Classification and Features of Student Success in Online Programs

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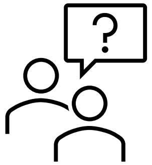
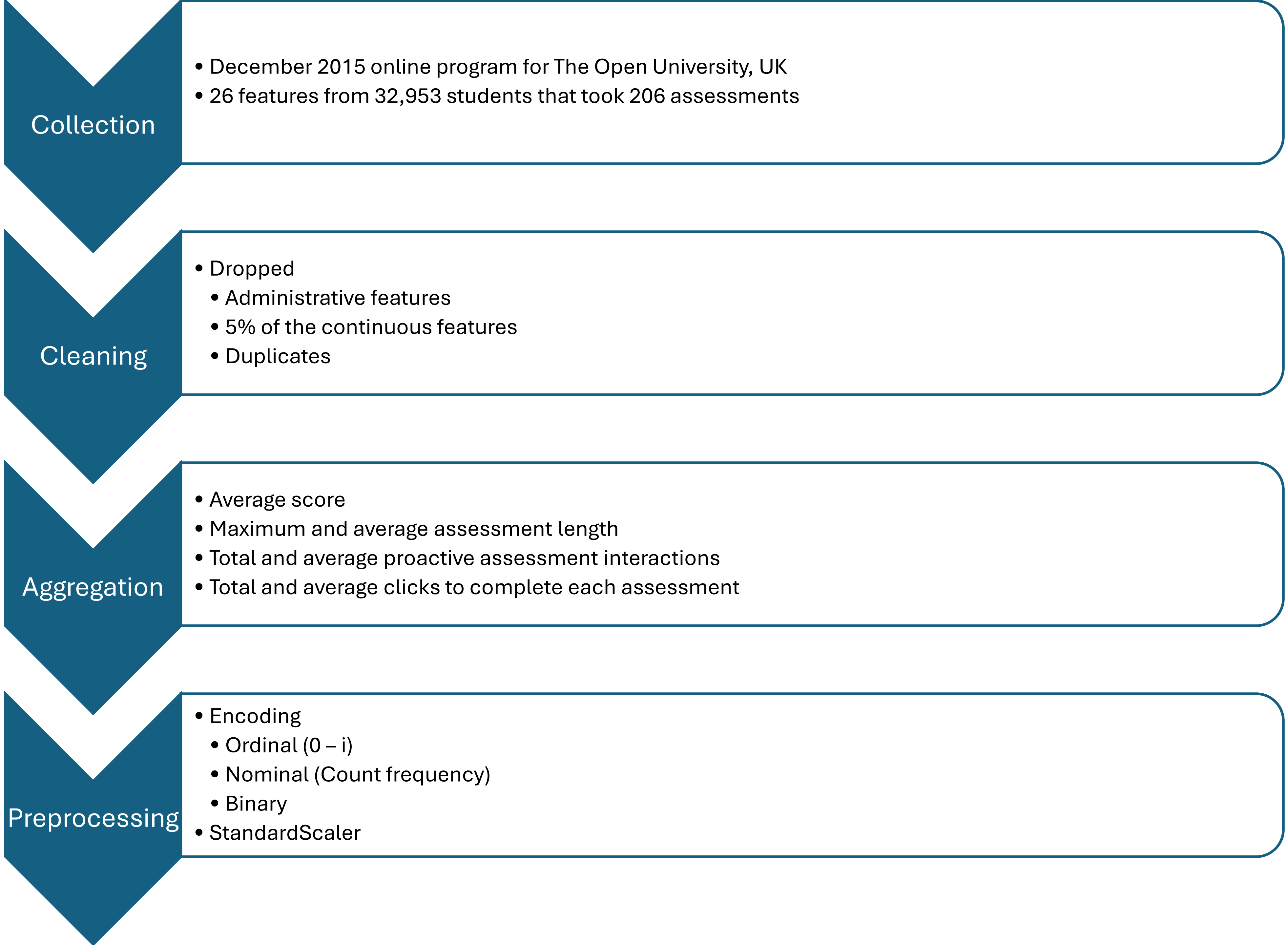
Communication is one of the biggest challenges to online learning

