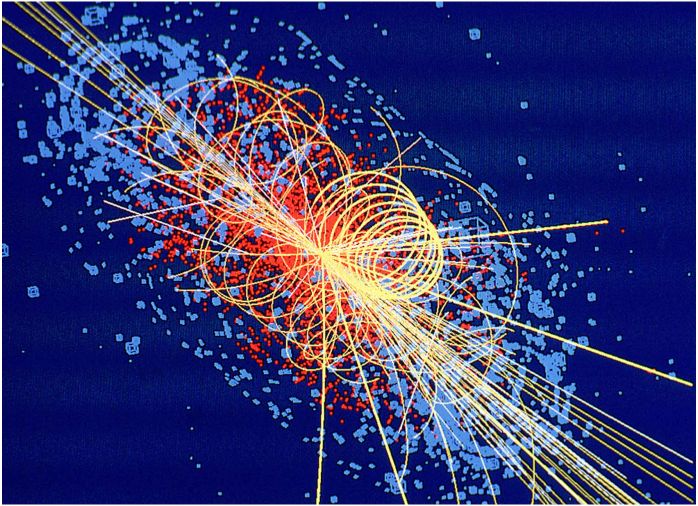
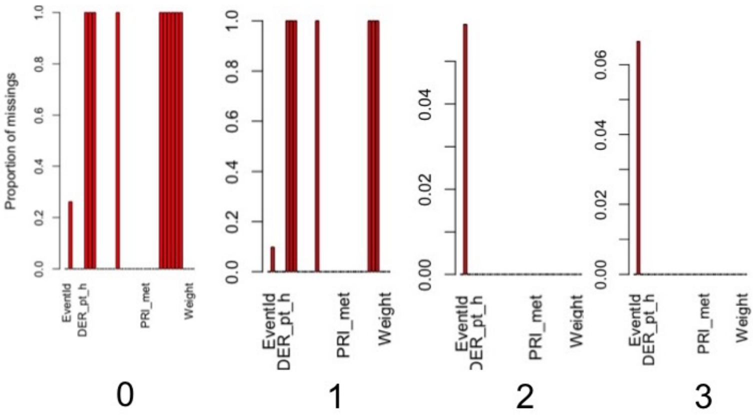
Higgs Boson dataset: From Description to Ensemble

Robert Castellano, Yannick Kimmel, Wanda Wang, Ho Fai Wong



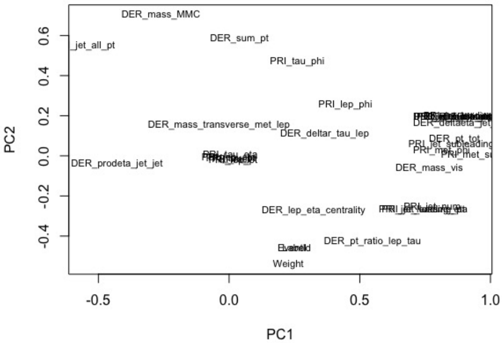
Exploratory data analysis

Sparse dataset



- Jet number can be treated as a factor for missingness.

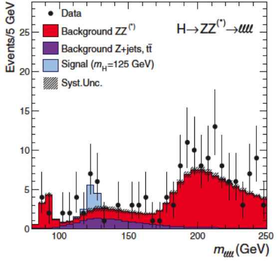
Principal component analysis

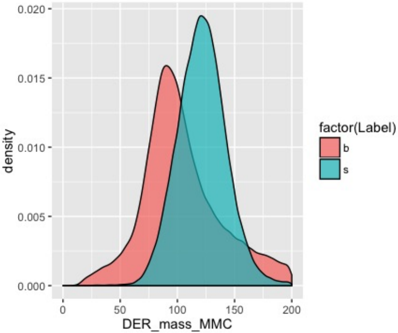


	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	h2	u2	com
DER_mass_MMC	0.25	-0.45	-0.02	0.55	0.04	-0.02	0.01	-0.24	0.00	0.63	0.3693	2.8
Label	0.23	-0.54	-0.07	0.11	0.24	0.01	-0.01	-0.36	-0.04	0.55	0.4476	2.8

- PCA shows that derived mass and label have a very strong relationship.

