Horse Racing Prediction using Deep Probabilistic Programming with Python and PyTorch (Uber Pyro)

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Outline

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- Methodology
- Model Structure
- Data Preparation
- Feature Analysis
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- Future Work

Background – Probabilistic Programming

- Probabilistic Programming describes probabilistic models with programming
- Enables automated inference given probabilistic model
- Mainly applied for making decisions under incomplete information and uncertainty

Background - Deep Probabilistic Programming

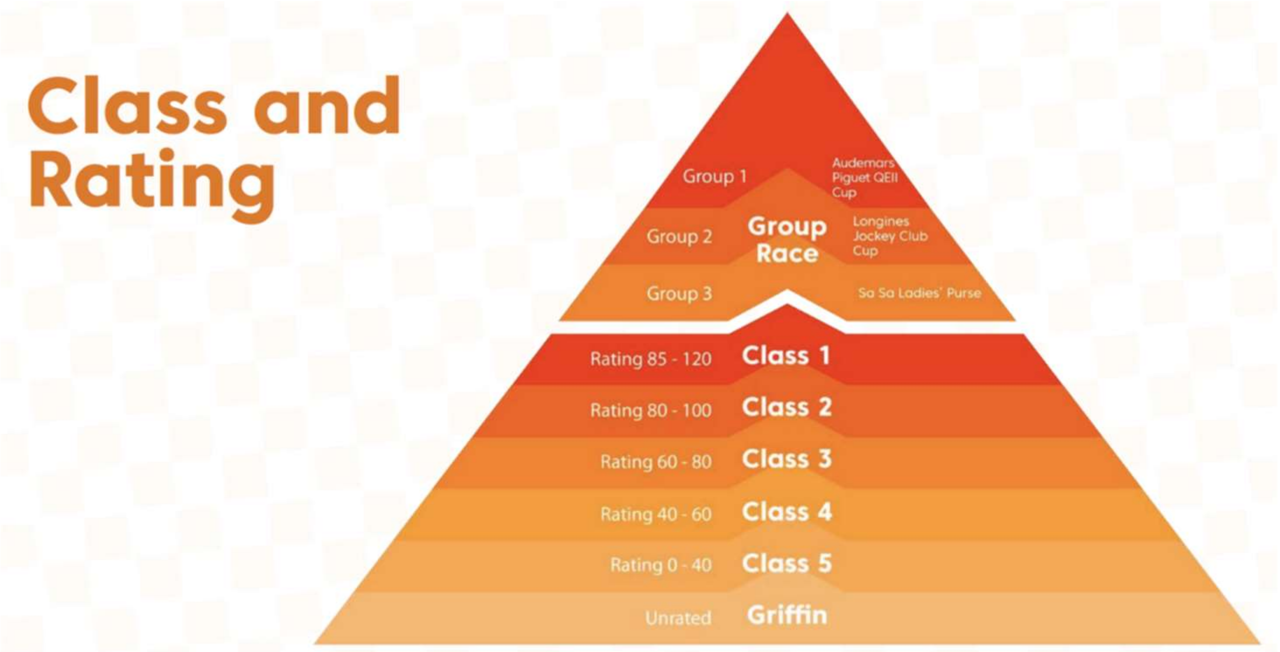
- Deep Probabilistic Programming combines deep learning and probabilistic programming
- This project combines deep neural network with probabilistic programming
- Treat weights and biases of neural networks as random variable instead of single point values
  - Usually within a narrow range, may or may not converge to a single point
  - Range represent our uncertainty regarding individual weights and biases
  - If converge to a single point, then reduces to traditional neural network

Background – Horse Racing

- Horse racing is the sport of running horses at speed
- Many factors leading to uncertainty and incomplete information
  - Suitable for Probabilistic Programming
- Hong Kong Jockey Club hosts betting and offers different types of bet
- We focus on 2 types:
  - Win – the horse betted has won the race
  - Place – the horse betted is 1^{st}, 2^{nd}, or 3^{rd} in the race

Background – Horse Class

- HKJC classify horse in classes according to its own rating
- Only horses of the same class race against each other



Related Works

- Relatively few published works
- Previous FYPs have been exploring this topic
- LYU1703
  - Predicted horse finishing time of all horses
  - Sophisticated training by Rank Network
  - Actual net gain for some specific classes (Class 1 and Class 2)
  - Formulated strategy on testing results (lack validation of strategy)
- LYU1603
  - Predicted horse finishing time of all horses
  - Actual net gain obtained for specific threshold (95%)
  - However, the number of bets made are too small

Objective

- Build a prediction model to obtain positive net gain under general circumstances

Evaluation Criteria

- Accuracy of predicting win
- Accuracy of predicting place
- Bet return of predicting win
  - return equals to win odds if correct
  - return equals to -1 if incorrect
- Bet return of predicting place
  - return equals to win odds if correct
  - return equals to -1 if incorrect