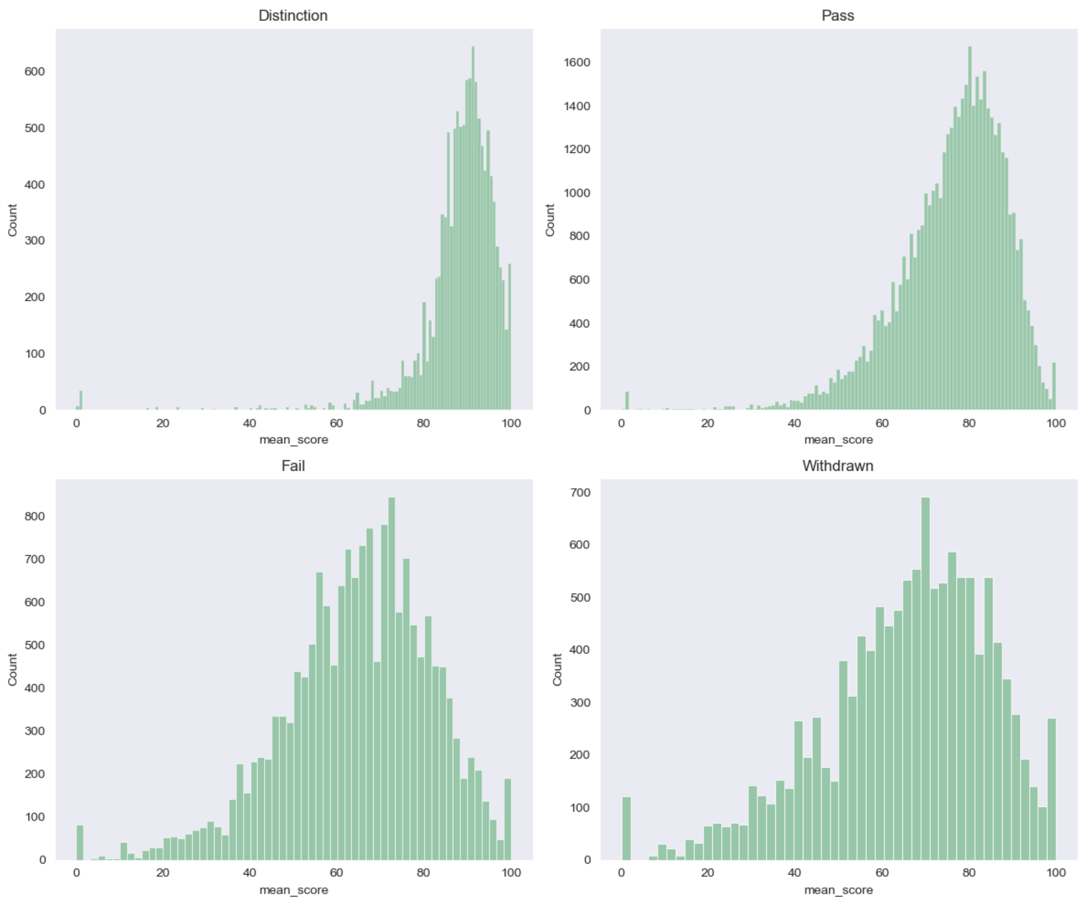


How can educators effectively gauge their students' engagement with the material in online programs?

- What features dictate student success in online programs, and can those features predict the trajectory of future cohorts as an advising tool?
  - The model must identify key features that determine final result classification.
  - The model must predict student outcomes to an 85% success rate.


