from wrong jet-parton assignments



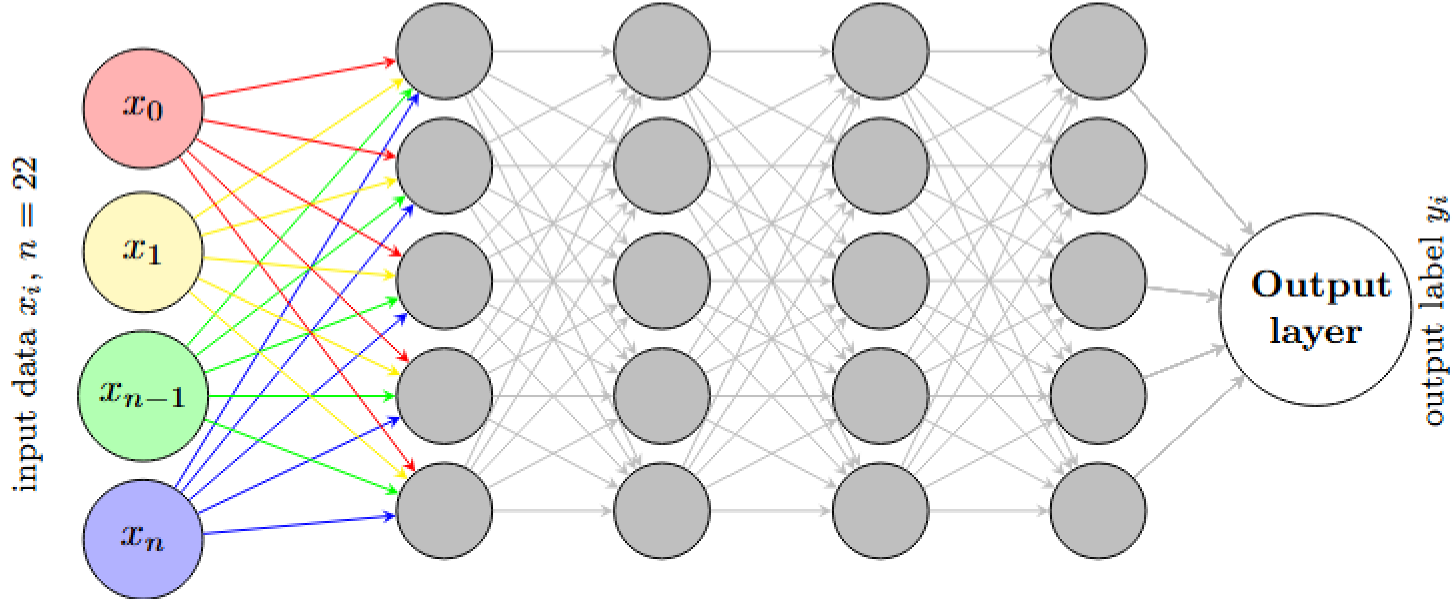


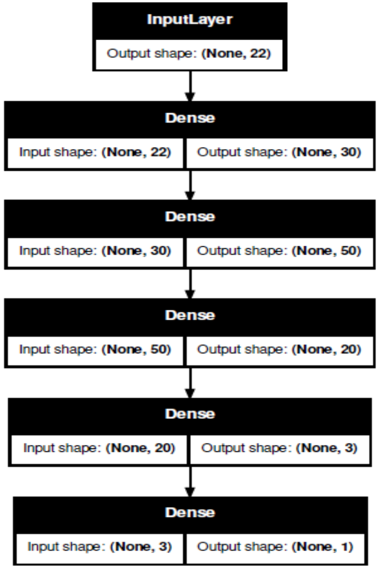
Difficulty to assign quarks to detected jets!

Now, the **main problem**:

- To compute the **observables**, we must assign which jet corresponds to which **quark**:
  - Which jet is **b**?
  - Which jets are **q and $\bar{q}'$**?

DNN Architecture





- Signal: correct permutation, background: all wrong permutations
- Input variables: four momenta of lepton and jets and missing E_T
- For each event, all permutations are evaluated and the one obtaining the highest DNN score, DNN_{High}, is selected.

Event selection

Event selection criteria:

- Single-lepton channel: exactly one isolated electron or muon.
- Events required to pass a single-lepton trigger (electron or muon + jets).
- At least one reconstructed primary vertex.
- At least four reconstructed jets with $p_T > 25\ GeV$ and $|\ \eta\ | < 2.5$.
- At least two jets must be b-tagged.

Jet-Parton matching

Matching criteria:

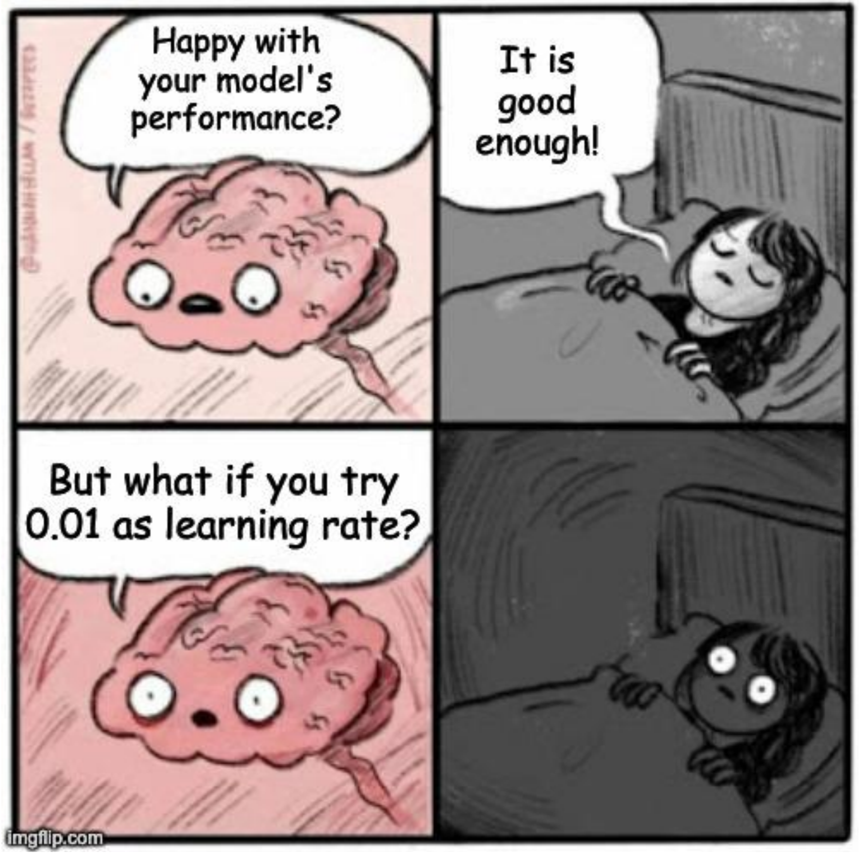
- Only **b-tagged jets** can be assigned to **b-quark positions** (i.e., b_{had}, b_{lep})
- Only **untagged jets** are allowed for **light-quark positions** (i.e., q_1, q_2) from hadronic W decay
- Matching criterion: if ΔR (parton, jet) < 0.3: consider jet as matched
- Matching criterion for event: all four partons are matched to a jet

Why use $p_T > 25\ GeV$ for selection:

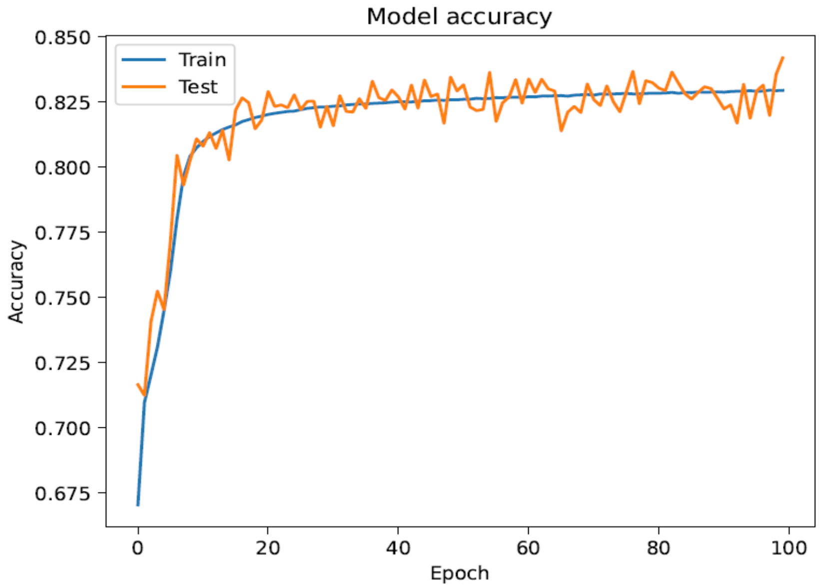
- **Jets with higher p_T have smaller uncertainties** and are more likely to be well-reconstructed.
- For lower p_T, jets are harder to match accurately due to increased detector **uncertainties**.
- For a jet with p_T (J3) $= 24.5\ GeV$, it **does not** meet the $p_T > 25\ GeV$ requirement
  - **J3** missing → lq2 does not have a matched jet (lq2 is unmatched).
- The training takes 2 days and it corresponds to the 2017 dataset and I used simulation for 172.5 GeV
- The training was done for 5 mass points (171 GeV, 172 GeV, 172.5 GeV, 173 GeV, 174 GeV)

Optimization features

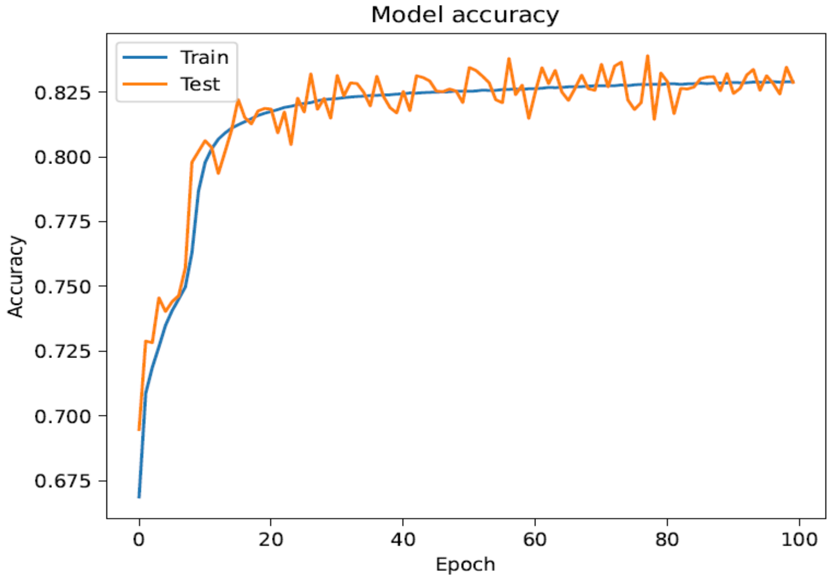
- Number of nodes in input layer: 22 variables
- Number of nodes in hidden layers: 30, 50, 20, 3
- Output layer: 1
- N_{batch}: 5000
- N_{epoch}: 100
- Optimisation algorithm: ADAM
- Learning rate: 0.005
- Loss function: Binary cross-entropy
- Activation function (hidden layer): ReLU
- Activation function (output layers): Sigmoid



First DNN training: Accuracy



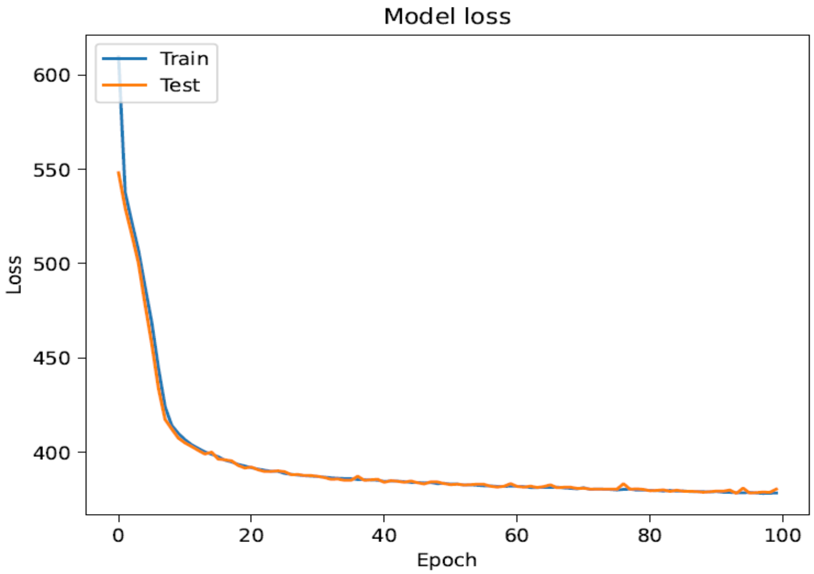
Even



Odd

- DNN reaches 82–83% accuracy after ~30 epochs
- Both training and test accuracy curves are closely aligned
- Very small gap between train and test accuracy → excellent generalization
- No signs of overfitting

First DNN training: Model loss



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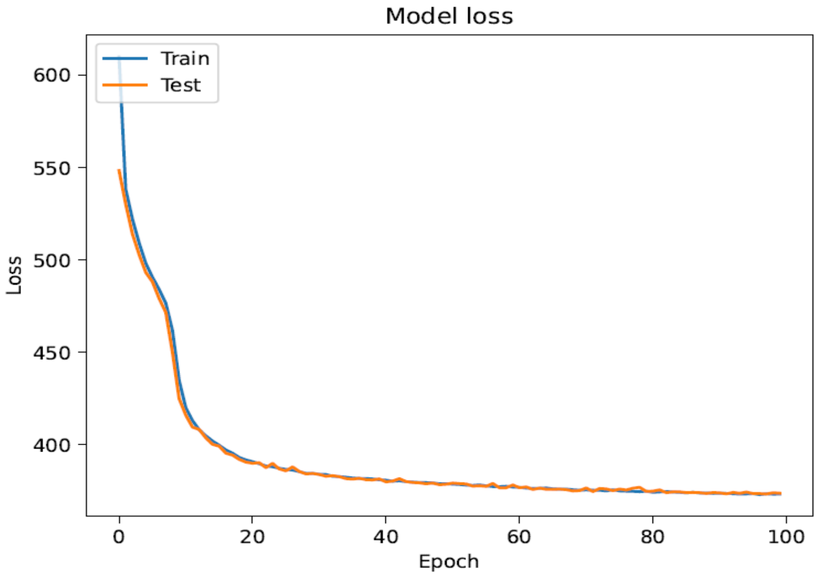


Odd

- Both show a smooth exponential decay – from ~600+ down to below ~370
- Train and Test Loss are almost identical – overlap closely
- ○ Very good generalization
- ○ No overfitting
- ○ Stable convergence

