Dimensionality reduction for classification using Higgs dataset

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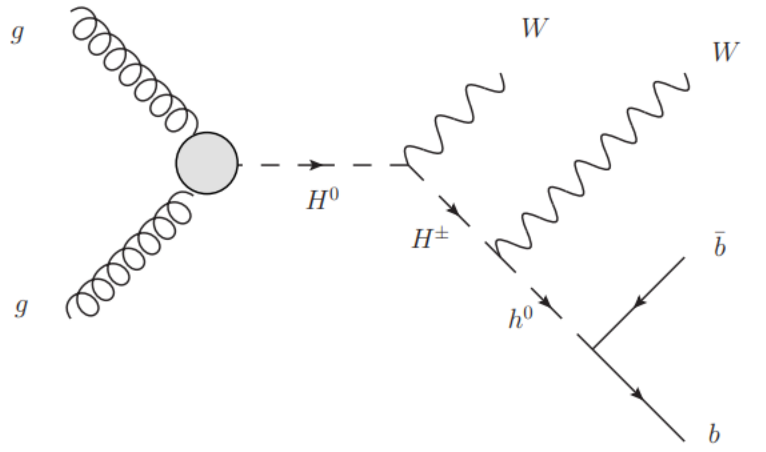
Overview

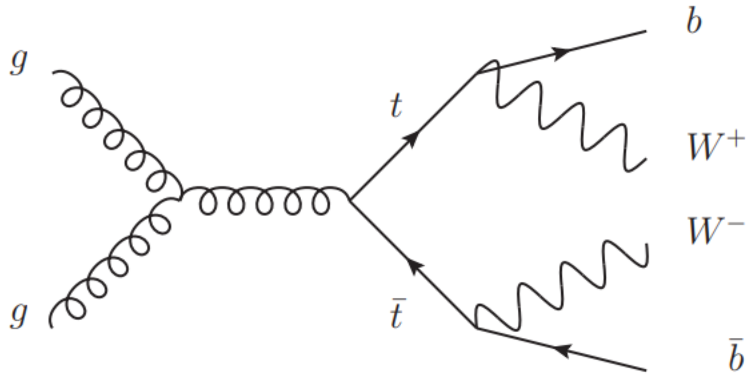
1. Introduction
2. Higgs dataset
3. Neural network design
4. Benchmark cases
5. PCA description
6. AutoEncoder description
7. Comparing performance
8. Selected features removal
9. Conclusions

Introduction

- Signal event (a) in which a Higgs boson decays into a pair of *W* bosons and a pair of bottom quarks.
- Background event (b) in which a pair of top quarks each decays into a *W* boson and a bottom quark.
- We can use low-level and high-level features to distinguish between signal and background events.



(a)



(b)

Higgs Dataset

- The data can be found on the UC Irvine ML repository:

  https://archive.ics.uci.edu/dataset/280/higgs

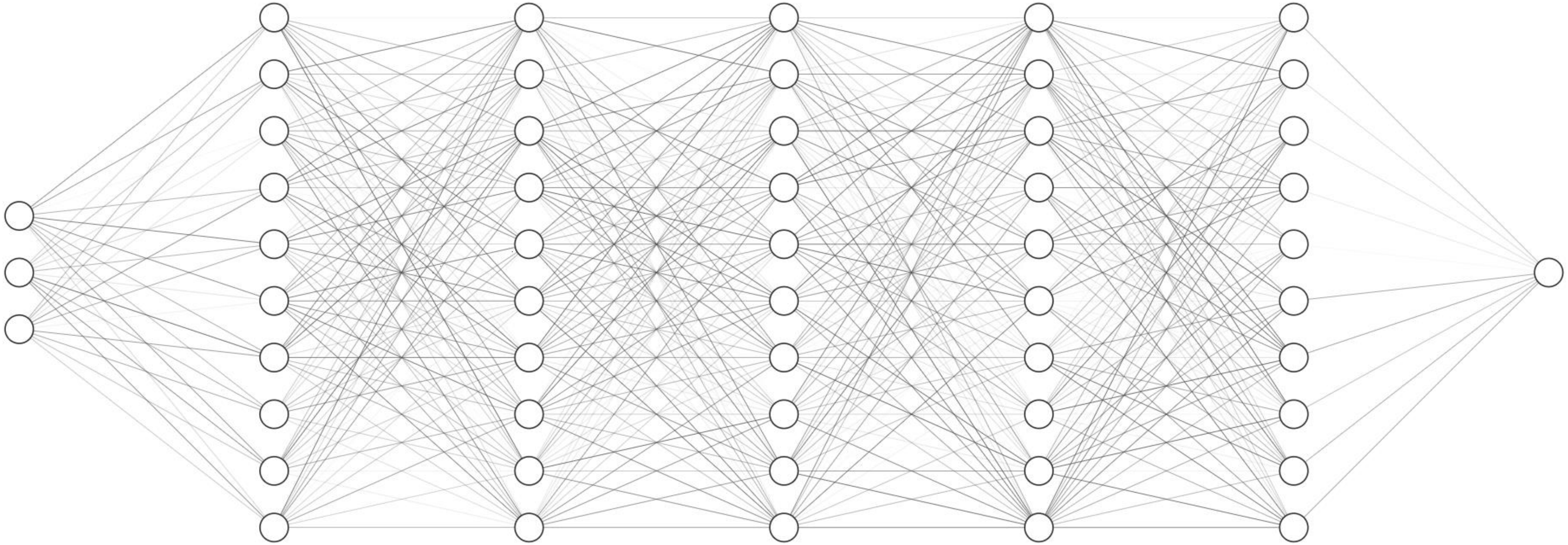
Low-level features

Lepton	Missing Energy	Jet 1	Jet 2	Jet 3	Jet 4
P_T	Magnitude	P_T	P_T	P_T	P_T
η	N/A	η	η	η	η
ϕ	ϕ	ϕ	ϕ	ϕ	ϕ
N/A	N/A	b-tag	b-tag	b-tag	b-tag

High-level features

m_{lv}	m_{jlv}	m_{bb}	m_{wbb}	m_{wwbb}	m_{jj}	m_{jjj}

Neural Network Design



Dataset features 5 300-neurons dense layers Predicition

Final Architecture and Benchmark

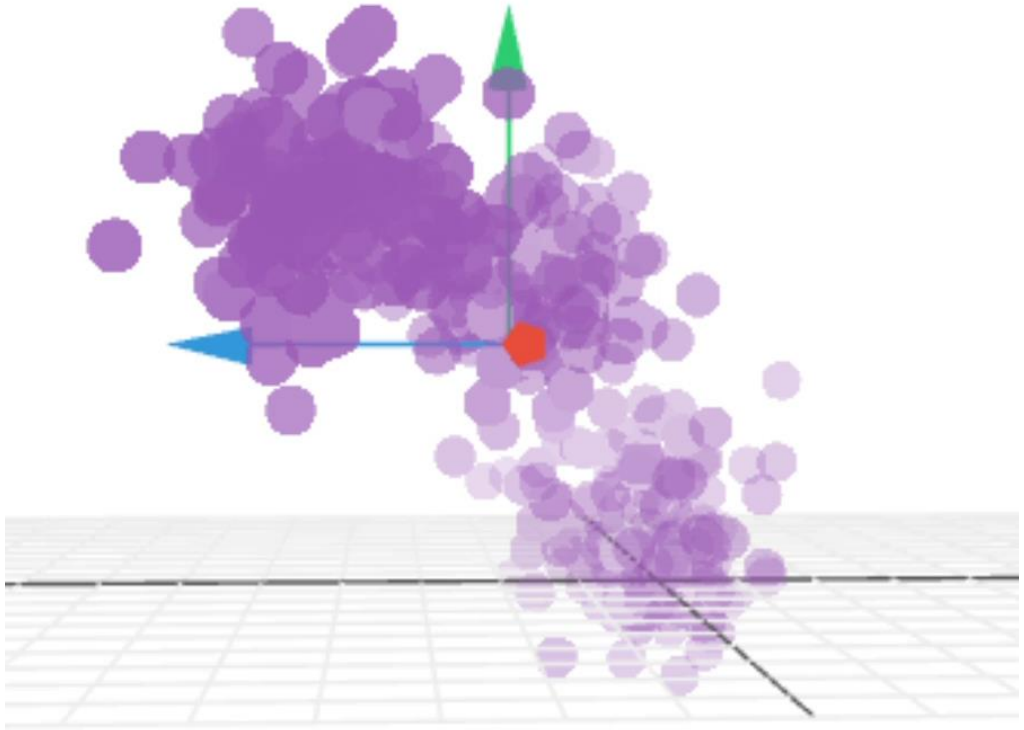
- Leaky ReLU activation function
- LR 0.05 decaying by 0.5 with a patience of 5 epochs.
- 2,500,000 events
- Dropout in every layer of 0.15
- Momentum of 0.9 and Nesterov True
- High and low-level features: ROC-AUC of 0.857
- Low-level features only: ROC-AUC of 0.828