Collection
• December 2015 online program for The Open University, UK
• 26 features from 32,953 students that took 206 assessments
Cleaning
• Dropped
• Administrative features
• 5% of the continuous features
• Duplicates
Aggregation
• Average score
• Maximum and average assessment length
• Total and average proactive assessment interactions
• Total and average clicks to complete each assessment
Preprocessing
• Encoding
• Ordinal (0 – i)
• Nominal (Count frequency)
• Binary
• StandardScaler

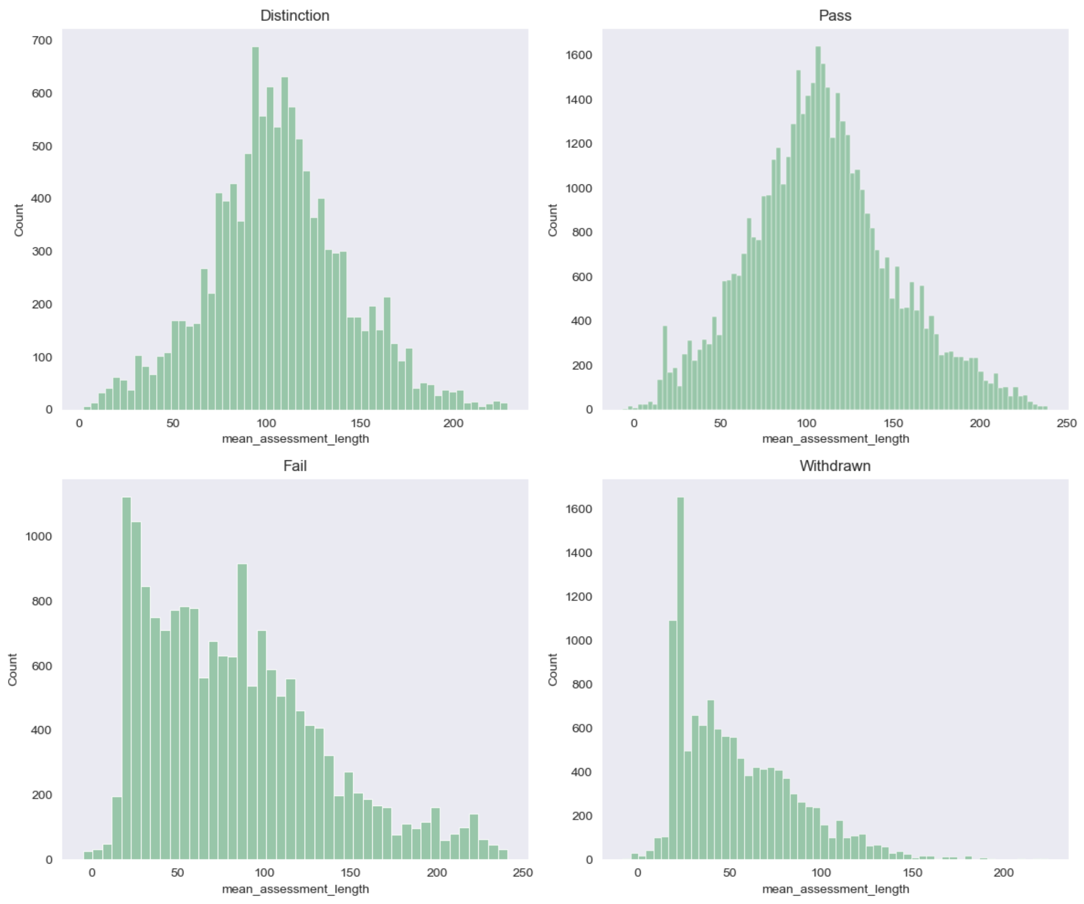
How does the average score for each assessment differ between the final results?



F-Stat	P-value
8332.65	0.0

Final Result	Average Score (%)
Distinction	89.28
Pass	77.03
Fail	65.15
Withdrawn	63.74

How does the material interaction for each assessment differ between the final results?