DNN matching performance at m_{top} = 172.5 GeV

The matching efficiency is defined as the fraction of matchable events among all selected events:

$$\epsilon_{matching} = \frac{N_{matchable}}{N_{matchable} + N_{unmatchable}} = \frac{N_c + N_i}{N_c + N_i + N_u}$$

The reconstruction efficiency is the fraction of correctly matched events among all matched events:

$$\epsilon_{cm} = \frac{N_c}{N_c + N_i}$$

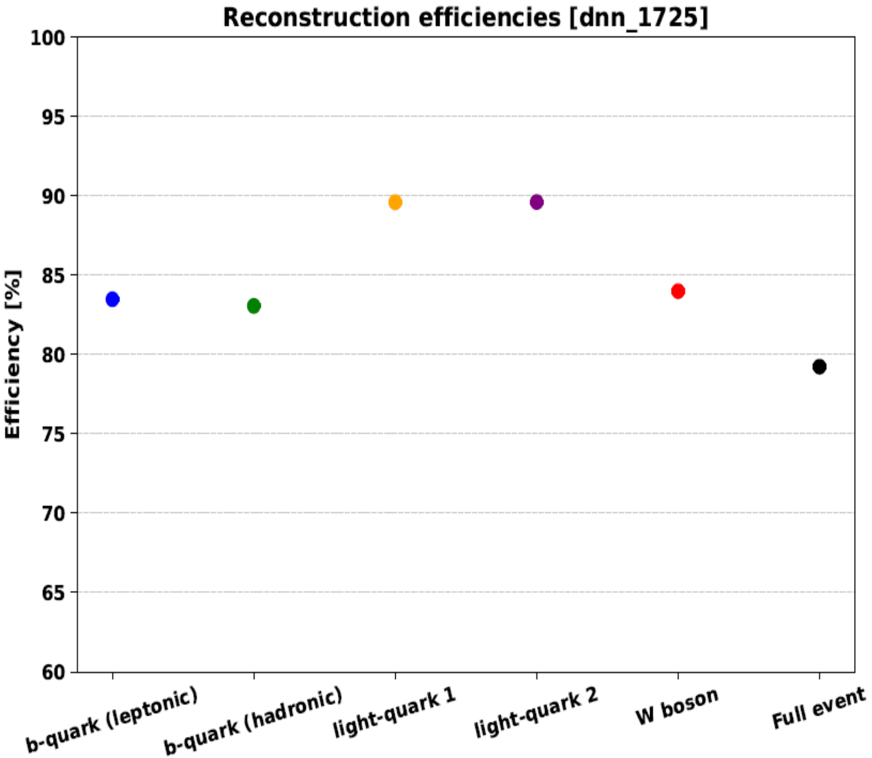
The selection purity is the fraction of correctly matched events among all selected events, regardless of matchability:

$$\pi_{cm} = \frac{N_c}{N_c + N_i + N_u}$$

- Low matching efficiency in $t\bar{t}$ events

  → Caused by low-p_T jets from W boson decays failing selection.

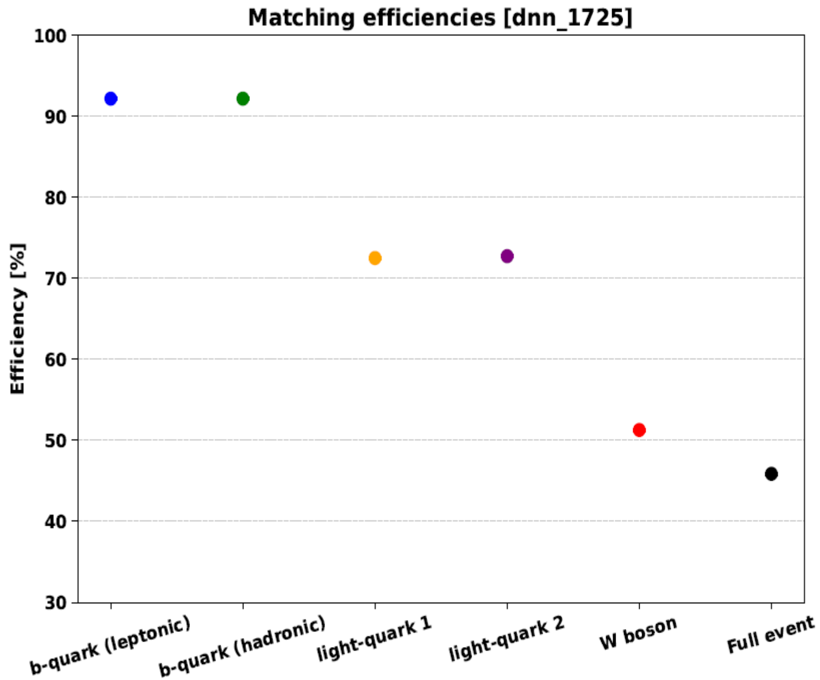
First reconstruction efficiency

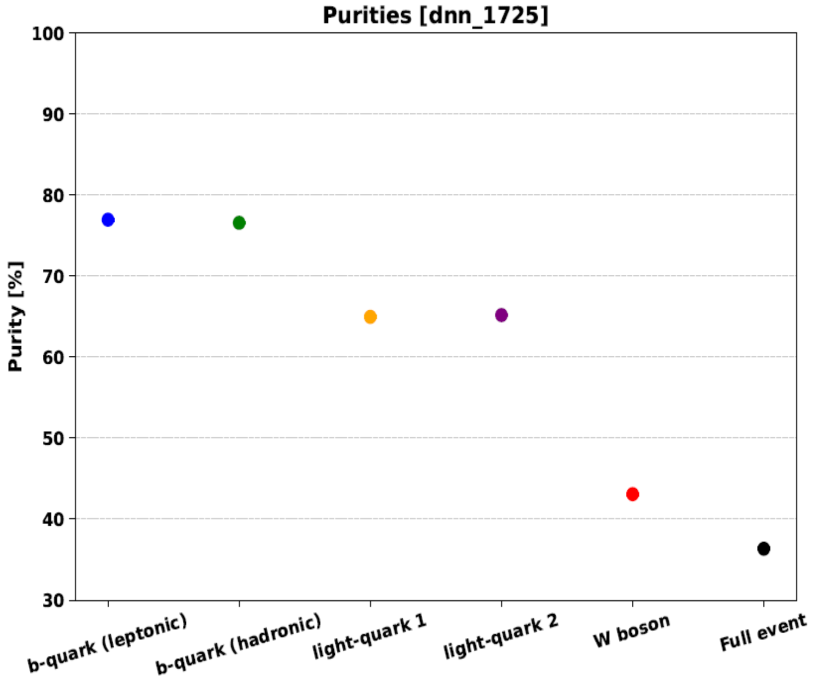


Reconstruction efficiency: Higher for light quarks (~89%) compared to b-quarks (~83%) and full event ~79%.

- Due to simpler kinematics, light quarks are easier to reconstruct.

Matching efficiency and purity





Matching efficiency: High for b-quarks (~92%), moderate for light quarks (~72%).

- **b-jets** are more accurately matched due to **b-tagging**.

Purity: High for b-quarks (~77%) due to **better matching** & **less background**, lower for light quarks (~65%).

