Betting Odds Calculation with Machine Learning

LYU 2102

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Outline

- Introduction
- Background Knowledge
- Data Preparation
- Methodology
- Experiment and Result
- Conclusion

Introduction - Motivation

- Revenue from horse racing is approximately HK$280 billion in 2020-2021 despite the economic downturn caused by the coronavirus pandemic
- Win odds enhance prediction accuracy as shown in previous FYP[1][2]
- Win odds keep changing before the start of the race
- Use machine learning methods to resemble the effect of winning odds in horse racing prediction

Introduction - Objective

- Apply statistical models(rating systems) to evaluate the performance of horses
- Apply techniques in natural language processing for winning horse classification
- Reproduce the effect of variable win odds from the Hong Kong Jockey Club in horse racing prediction by invariable features

Background Knowledge – Rating System

Glicko Rating System[3]

- Rating
  - Performance of a horse
- Rating deviation
  - Reliability of a horse’s rating
  - a low value of rating deviation indicates that the horse joins races frequently and the rating is more reliable
  - uncertainty of a horse’s ability reduces because more information is obtained when the horse joins more races

Background Knowledge – Rating System

TrueSkill Rating System[4]

- Rating
  - Performance of a horse
- Rating deviation
  - Reliability of a horse's rating
- Multiple horse environment
  - Assume outcome of each race is a permutation of multiple horses
  - Allow horses to have the same rank

Background Knowledge – Rating System

Elo-MMR Rating System[5]

- Rating
  - Performance of a horse
- Rating deviation
  - Reliability of a horse's rating
- Multiple horse environment
  - Assume outcome of each race is a permutation of multiple horses
  - Assume horses have distinct ranks
- incentive compatible
  - horses' ratings should not have opposite changes to their performance

Background Knowledge – Transformer

Self Attention mechanism[6]

- Features in the sequence interact with each other
- Assign weights to features according to the relative importance
- Decide dependency relationships between features of the sequence

Data Preparation - Collection

- Write web crawlers by using BeautifulSoup library in python
- Collect data on the HKJC official websites
- Obtain 9191 race records in our dataset dated from June 2008 to October 2021
- Obtain horse records of 6642 horses which participated in those 9191 race records

Data Preparation – Feature Analysis

- By Bayes' formula,

  Pr(Y = win | X = x1, x2, …)

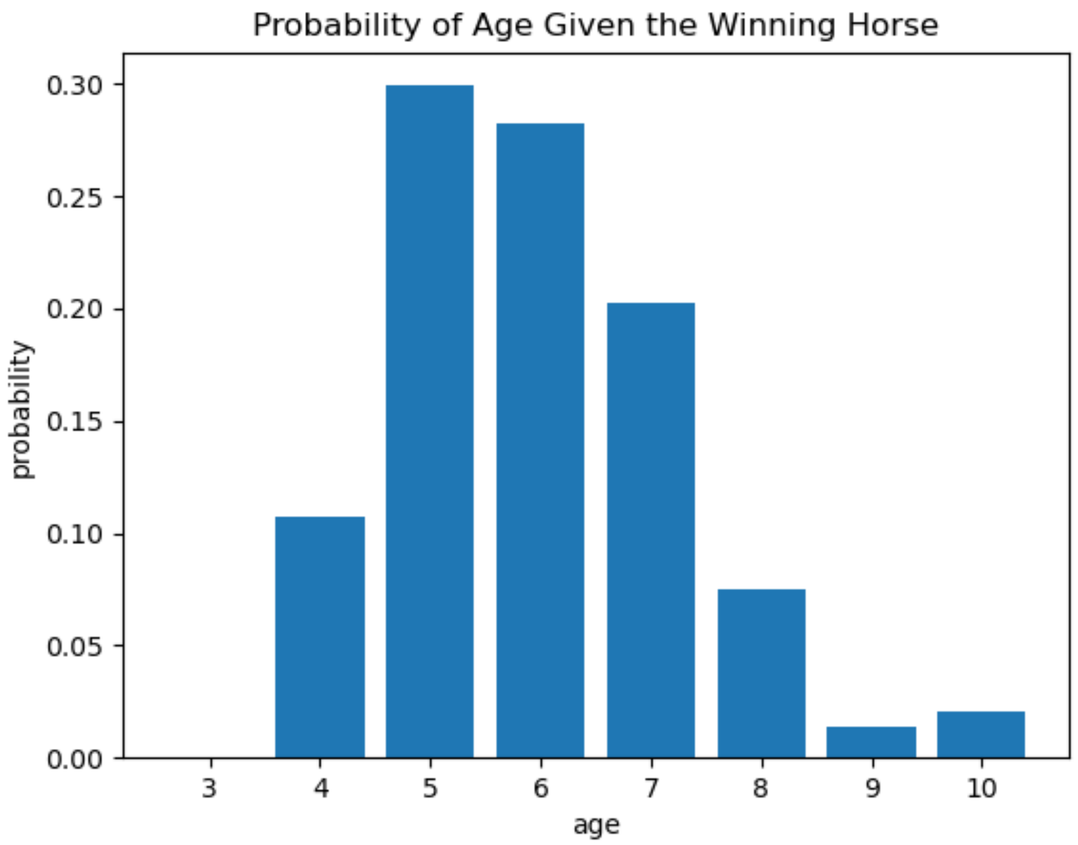
  = Pr(X = x1, x2, … | Y = win) Pr (Y = win) / Pr (X = x1, x2, …)

- Likelihood estimation in machine learning is simplified by assuming that features are conditional independent.

- We observe the likelihood Pr(X = x | Y = win) one by one.