Methodology

- 3 different way to model race results
  - Finishing time regression
  - Win/loss binary classification
  - Place multiclass classification
- Both LYU1603 and LYU1703 do regression on finishing time
  - Difficult to model the distribution of finishing time
  - Normal distribution may be a good assumption
- This project uses multiclass classification on place
  - Predict the probabilities of different places given input data of horse
  - Races are single events, how to get different place probabilities?
  - Sampling layer of Uber Pyro handles this automatically

Model Structure

1
- Normalize numerical data
- One-hot encode other data

2
- Neural Network
- SoftMax for last layer

3
- Sampling layer
- NN output as probabilities

1. Data preprocessing
2. Bayesian Neural Network
   - Outputs place probabilities
3. Sampling Layer (Training only)
   - Sample the predicted place

Data Preparation

- Data obtained from HKJC website from Jan 1 2011 to April 21 2018
- Training Data from Jan 1 2011 to Mar 29 2017 (57334 entries)
- Testing Data from Apr 2 2017 to April 21 2018 (10063 entries)

Data Preparation – Preprocessing

- Normalize real value data according to following equation:

$$\hat{X} = \frac{X - mean(X)}{std(X)}$$

- One-hot encode categorical data

Color
Red
Red
Yellow
Green
Yellow

Red	Yellow	Green
1	0	0
1	0	0
0	1	0
0	0	1

Feature Analysis

- There are many data from HKJC website
- In this section, we explore the effect of differrent features on racing results