Stat	F-Stat	P-value
Average active	2.26	0.08
Average duration	6453.60	0.0

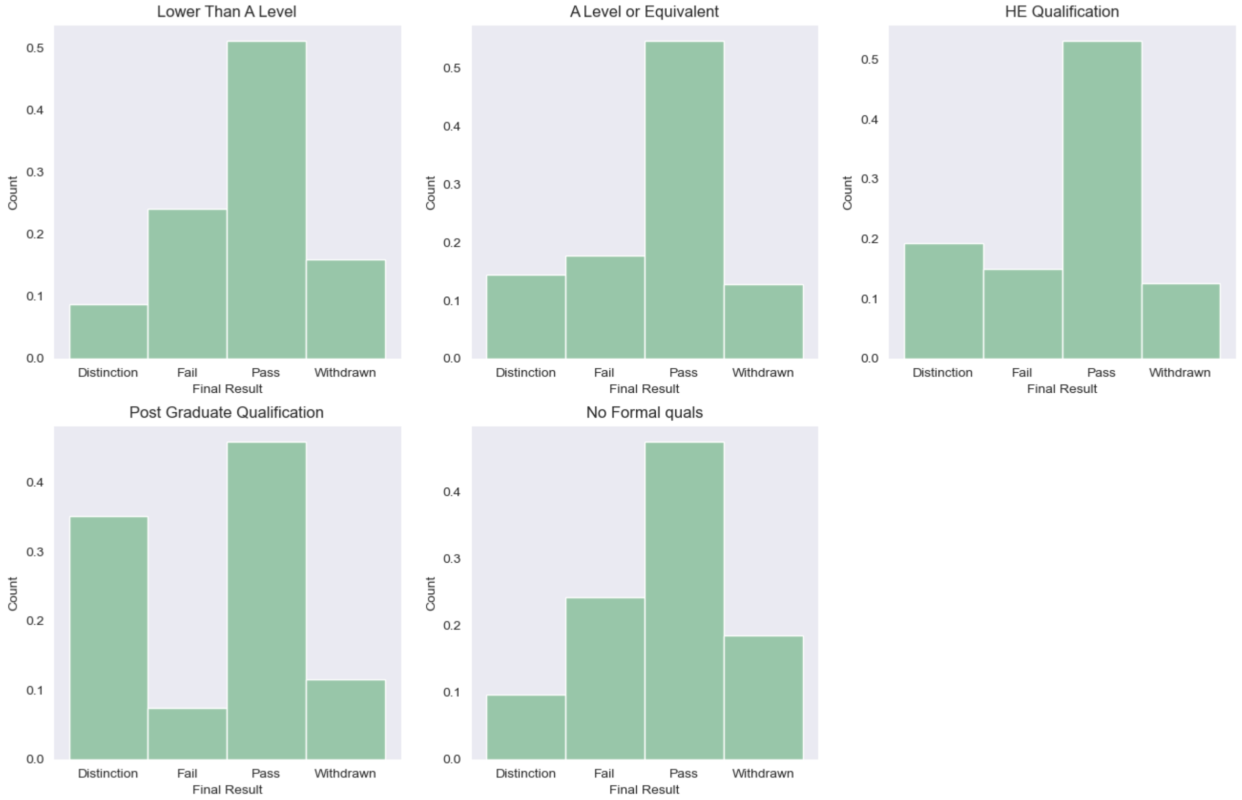
Final Result	Average duration (days)
Distinction	105.99
Pass	108.87
Fail	83.11
Withdrawn	53.93

Is there a difference between activity types that determine the final results?

χ^2	P-value
87.53	0.0

Is there a difference between activity types that determine the final results?