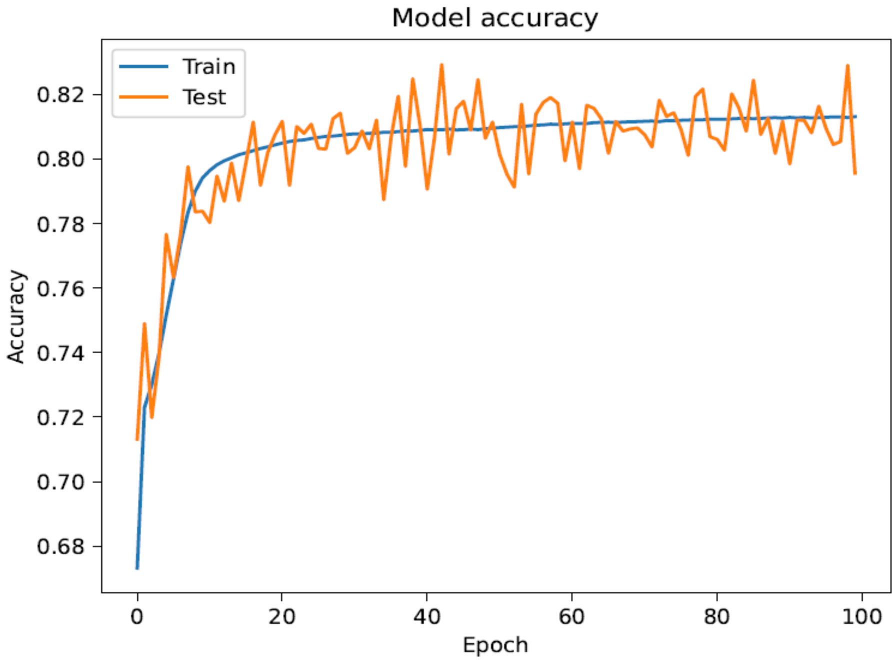
The impact of P_T > 20 GeV on DNN performance

If I lower P_T:

- Do I get more pileup? High prob. of more pileup contamination
- Do I get larger JES uncertainty? Highly possible
- Higher event yield → less clean jets
- Poorer energy resolution
- Worse b-tagging performance
- Longer training, more permutations

○ More jets = More combinations = More permutations

(e.g., using 6 jets instead of 4).



Effect of p_T cuts on efficiency and purity

Quantity	$p_T > 25$ GeV	$p_T > 20$ GeV
Overall metrics		
Matching efficiency (%)	45.88 ± 0.05	48.29 ± 0.39
Reconstruction efficiency (%)	79.24 ± 0.06	71.90 ± 0.50
Purity (%)	36.35 ± 0.05	34.72 ± 0.37
Reconstruction efficiencies (%)		
b_{lep}	80.30 ± 0.04	81.35 ± 0.31
b_{had}	79.43 ± 0.05	81.52 ± 0.31
lq_1	89.08 ± 0.04	84.85 ± 0.32
lq_2	89.07 ± 0.04	85.22 ± 0.32
m_W	83.09 ± 0.06	76.88 ± 0.44
Matching efficiencies (%)		
b_{lep}	92.19 ± 0.03	91.39 ± 0.22
b_{had}	92.21 ± 0.03	91.90 ± 0.21
lq_1	72.56 ± 0.05	74.60 ± 0.34
lq_2	72.79 ± 0.05	74.53 ± 0.34
m_W	51.36 ± 0.05	54.91 ± 0.38
Purities (%)		
b_{lep}	74.02 ± 0.05	74.35 ± 0.34
b_{had}	73.24 ± 0.05	74.91 ± 0.33
lq_1	64.64 ± 0.05	63.30 ± 0.37
lq_2	64.83 ± 0.05	63.51 ± 0.37
m_W	42.67 ± 0.05	42.21 ± 0.38

❖ **Reconstruction Efficiencies:**

- Increase for b_{lep}, b_{had} at $p_T > 20\ GeV$ due to more signal events at lower threshold
- Decrease for light quarks due to more low p_T jets that are harder to match correctly.

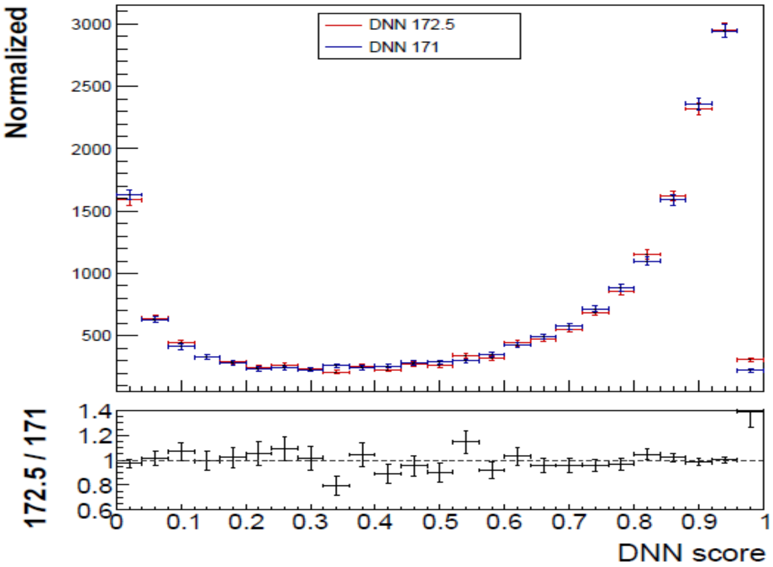
❖ **Matching Efficiencies:**

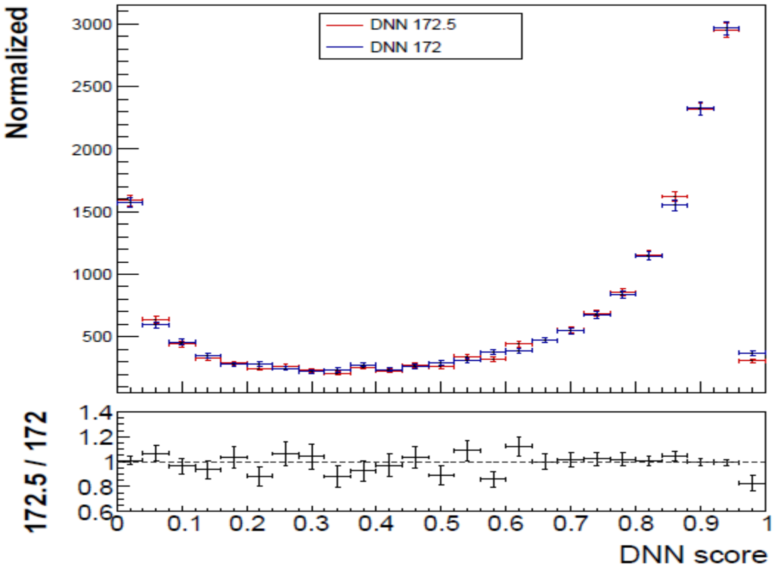
- Increase for $lq_1,\ lq_2$ at $p_T > 20\ GeV$ due to more inclusive jet reconstruction.
- Decrease for m_W and b_{lep} due to background contamination at lower p_T.

❖ **Purity:**

- Increase for b_{lep}, b_{had} at $p_T > 20\ GeV$ because lower threshold allows more high-quality b-jet events to be selected, improving signal purity.
- Decrease for other variables (light quarks, m_W (due to increased background contamination as more low p_T events are included.