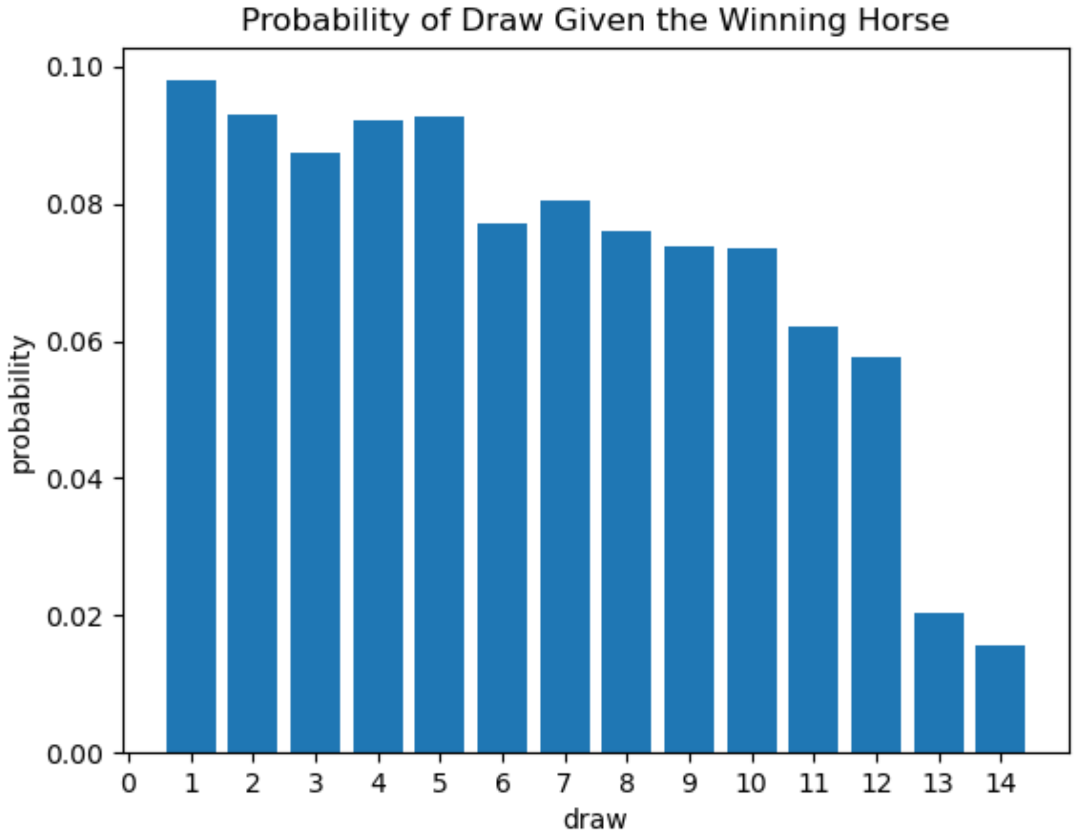
Data Preparation – Feature Analysis (Age)

- Most winning horses are aged between 5 and 6



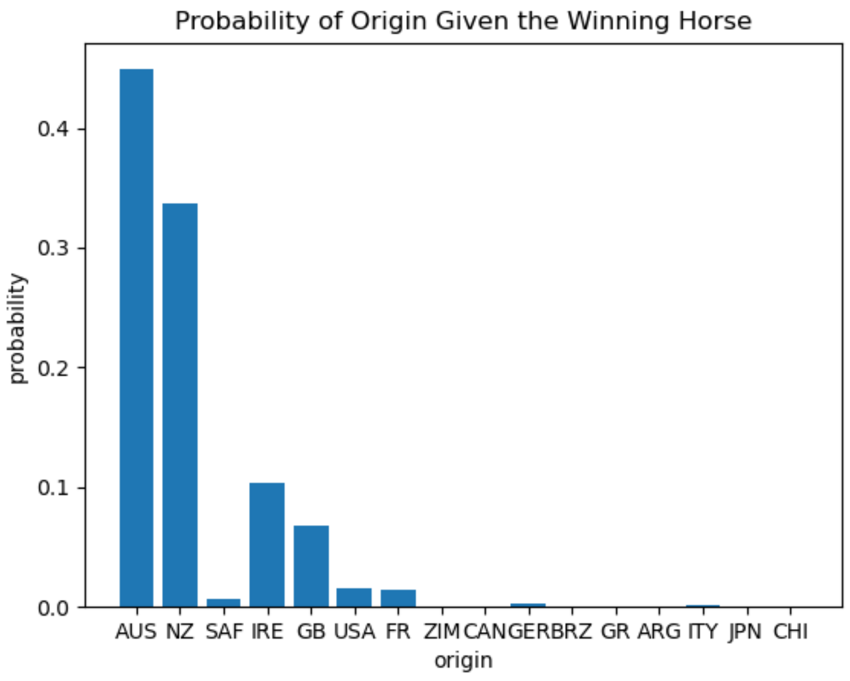
Data Preparation – Feature Analysis (Draw)

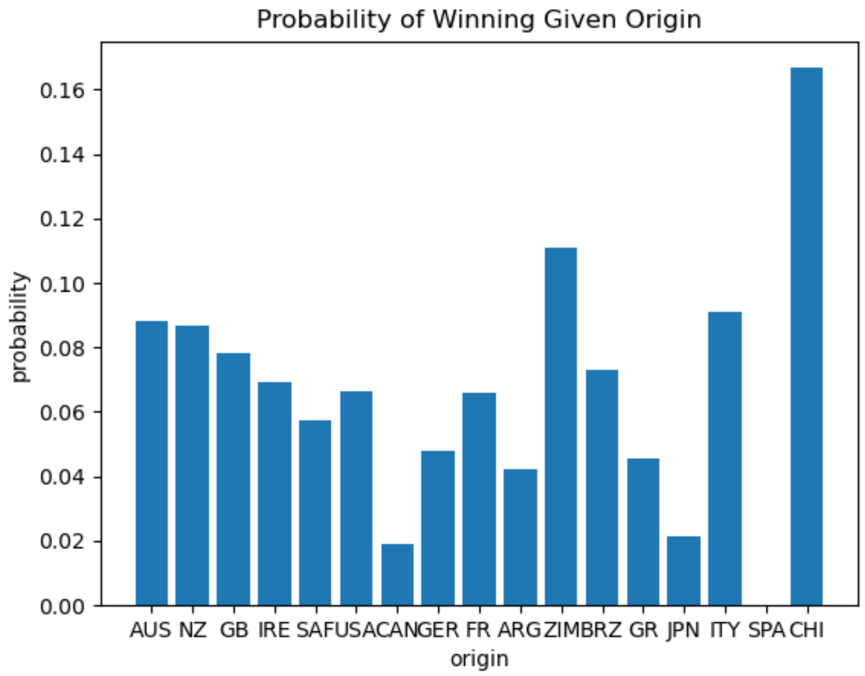
- Most winning horses have smaller draw number.