χ^2	P-value
26.22	0.0

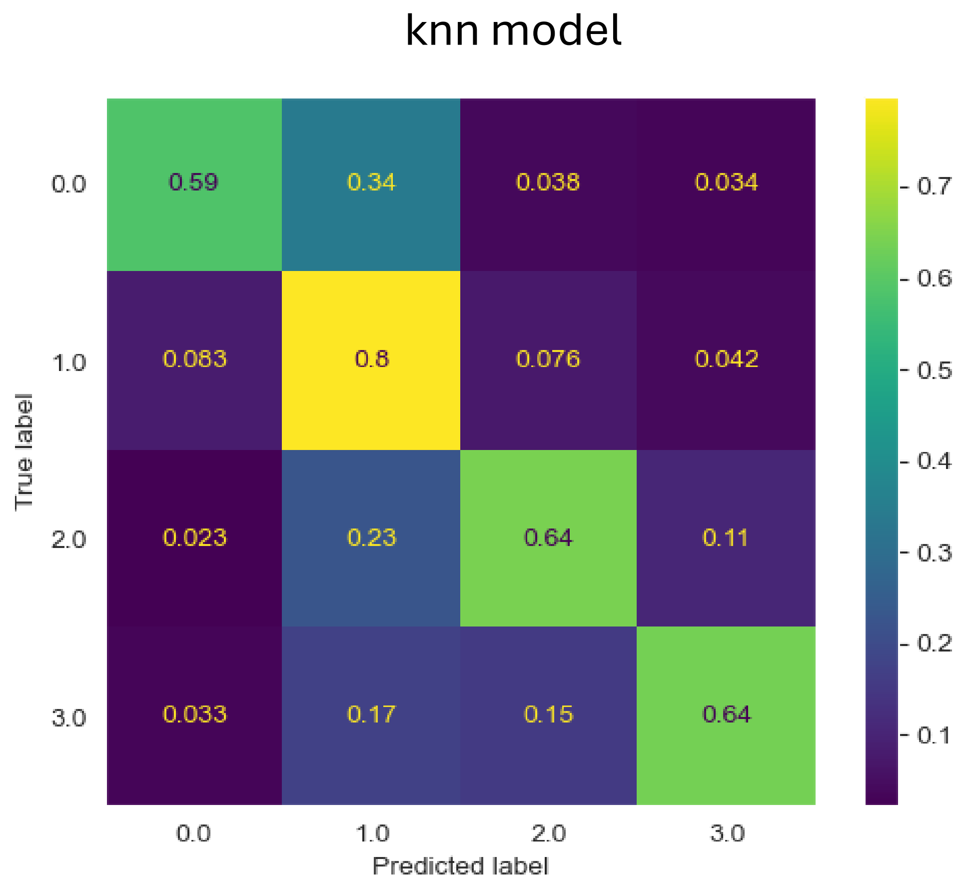


Supervised Multivariate Classification Modeling

- Splitting
  - 25% test set
  - Stratified: class imbalance
  - Shuffled: ordered data
- Hypertuning
  - RandomizedSearchCV
  - Stratified 5 fold
  - 250 iterations
  - Scoring: F1-score
- Models
  - Decision Tree (dt)
  - Random Forest (rf)*
  - K-Nearest Neighbors (knn)*
  - Logistic Regression (lr)