Comparison of m_t hypotheses in the DNN output



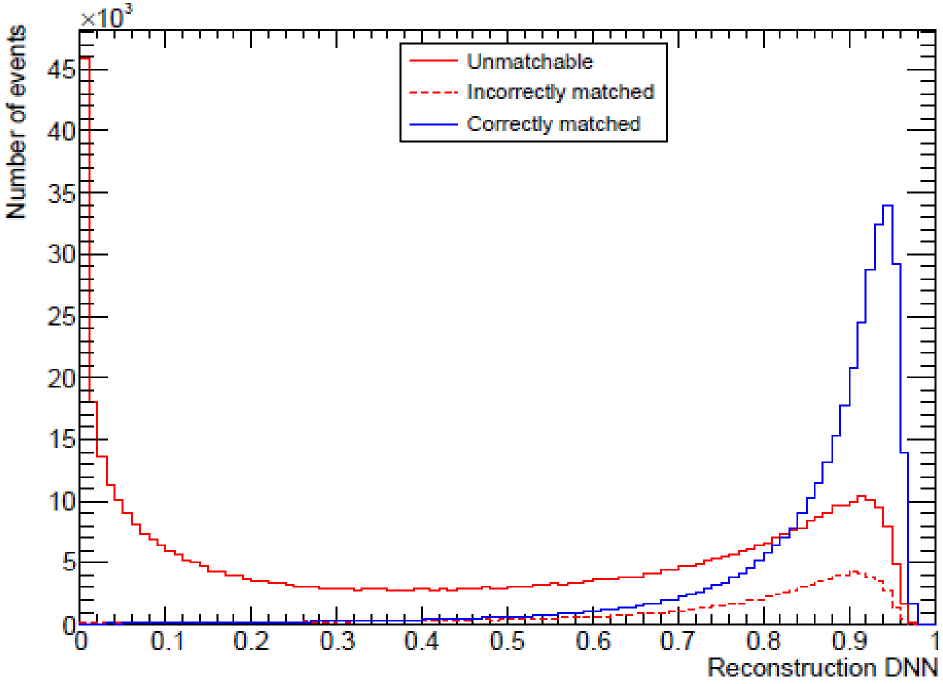


DNN score comparison: Both mass hypotheses show clear peaks as the DNN score increases.

Ratio plots:

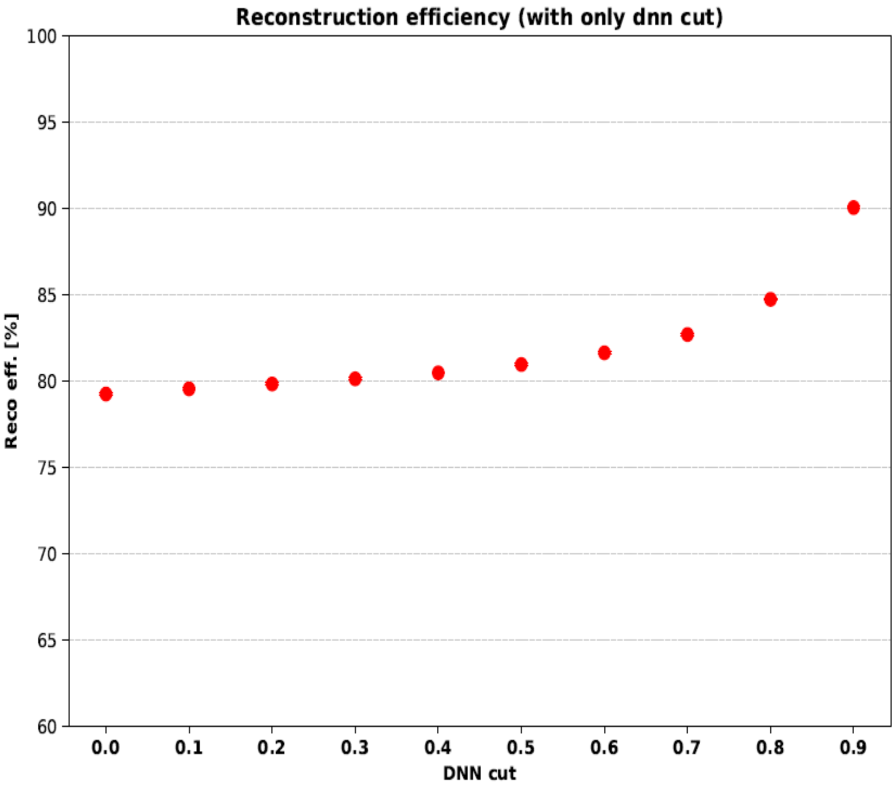
- Ratios (172.5/171 and 172.5/172) stay near 1, indicating minimal difference at high DNN scores.

Reconstruction DNN Output



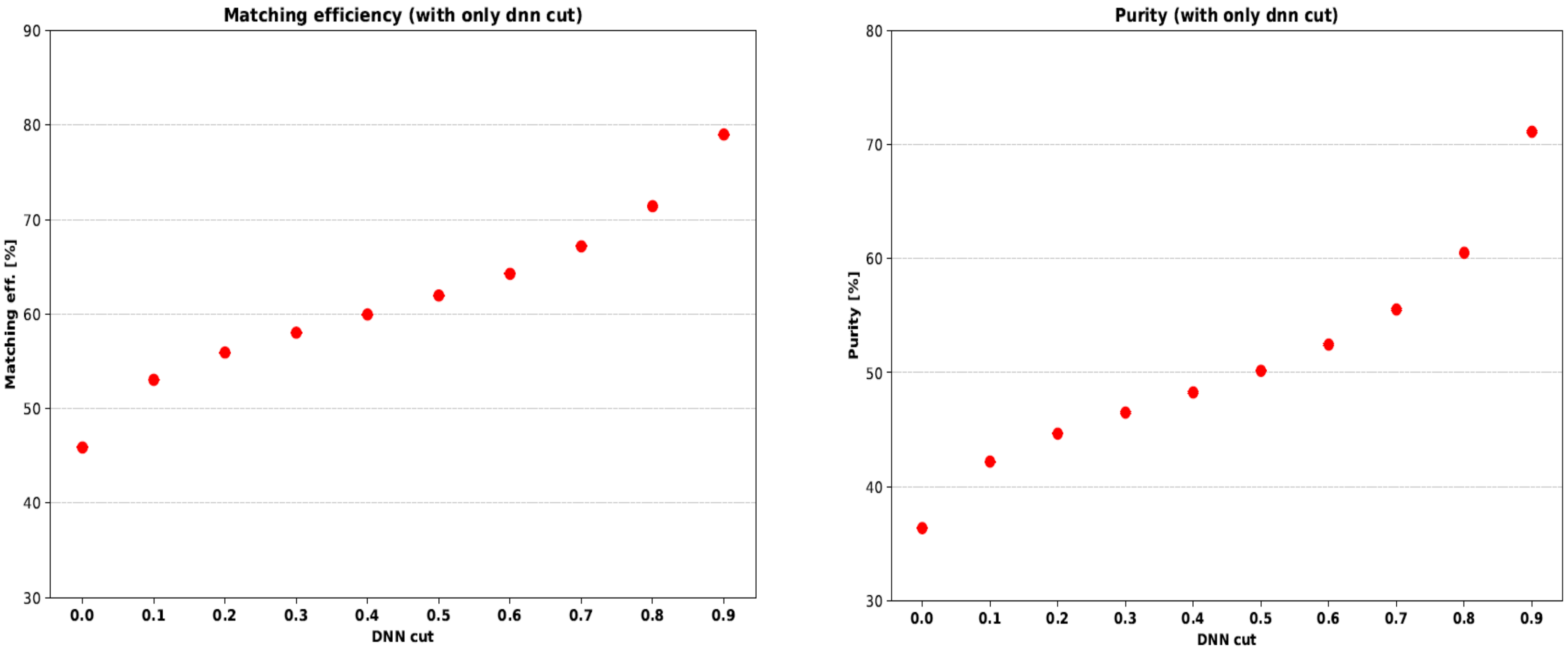
- Sharp peak at $\sim 1 \rightarrow$ DNN confidence in classification.
- Correctly matched (blue) dominate near 1, unmatched (red) at lower DNN scores.
- Can we improve the reconstruction by cutting the on the DNN output?