Data Preparation – Feature Analysis (Origin)

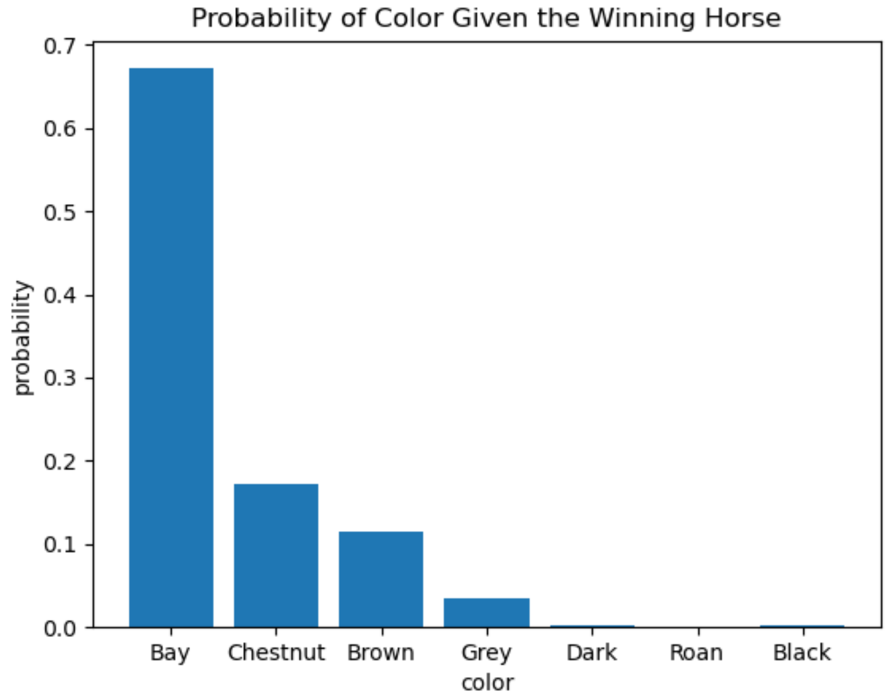
- Most winning horses come from Australia or New Zealand

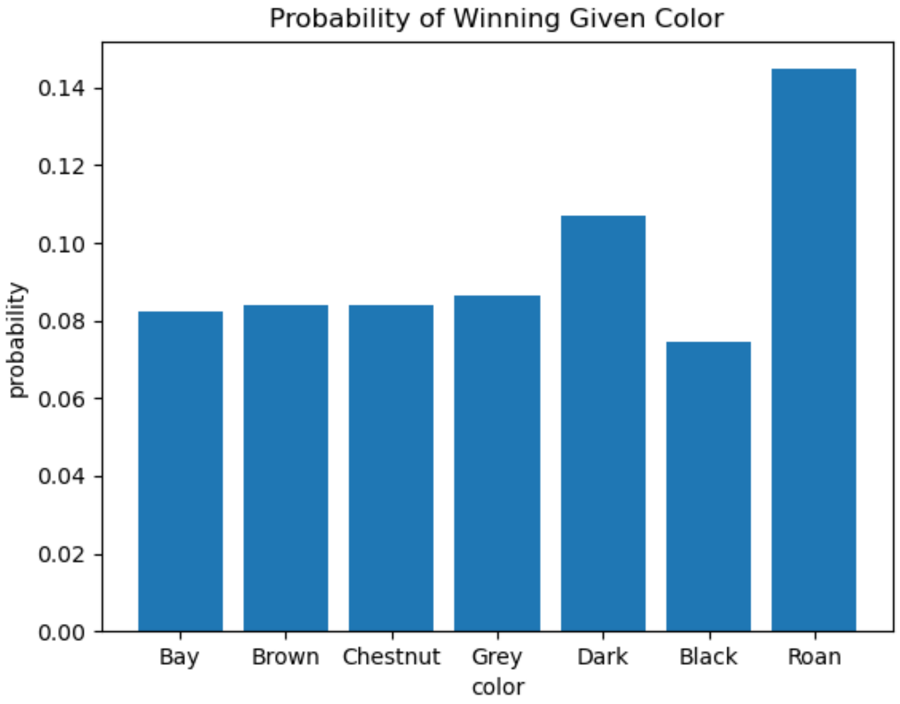




Data Preparation – Feature Analysis (Color)

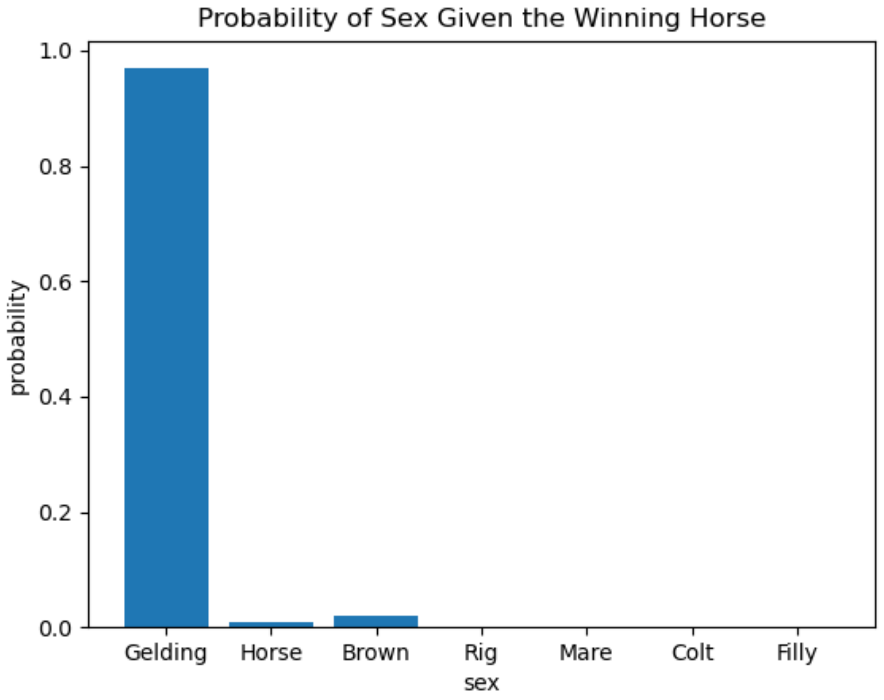
- Most winning horses have skin color Bay