Mass as a predictor of Higgs Boson presence





- Derived mass of Higgs Boson is different from other Bosons and subatomic particles.

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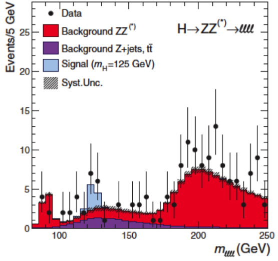
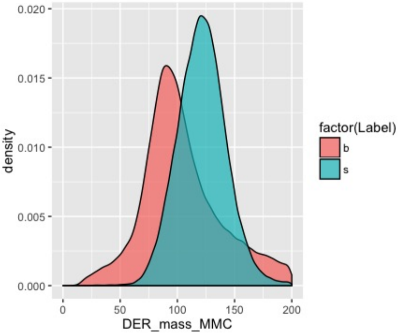
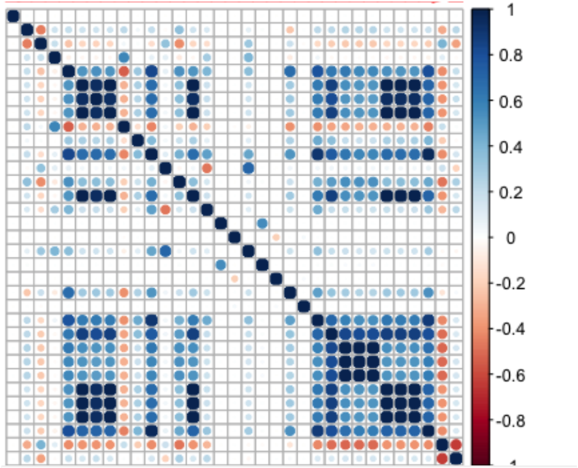




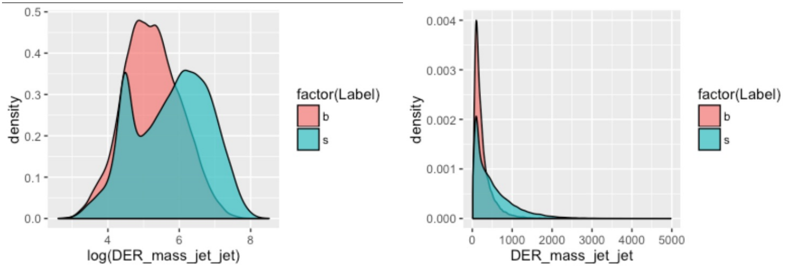
- Derived mass of Higgs Boson is different from other Bosons and subatomic particles.
- Simulated dataset increases signal, and must be offset using weights.

Correlation matrix



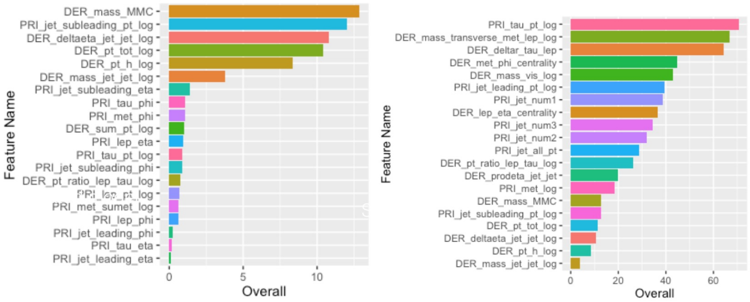
- There are several variables with strong covariance among the 33 variables.

Initial Feature Engineering



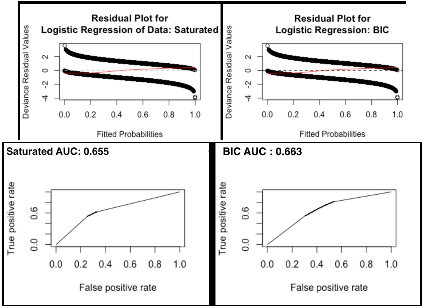
- 14 Features with long-tailed distributions were log transformed to reduce the positive skew towards smaller values, generating a more uniform distribution.. E.g. DER_mass_jet_jet: The invariant mass of the two jets.