Impact of DNN cut on reconstruction efficiency



Reconstruction efficiency: Increases from ~79% to ~90% with higher DNN cuts, selecting higher-quality events.

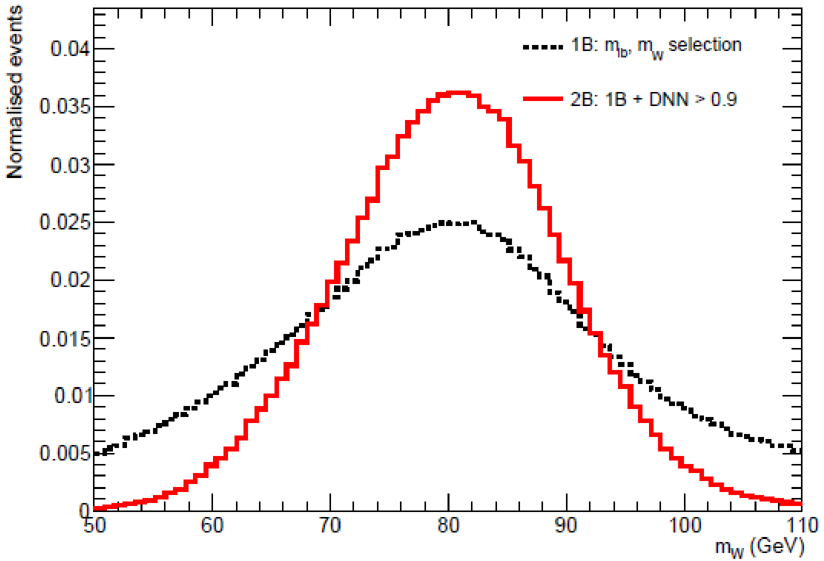
Impact of DNN cut on matching efficiency & purity

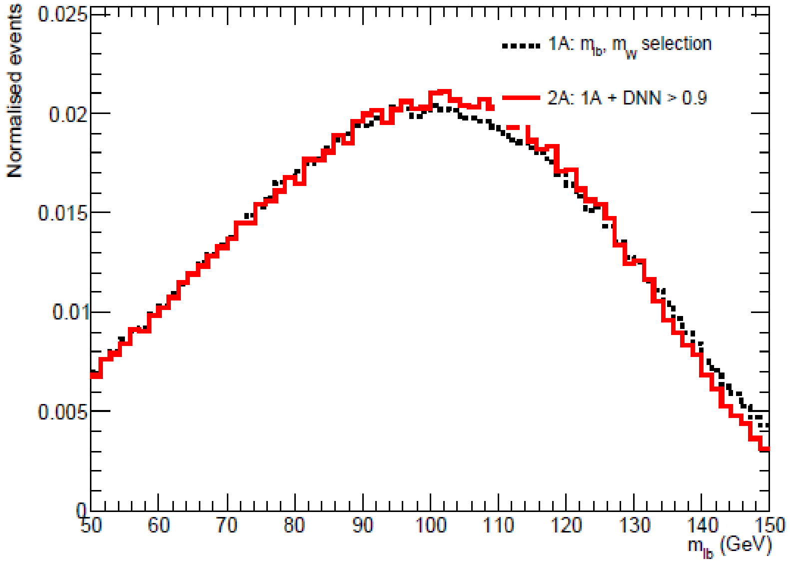


Matching efficiency: Improves with higher DNN cuts, reaching up to ~79%, enhancing signal-to-background ratio.

Purity: Increases to ~71% as DNN cut improves, reducing background contamination.

Effect of DNN cut on m_W and m_{lb} distributions





- DNN cut (less unmatchable events) → m_w distribution becomes more symmetric and narrow.
- **Increased signal-to-background:** Correctly matched events dominate around $m_W \approx 80$GeV.
- Better resolution & sharper mass peak → Improved precision for m_W and m_{lb}.
- For m_{lb} **the effect is small because the efficiency for the b-quark was very high before the cut.**

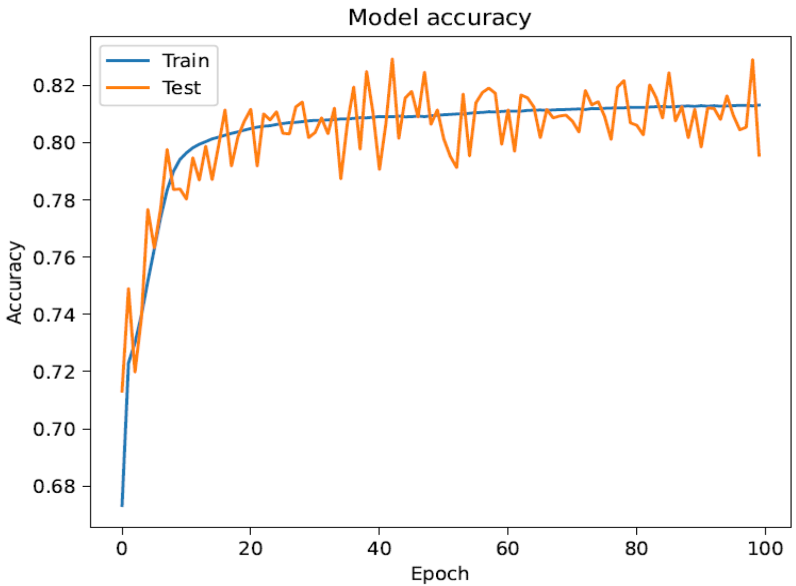
Conclusions

- Reconstruction efficiency, matching efficiency, and purity were enhanced through DNN cut and kinematic selections.
- DNN cuts, combined with m_W and m_{lb} cuts, improved signal-to-background ratio and reduced unmatchable events.
- Clean mass peaks and improved resolution, leading to higher precision in top-quark mass measurement was achieved.
- The study demonstrates that a well-trained DNN provides a robust tool for high-precision top-quark mass measurements at ATLAS.