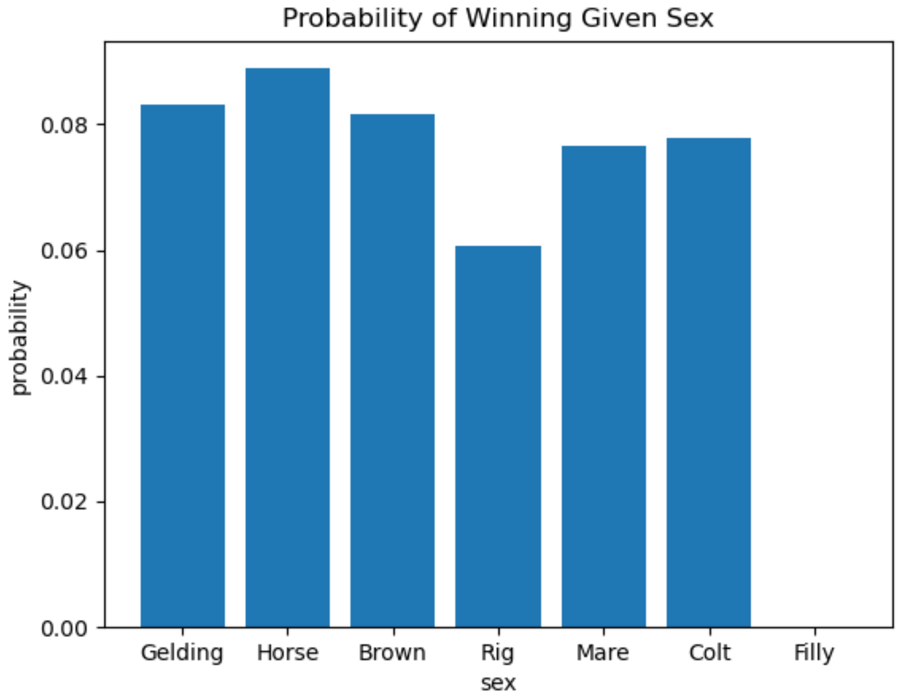




Data Preparation – Feature Analysis (Sex)

- Most winning horses are of sex Gelding.

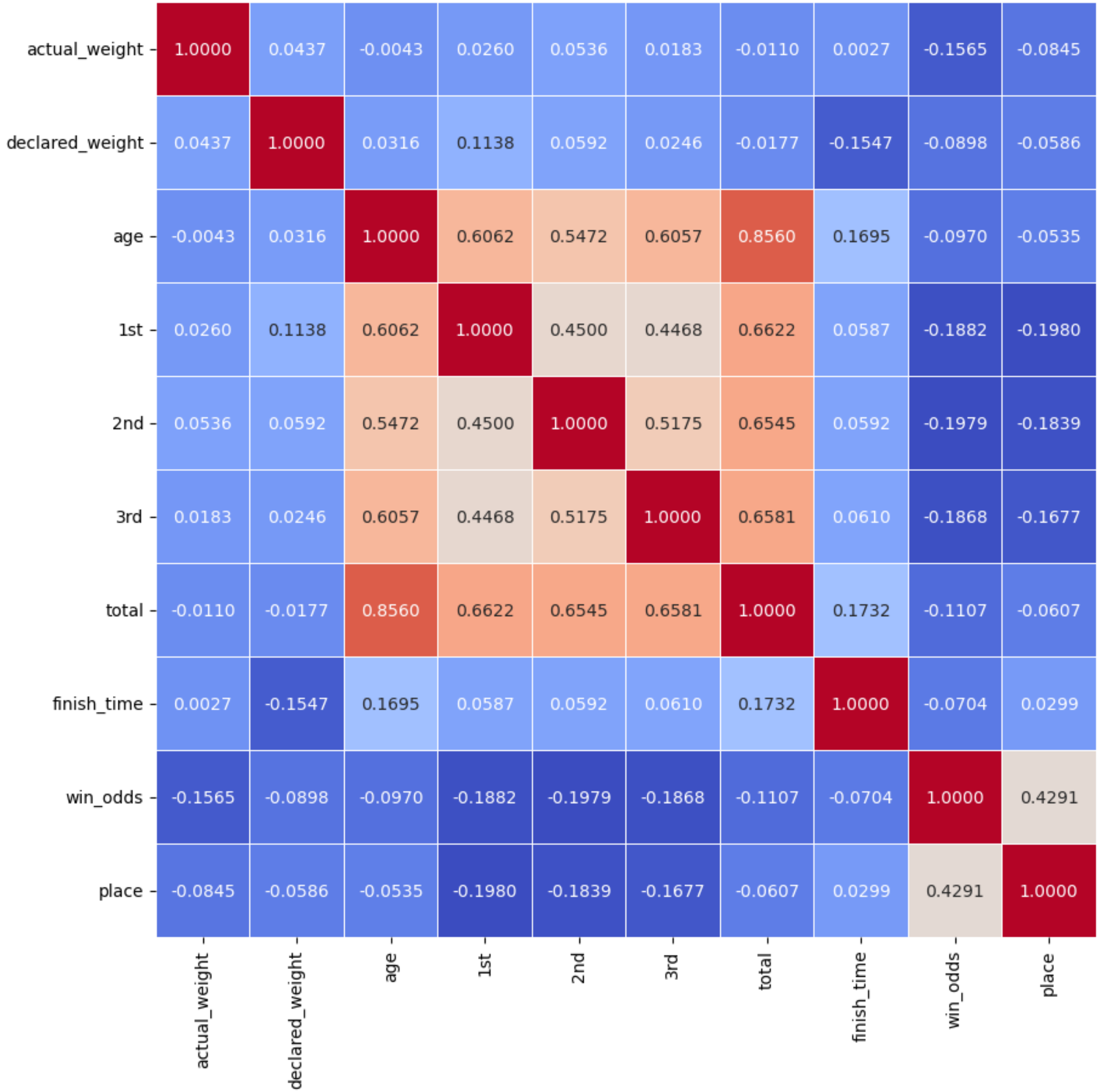




Data Preparation – Feature Analysis (Numerical features)