Logistic Regression - Variable Importance



- Saturated Model vs. Stepwise BIC Model

Logistic Regression - Analysis



- Saturated Model: R.Squared: 0.20227; Stepwise BIC model: R.Squared: 0.20223.

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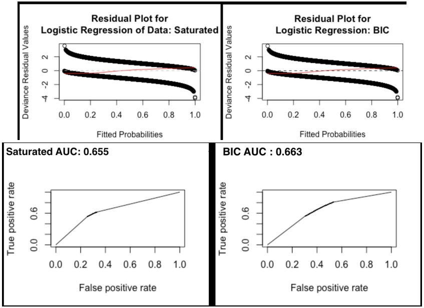

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- Chi-Squared P-value: 3.77 e-16 (Saturated) and 3.90 e-16 (Stepwise).

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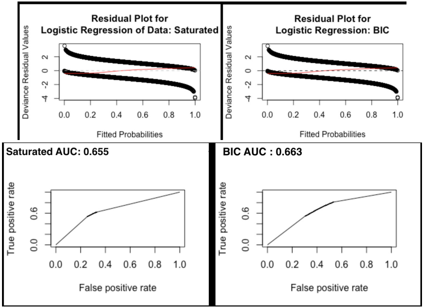

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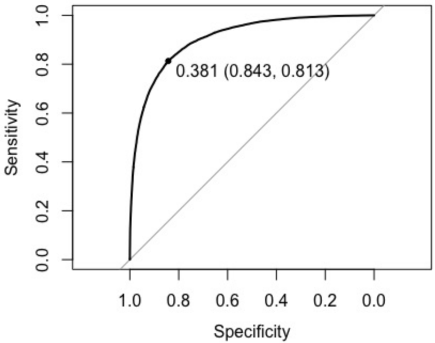
- Chi-Squared P-value: 3.77 e-16 (Saturated) and 3.90 e-16 (Stepwise).
- AUC plots are also not very different from one another.

Choice of AUC as model fit metric



- Maximizes the true positive rate while also minimizes the false positive rate.

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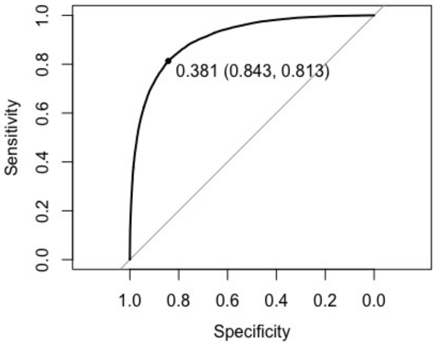

- Maximizes the true positive rate while also minimizes the false positive rate.
- Produces a smooth and continuous function unlike AMS.

Models

Our models

- Random forest

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- Gbm

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- Gbm
- Xgboost

Random forest model

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- Tuning parameters
  - mtry: Number of splits per tree

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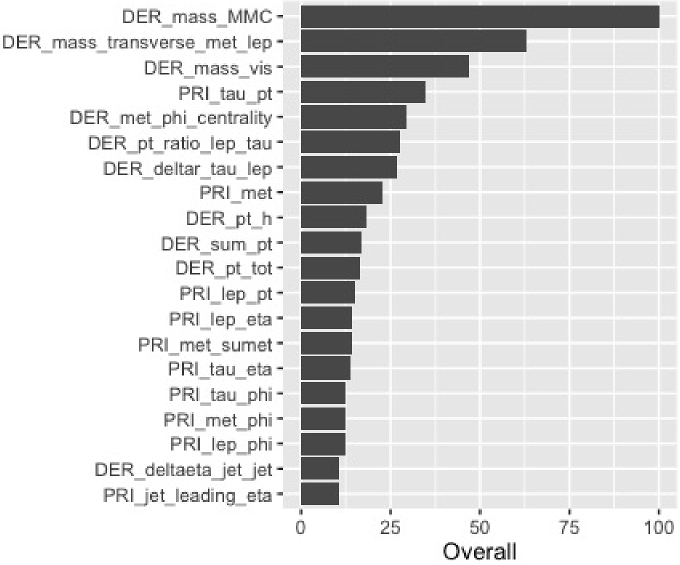
- Kaggle rank = 1311
- AMS = 2.57949