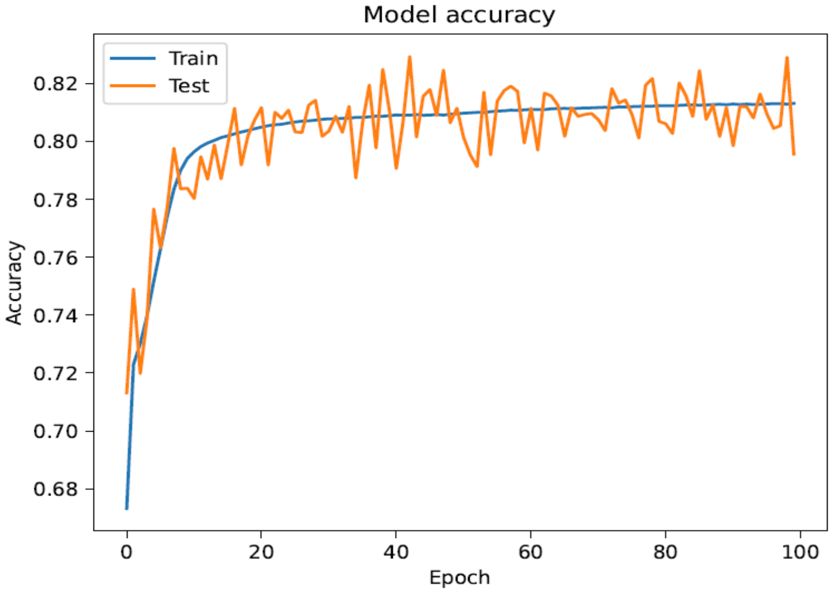
Thank you for listening

BACKUP

Low P_T selection DNN training: Accuracy



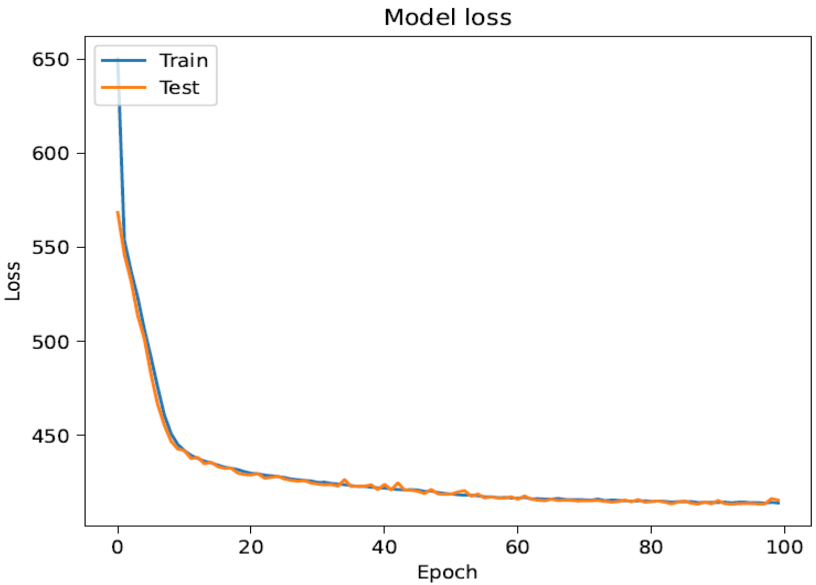
Accuracy for the training on even low P_T selection



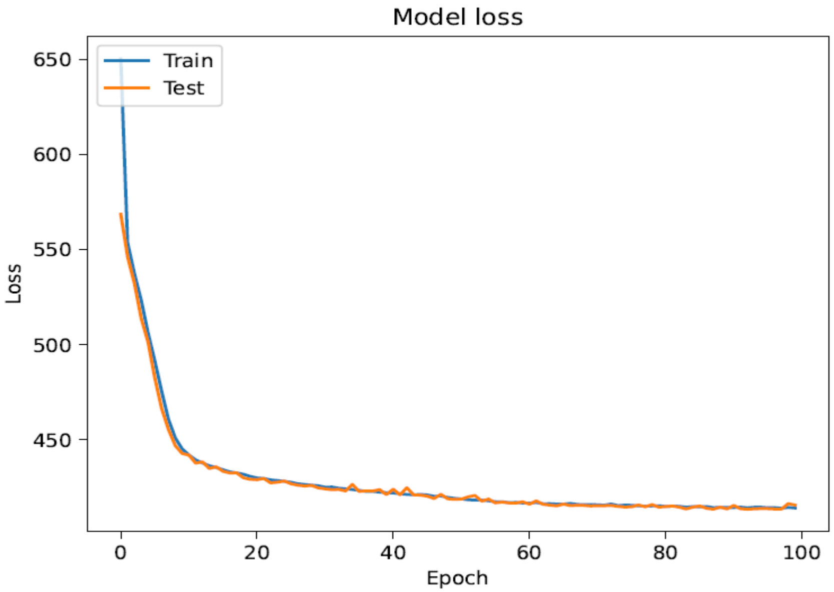
Accuracy for the training on odd low P_T selection

- DNN reaches 80% accuracy after ~30 epochs
- Test accuracy fluctuates but improves, aligning with training.
- Slight **overfitting** observed, with the gap between training and test accuracy narrowing.
- **Convergence** occurs after several epochs, showing stable model learning.

Low P_T selection DNN training: Loss



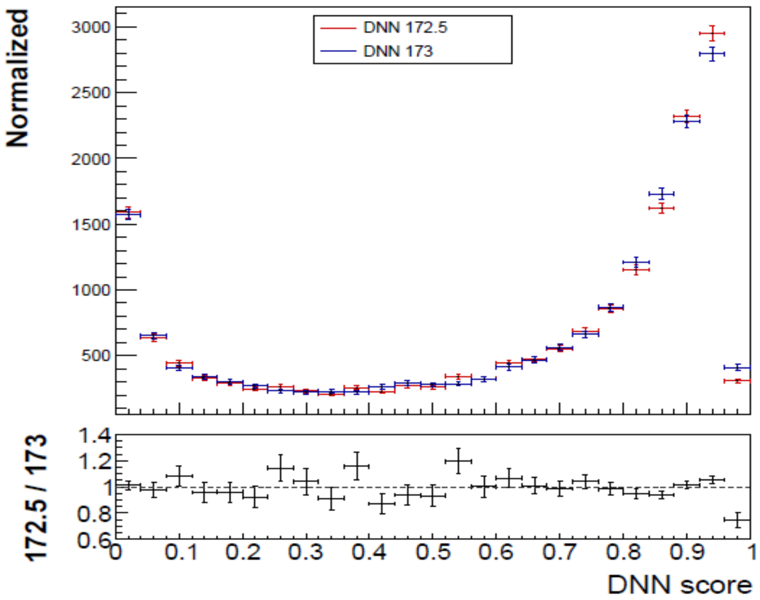
Loss for the training on even low P_T selection

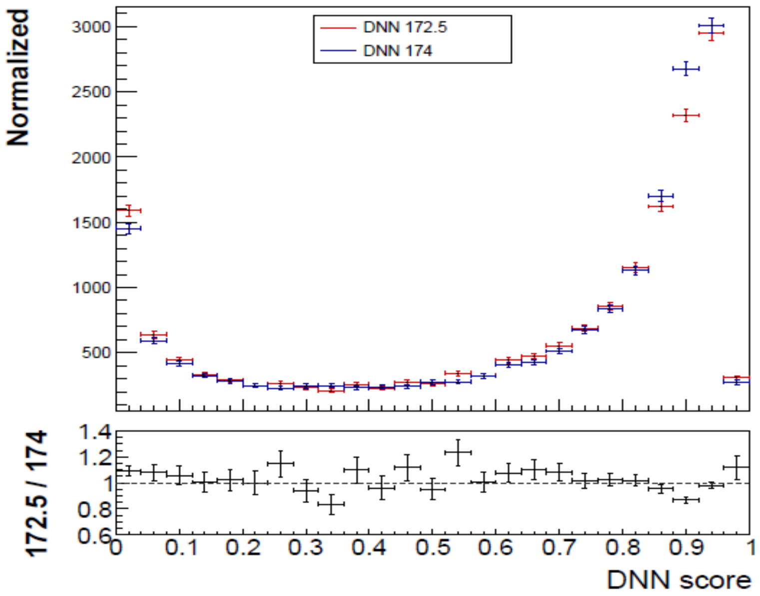


Loss for the training on odd low P_T selection

- Both decreases rapidly from ~600 to ~450.
- Train and test loss are almost identical, indicating good generalization
- Stable convergence, no significant overfitting, with loss flattening as training progresses.
- Model loss stabilizes, showing reliable training and test outcomes.