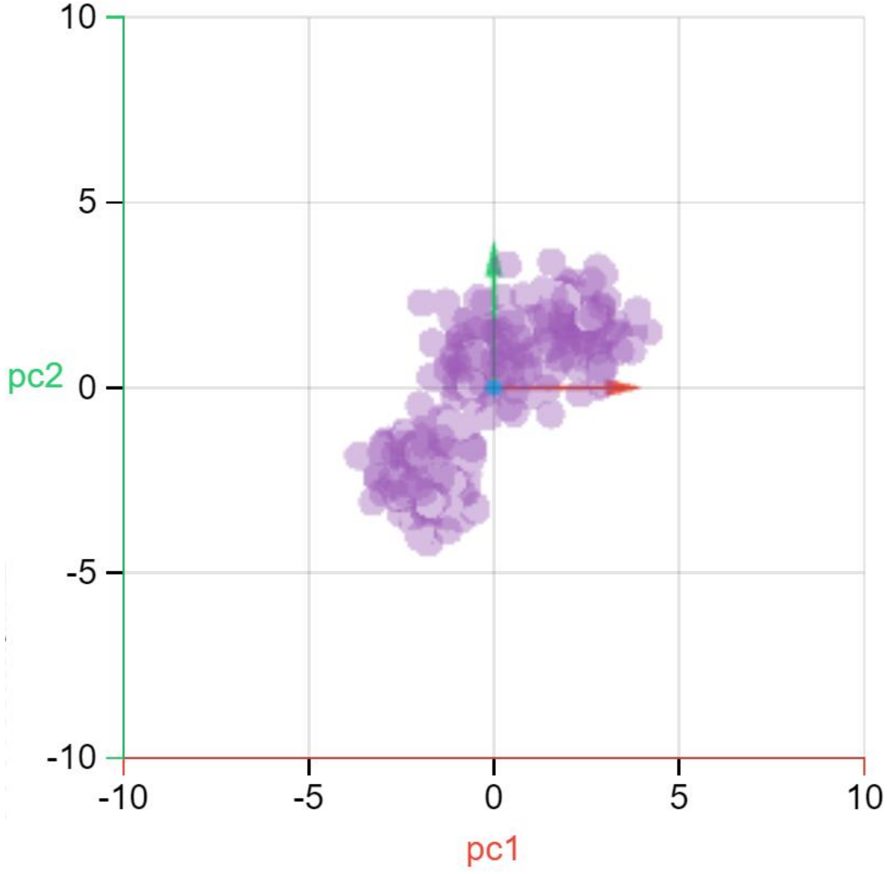
Motivation for Dimensionality Reduction

- CMS experiment produces a huge amount of data.
- The more we can reduce it, the better.
- Faster to perform analysis on events with less features.
- We do not want to lose information.

PCA

- Unsupervised ML technique that transforms high-dimension data into lower-dimensions while retaining as much information as possible.