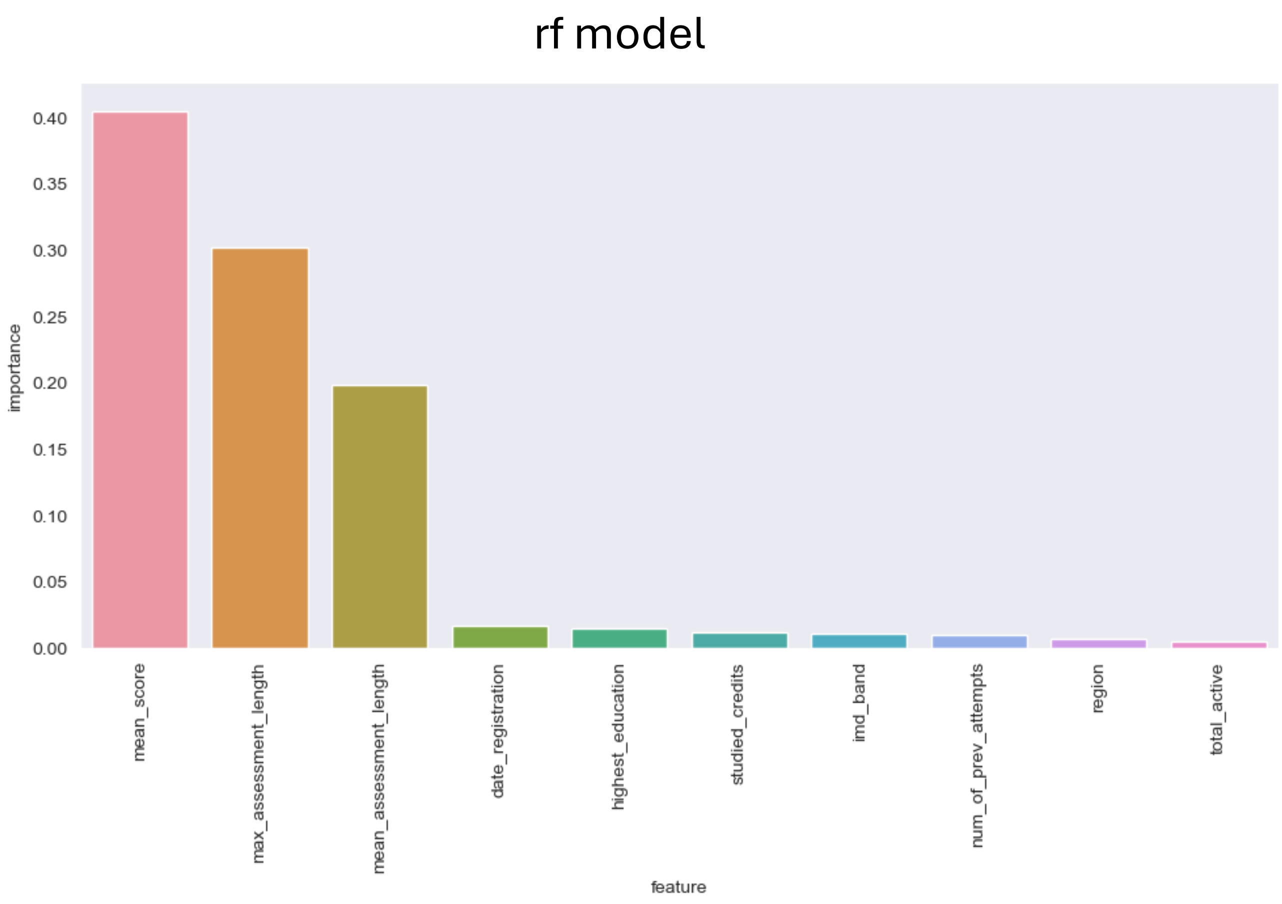
Classification

- K-Nearest Neighbors
  - Hyperparameters
    - Weights: Distance
    - Algorithm: Ball tree
    - Neighbors = 2
  - Metrics
    - Accuracy = 0.72
    - Weighted F1-score = 0.72
- Model best classified passing students
  - 79% of the students were identified correctly
  - Passing students account for 53% of the students



Feature Importance

- Random Forest
  - Hyperparameters
    - Max features: squareroot
    - Criterion: gini index
    - Estimators = 300
    - Max depth = 60
    - Min samples = 0.01
  - Metrics
    - Accuracy = 0.64
    - Weighted F1-score = 0.59
- Features
  - Average score (importance = 0.40)
  - Max Assessment Length (Importance = 0.30)
  - Mean Assessment Length (Importance = 0.20)



Conclusion

- The model must identify key features that determine final result classification.
  - Random forest identified average score and how long the assessments were active
  - The model had relatively mediocre metrics so new iterations will need to reassess feature importances
- The model must predict student outcomes to an 85% success rate.
  - The highest accuracy was 72% with the K-Nearest Neighbors classifier.
  - Using resampling techniques to reduce the class imbalance may improve the results.

Future Work

Data

- Rebalance classes
- Feature importances by
  - Average score
  - Highest education
  - VLE activity type

Additional Studies

- What factors lead to students turning in their assessments later than others?
- How has online learning changed between 2015 to present?