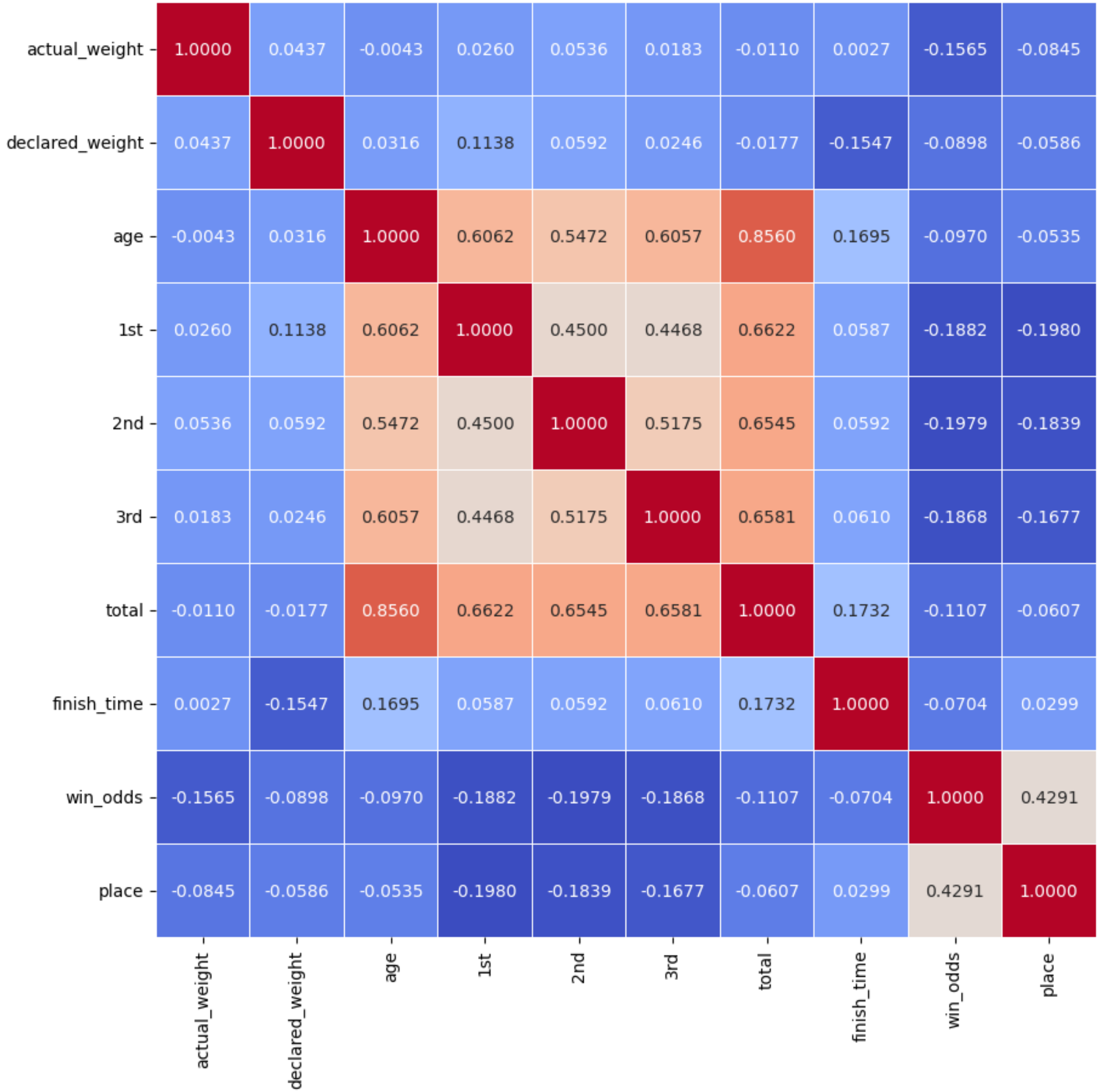
- Frequency of 1st place has a significant correlation with the frequency of 2nd place and 3rd place which are 0.4500 and 0.4468 respectively

- Rating systems are applicable in prediction



Data Preparation – Feature Analysis (Numerical features)

- A positive correlation of 0.4291 between the win odds and the place
- Winning odds help the prediction of horse racing result



Data Preparation – Data Imputation

- A small part of horse data about those retired horses is missing in our data set
- do data imputation on our dataset by using the k nearest neighbors method
- Invoke the KNN Imputer from Scikit Learn library to impute the missing values

Data Preparation – Data Encoding

- Input of our neural network models must be numerical but some of our data are categorical
- One hot encoding[7]
  - dimension of our input will be increased drastically
  - requires extra memory and more computational time in training
- Ordinal Encoding scheme[7]
  - a unique integer means a category
  - dimension of the data is the same as the original
- invoke the Ordinal Encoder from the Scikit Learn Library

Data Preparation – Normalization

- z-score normalization[8]
- Values of all variables are recomputed into the same scale
- the same scale of all variables balances the focus of error minimization in the weight correction algorithm

$$x_i' = \frac{x_i - \bar{x_i}}{\sigma_i}$$

Data Preparation – Rating Generation

- Ratings mentioned before do not exist on the HKJC websites
- need to calculate those ratings with the information provided by our dataset

contest_index	rating_mu	rating_sig	perf_score	place
66	1400	174	1381	9
107	1384	133	1365	11
162	1481	114	1724	5
199	1443	102	1370	9
275	1463	95	1511	7
322	1482	90	1540	7
351	1491	87	1517	6
380	1522	85	1639	6
417	1543	84	1620	4
446	1563	82	1642	6
468	1527	82	1370	10
533	1562	81	1700	2
592	1610	81	1833	1
632	1613	81	1623	5
687	1626	80	1677	6

Methodology - Overview

- Rating systems estimate the relative skill level of horses based on their historical performance
- Self attention mechanism captures the dependencies between horses
- Multiclass classification on place
  - The winning horse number is the output
- Transformer classification model including ratings in the feature list

Methodology - Evaluation

- Accuracy
  - Accurate prediction about the winner
- Betting simulation
  - Net gain
  - Bet $10 for each race in test data

- Combining transformer architecture and ratings give a better result
  - Multilayer perceptron with ratings
  - Transformer without ratings
  - Transformer with ratings

Methodology – Multilayer perceptron

1. Input layer
2. 3 linear hidden layer
3. Dropout layer
4. Output layer

- Relu Activation function
- Cross-Entropy Loss Function
- Stochastic gradient descent

Methodology – Transformer

1. Input layer
2. Word embedding layer
3. Position embedding layer
4. Transformer encoder
5. 2 linear hidden layers
6. Dropout layer
7. Output layer

- Relu Activation function
- Cross-Entropy Loss Function
- Stochastic gradient descent

Experiment and Result – Input Data

- Training data :
  - races from 22 June 2008 to 6 December 2020.
  - 8500 races
- Testing data
  - all races from 9 December 2020 to 17 October 2021.
  - 688 races