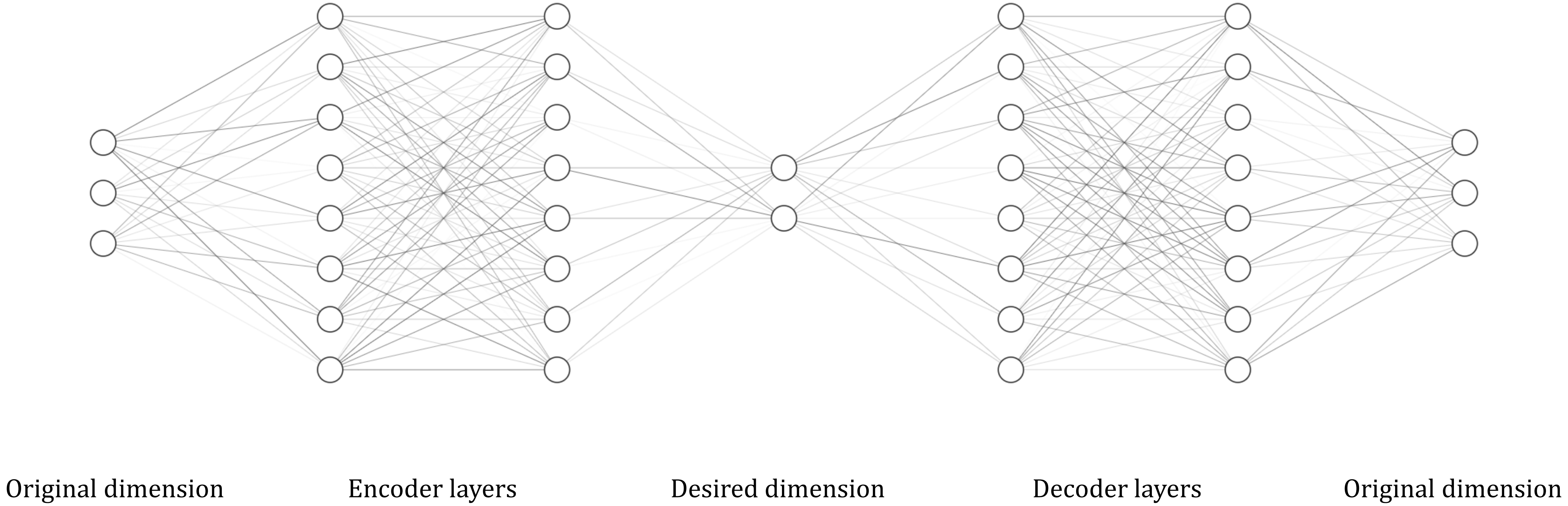




Animation and image from: https://setosa.io/ev/principal-component-analysis/

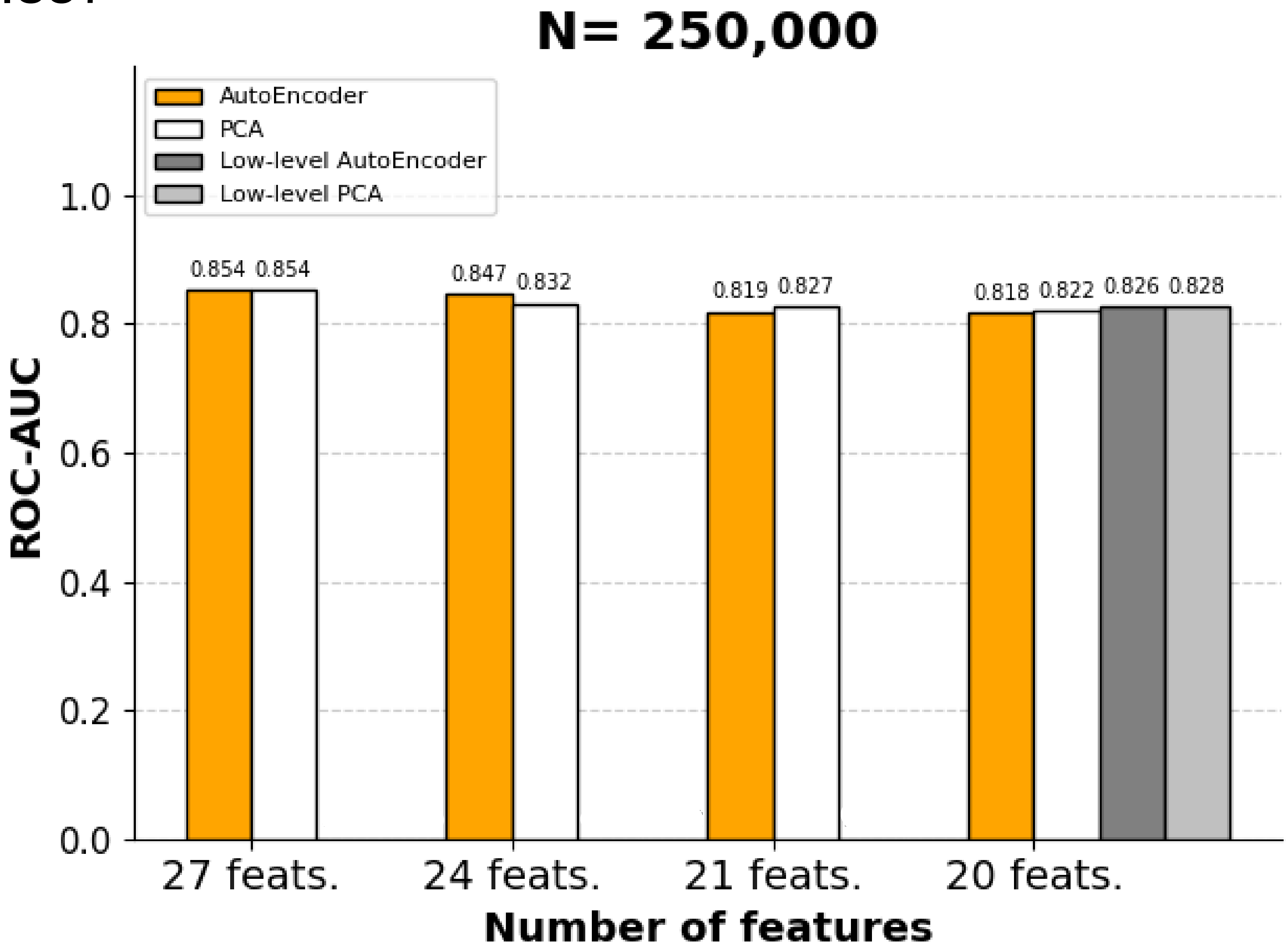
AutoEncoder

- Unsupervised neural network that encodes data by reducing dimensionality while retaining as much information as possible.