Random forest variable importance



Gbm model

- Gradient boosting model

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  - shrinkage: Learning rate
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  - n.trees: Number of trees
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- Performed 5-fold CV to tune parameters.
  - shrinkage = .1
  - interaction_depth = 3
  - n.trees = 150
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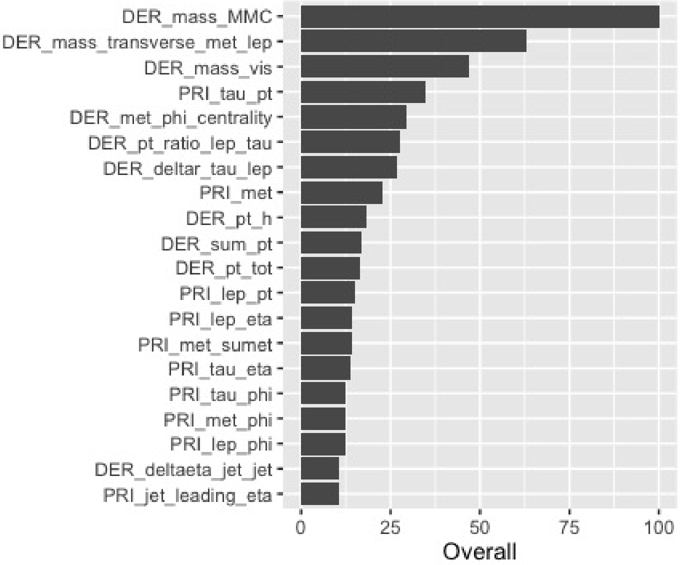

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- More tuning parameters
- Not completely greedy in tree creation
- Generally faster and performs better than gbm.

Xgboost model

- Parameters we tuned:
  - nrounds: Number of trees
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  - colsample_bytree = .85
  - eta = .2

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  - colsample_bytree: Percent of parameters used at each split. tree
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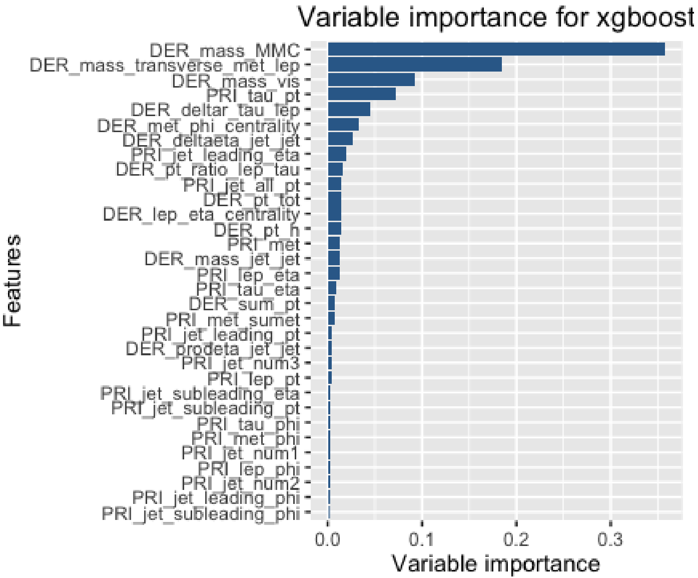
- Performed 5-fold CV to tune parameters.
  - nrounds = 200
  - max_depth = 5
  - colsample_bytree = .85
  - eta = .2
- AUC on training data = .9254
- Kaggle rank = 1340
- AMS = 2.49958

Xgboost variable importance



Ensemble

- Combined three models by majority vote

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Room for improvement

Feature engineering

- We did not include any additional variables
  - Basic physics. e.g. Cartesian coordinates of momentum

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- Log transforms

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- Run different random seeds for the same model