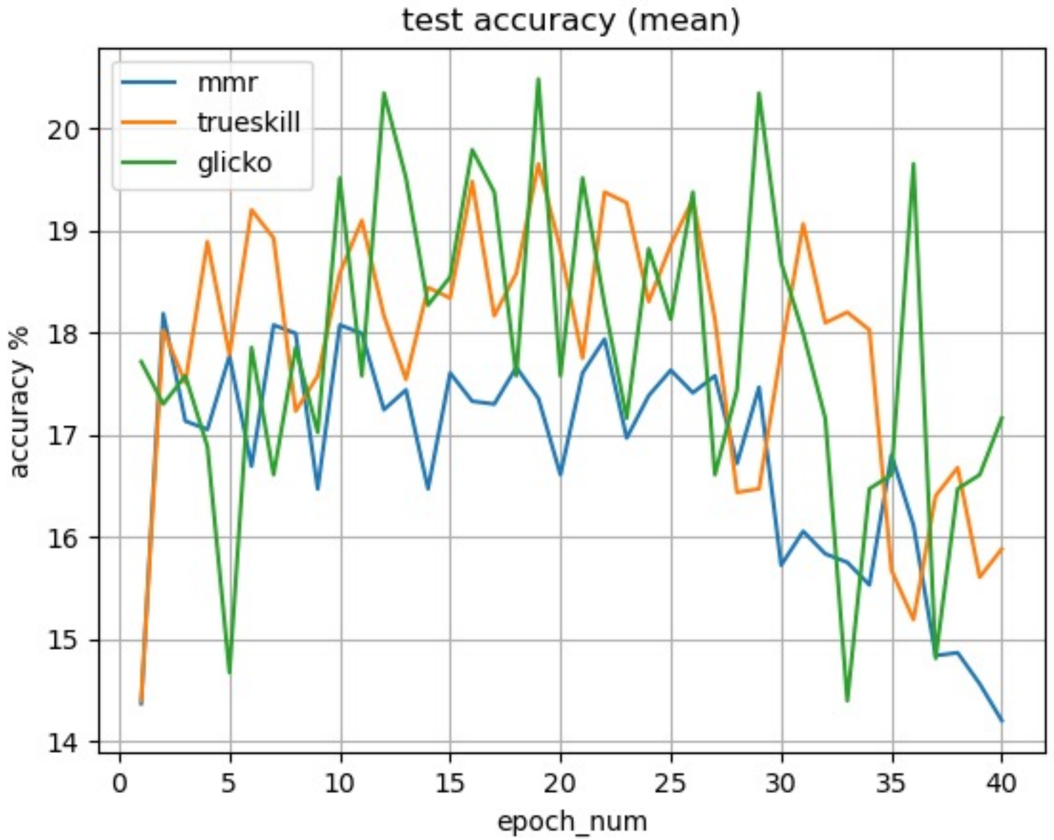
Experiment and Result – Input Data

Feature	Description
Venue	Location of the race
Horse_class	Class of the horses Stronger horses compete in high race class
Distance	The distance of the race
Going	Condition of the lane
Course_track	The lane of the race
Course_track_code	Description about the lane
Horse_i_number	The horse number in the race
Horse_i_name	The name of horse
Horse_i_jockey	The name of jockey
Horse_i_trainer	The name of trainer
Horse_i_declared_weight	The weight of horse
Horse_i_origin	The place of birth
Horse_i_age	The age of horse
Horse_i_color	The color of skin
Horse_i_sex	The gender of horse
Horse_i_1st_place_frequency	The frequency of getting 1st place
Horse_i_total_race	The total count of horse's participation
Horse_i_rating	The rating of the horse

Repeat 14 times

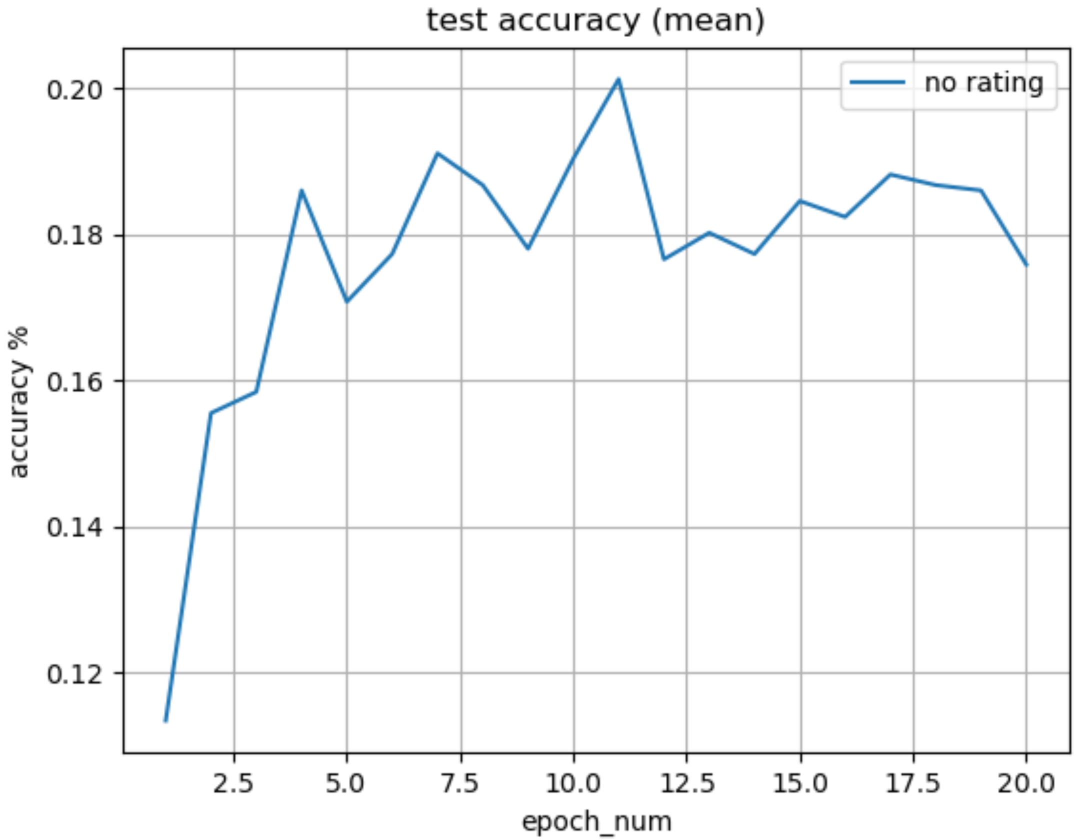
Experiment and Result – Accuracy

- Multilayer perceptron with ratings
- The model with Glicko ratings reaches the highest test accuracy of 20.4%
- The accuracy of the model with Glicko ratings fluctuates in a larger range than that with Elo-MMR and TrueSkill