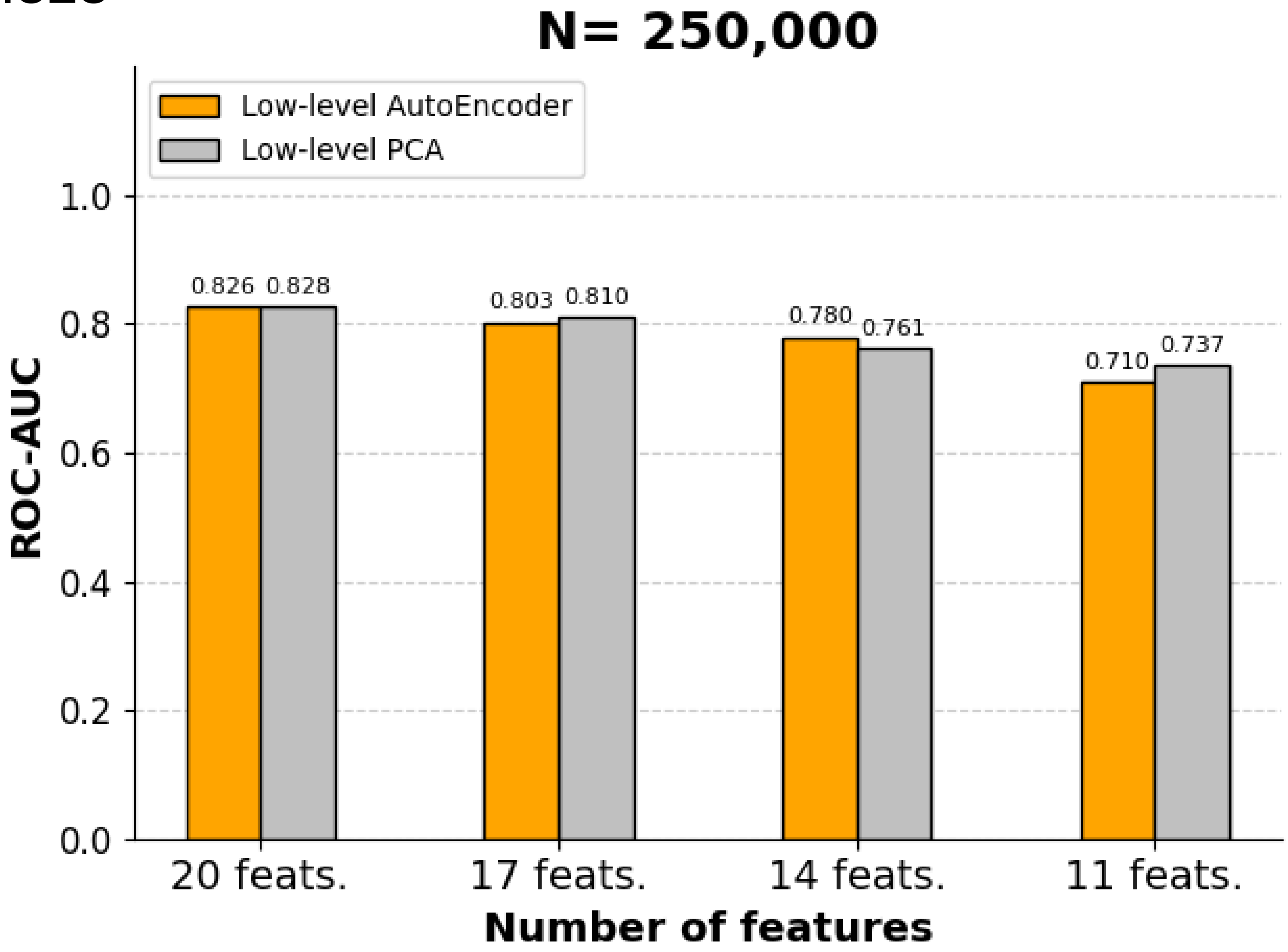
Comparing Performance

28 features: 0.857



Comparing Performance

21 features: 0.828



Selected Features Removal

- No missing energy features (19 features) : 0.815
- No b-tags from the four jets (17 features) : 0.775
- No b-tags from jets 1 and 2 (19 features) : 0.798
- No b-tags from jets 1 and 3 (19 features) : 0.801
- No b-tags from jets 1 and 4 (19 features) : 0.805
- No b-tags from jets 2 and 3 (19 features) : 0.802
- No b-tags from jets 2 and 4 (19 features) : 0.810
- No b-tags from jets 3 and 4 (19 features) : 0.814

Summary of Results

	Benchmark 28 features	Benchmark 21 features	20 features	17 features	14 features	11 features
Best Method	N/A	N/A	PCA	PCA	AutoEncoder	PCA
Best ROC-AUC	0.857	0.828	0.828	0.810	0.780	0.737

- PCA takes less time to implement than an AutoEncoder

Conclusions and Possible Future Steps

- PCA and AutoEncoders can be used to reduce dimensionality of the dataset.
- It is possible to handpick select features without losing too much information.
- Missing energy features are less important for classification.
- Higher transverse momentum jets are more important for classification.
- <u>Possible future steps</u>

  - Fine tune networks trained on reduced dataset.
  - Explore transformer autoencoder.

Thank you!

Considered parameters

- 5 layers of 256 neurons
- Dropout in every layer of 0.2
- First-layer only dropout of 0.5
- Learning rate decay scheduler