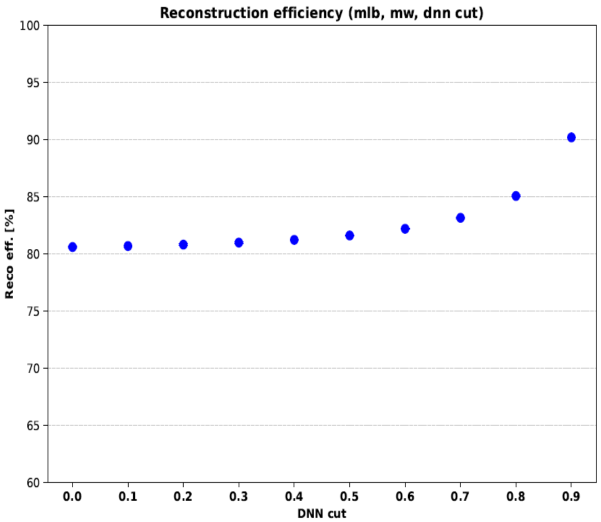
Comparison of m_t hypotheses in the DNN output

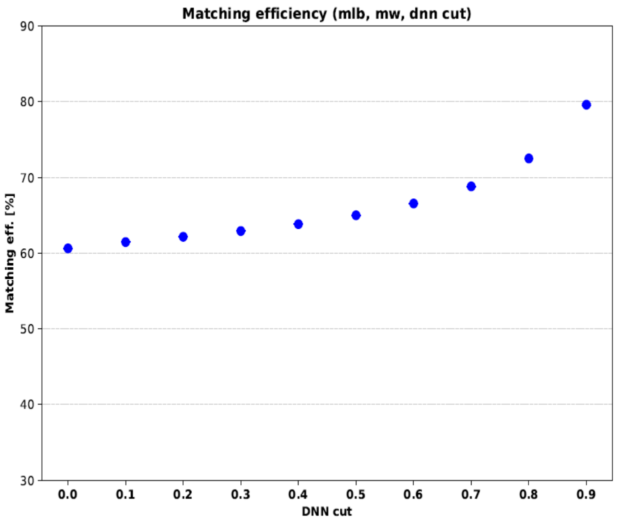


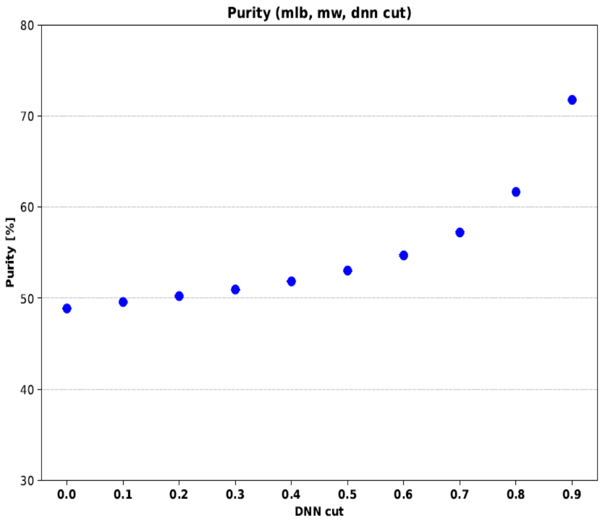


- **DNN score comparison:** Both mass hypotheses show **similar peaks** at high DNN scores.
- **Ratio plots:** Ratios (172.5/173, 172.5/174) stay **near 1**, indicating **minimal mass difference**.
- **DNN confidence:** The DNN **confidently classifies** the masses with **minimal variation**.

Effect of m_W, m_{lb}, & DNN cuts on efficiency and purity

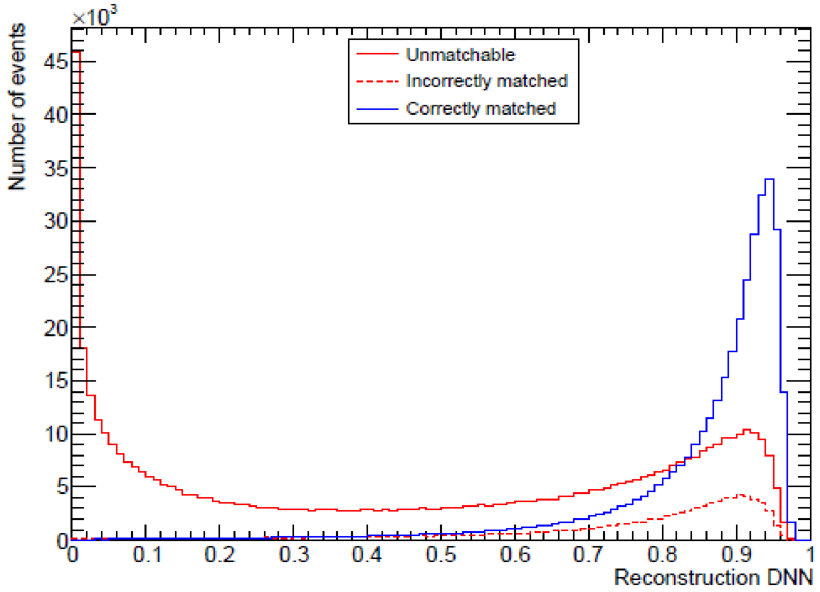




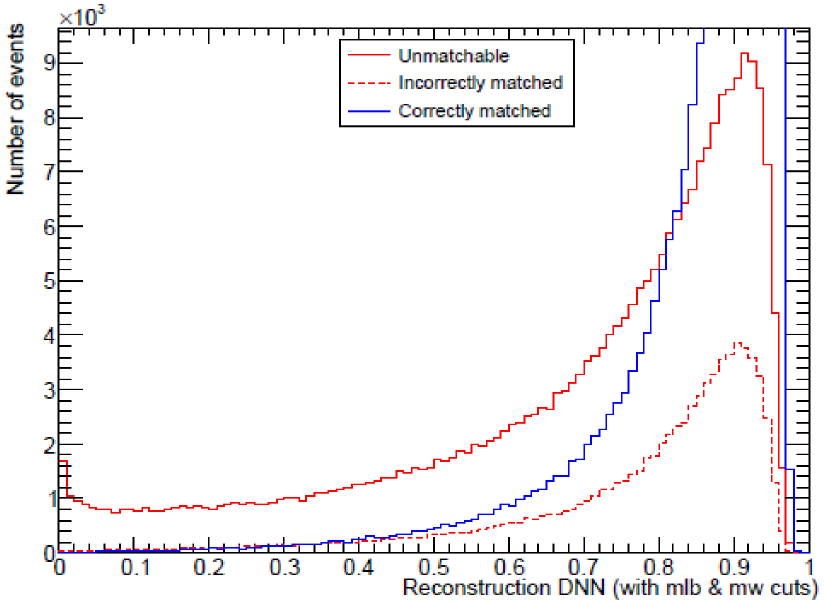


- **Reconstruction efficiency:** Steady increase from ~80% to ~90% as DNN, m_W, and m_{lb} cuts are applied, selecting higher-quality events.
- **Matching efficiency:** Increases to ~80%, with higher cuts improving the signal-to-background ratio by removing incorrect matches.
- **Purity:** Improves to ~72%, indicating a significant reduction in background contamination as the DNN cut increases.

Reconstruction DNN Output



- Sharp peak at $\sim 1 \rightarrow$ DNN confidence in classification.
- Correctly matched (blue) dominate near 1, unmatched (red) at lower DNN scores.
- About **85%** of events correctly matched near 1.



- Sharper peak for correctly matched events.
- Reduced incorrectly matched/unmatched events after cuts.
- Effective kinematic cuts improve purity without significant efficiency loss.