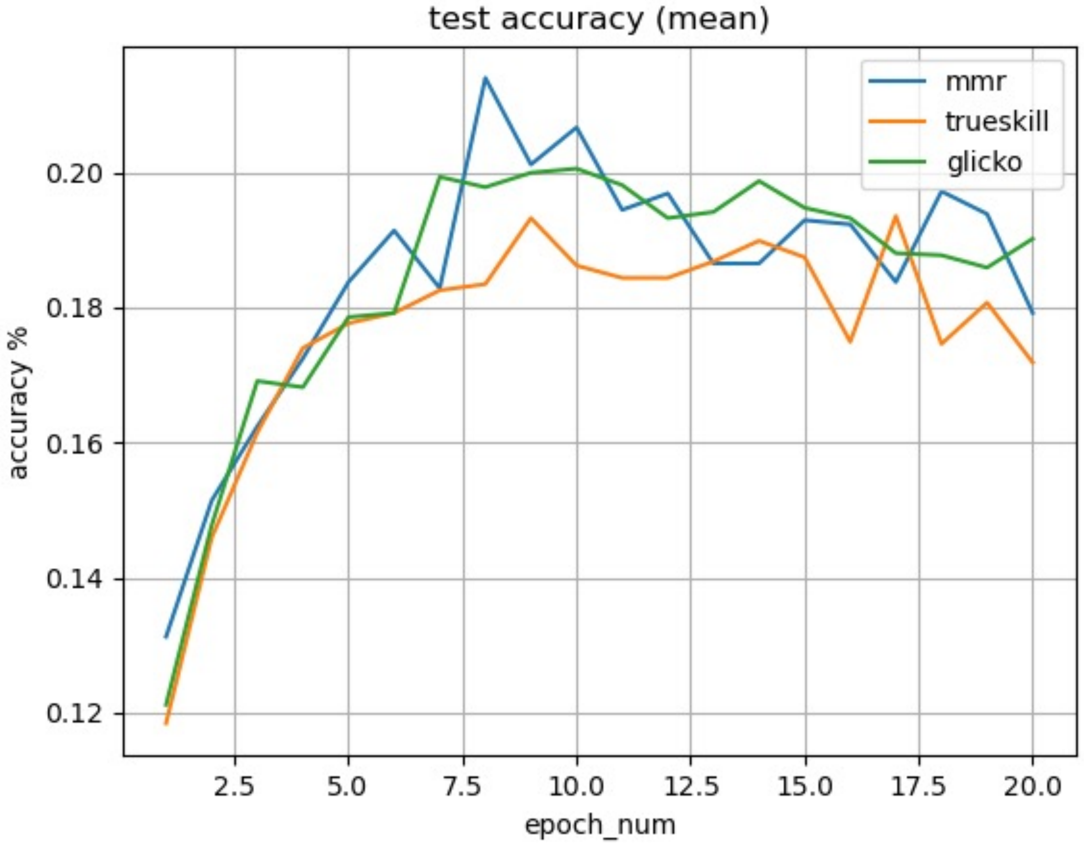
Experiment and Result – Accuracy

- Transformer without ratings
- the best performance of this model is having 19.2% before overfitting



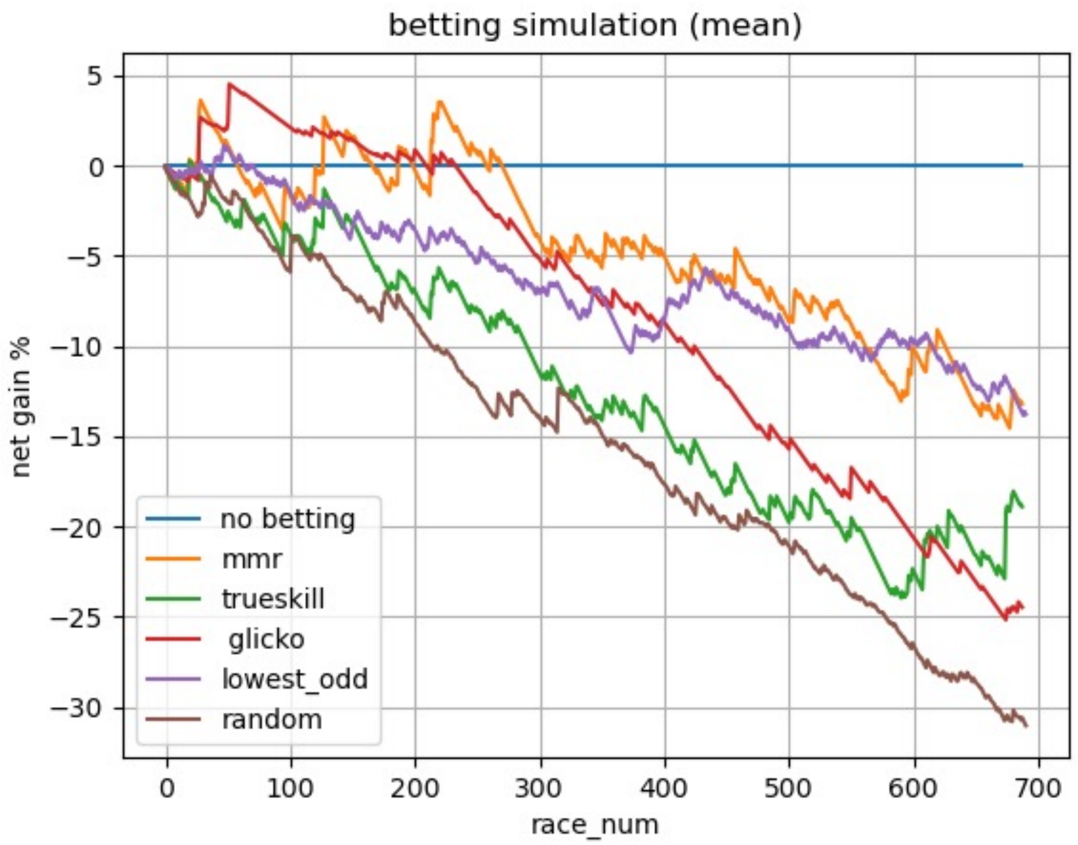
Experiment and Result – Accuracy

- Transformer with ratings
- The transformer model with Elo-MMR ratings has the highest test accuracy of 21.4% among the other models



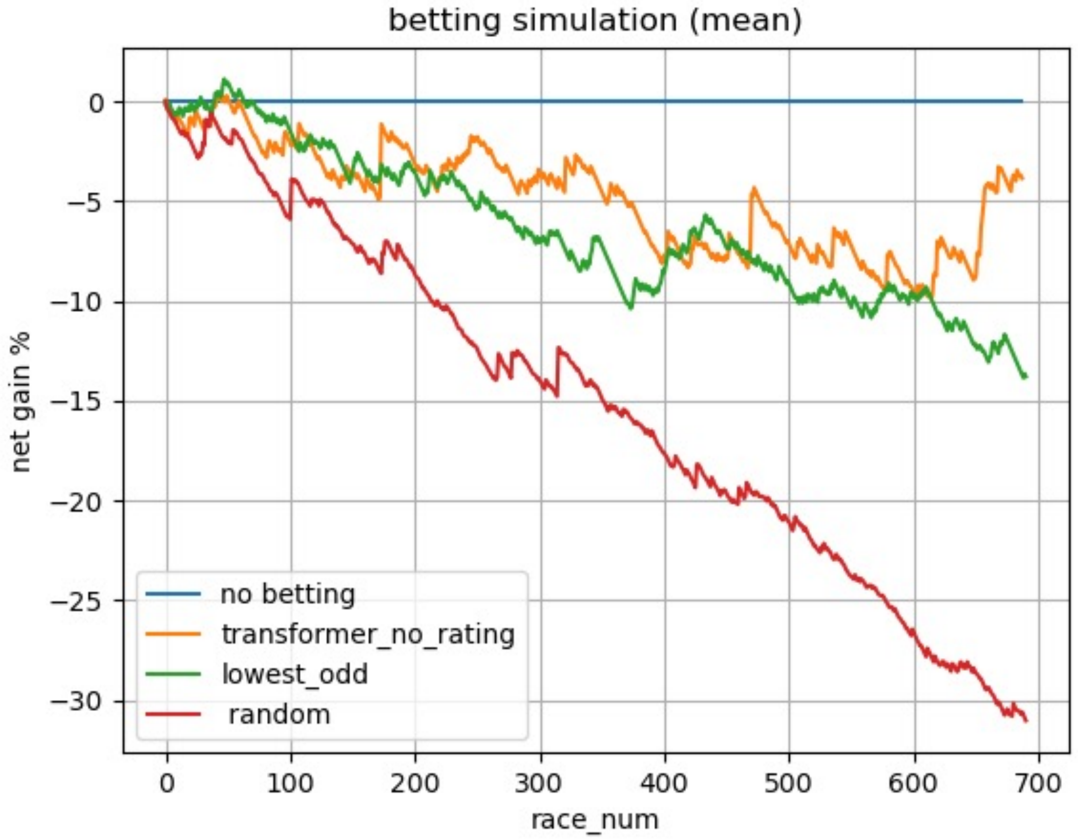
Experiment and Result – Betting Simulation

- Multilayer perceptron with ratings
- all three models perform better than random betting
- Multilayer perceptron with Elo-MMR ratings has the best performance
  - highest net gain : -13%



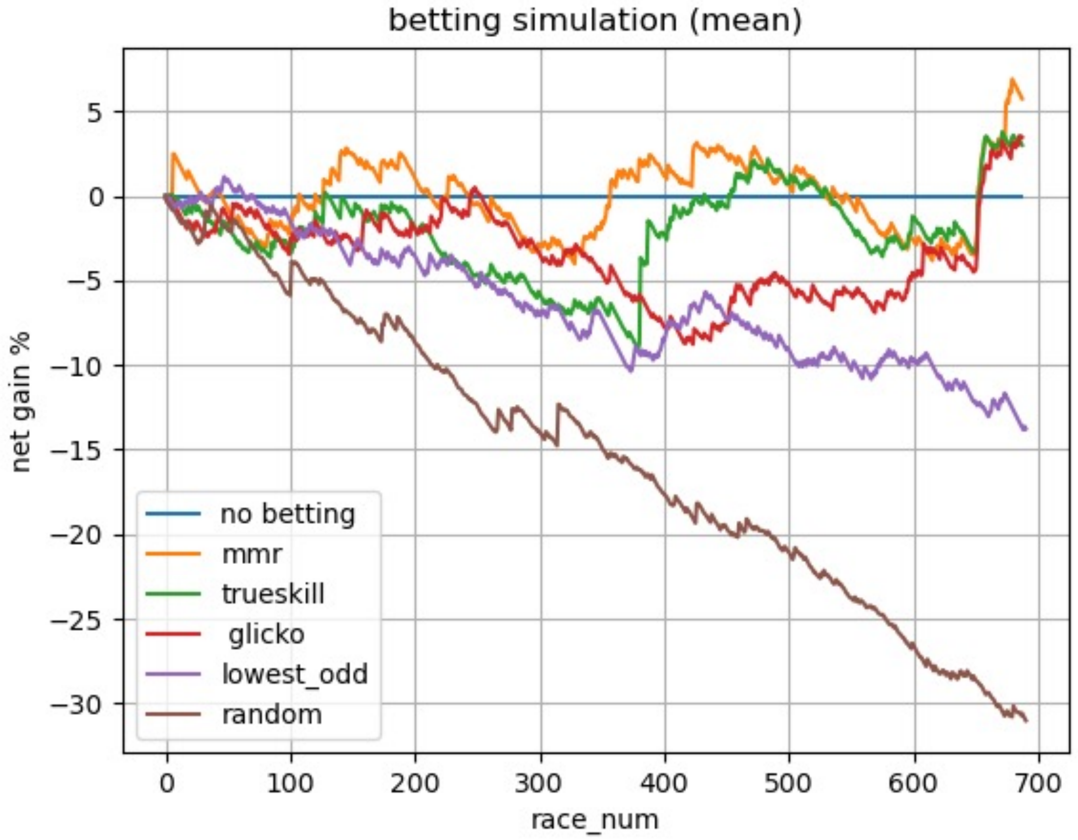
Experiment and Result – Betting Simulation

- Transformer without ratings
- The net gain is -4% after betting on all 688 races in our test data
- Better than the multilayer perceptron



Experiment and Result – Betting Simulation

- Transformer with ratings
- Positive net gain of 3% to 6% after betting on 688 races in the test data
- Transformer with Elo-MMR ratings has the best performance



Conclusion

- Win odds in the feature list have the effect of enhancing the accuracy and net gain
- Exclude the win odds from the feature list this time
- Resemble the effect of the winning odds by combining rating systems and the transformer architecture
- the best case of our models is the transformer with Elo-MMR ratings
  - the highest test accuracy : 21.4%
  - a positive net gain : 6%

Thank you!

References

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