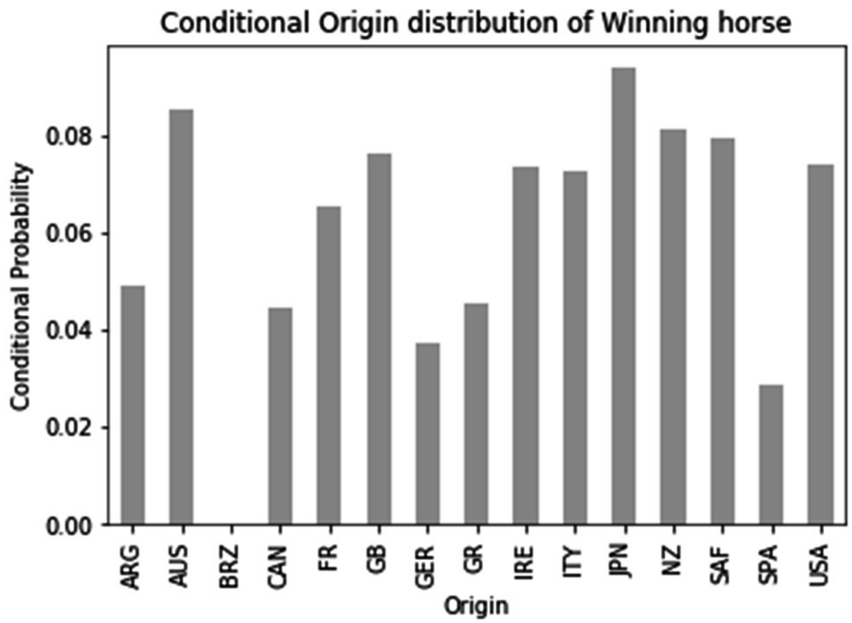
Feature Analysis – Excluded Features

- Year of the race
- Day of the race
- Race ID
- Race number
- Horse number

- Note that month of the race is included

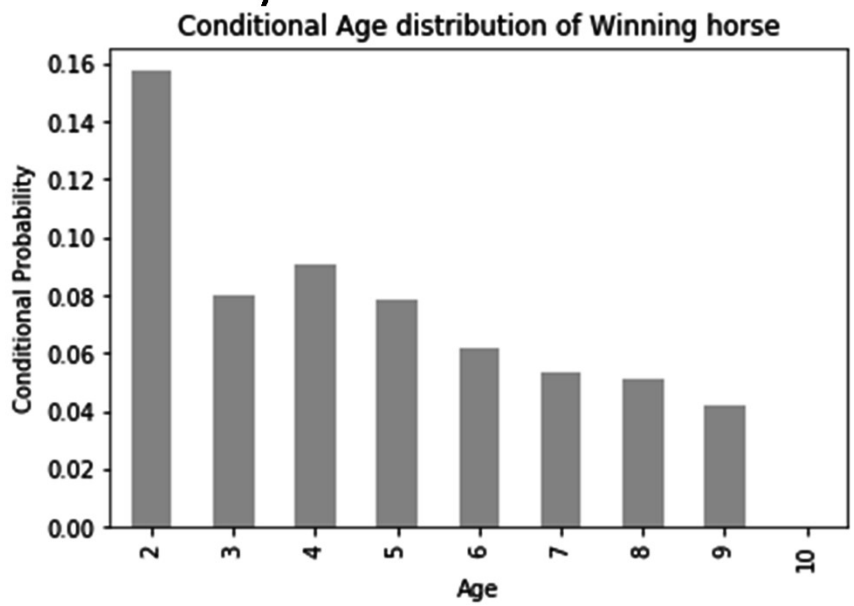
Feature Analysis – Horse Origin

- Quite evenly distributed at around 8%, close to random guess of 1/12



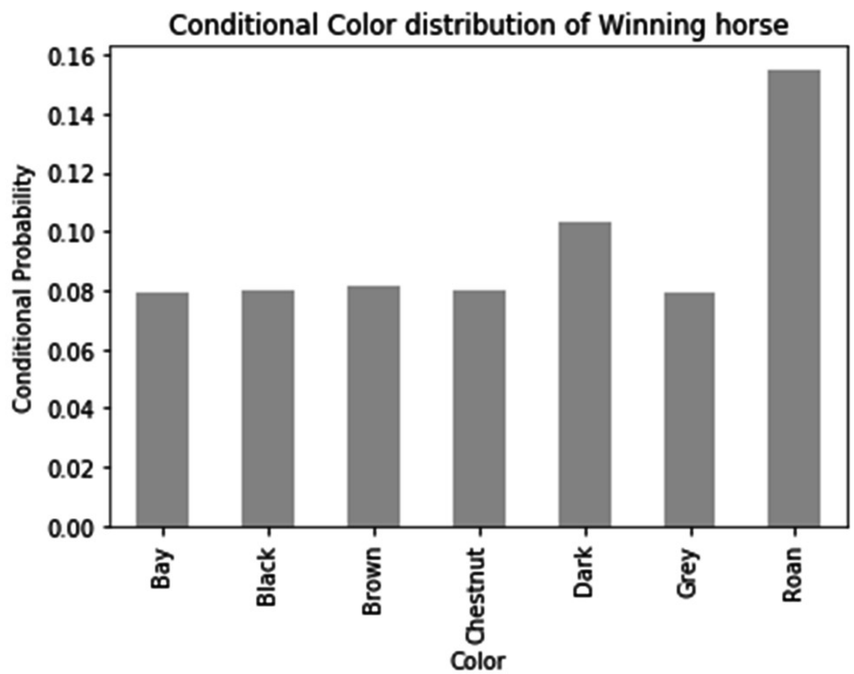
Feature Analysis – Horse Age

- If we only bet on horses of age 2, we have ~16% accuracy
- However, this results in very few number of bets



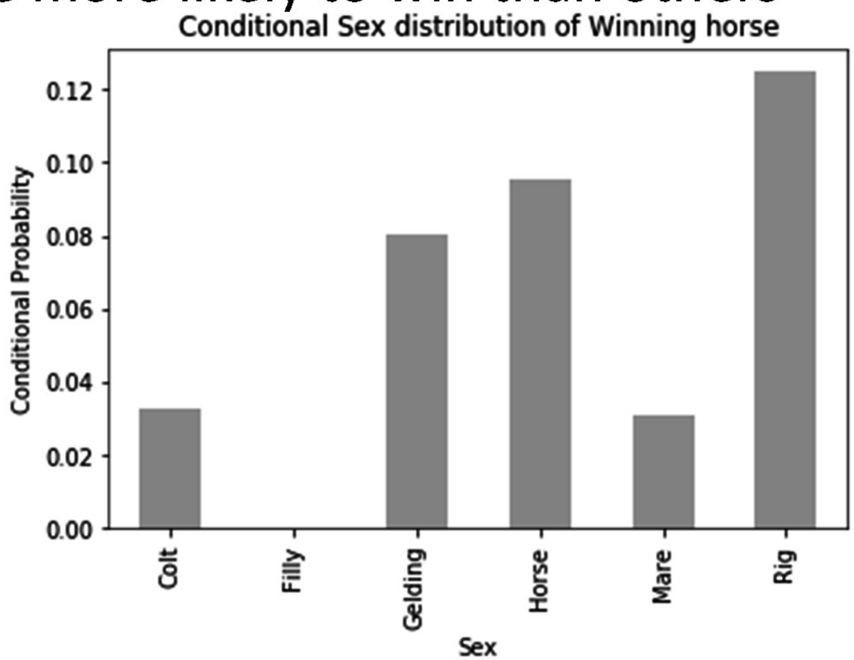
Feature Analysis – Horse Color

- If we only bet on color Roan, we have ~16% accuracy
- However, very few number of bets due to the rarity of Roan color



Feature Analysis – Horse Sex

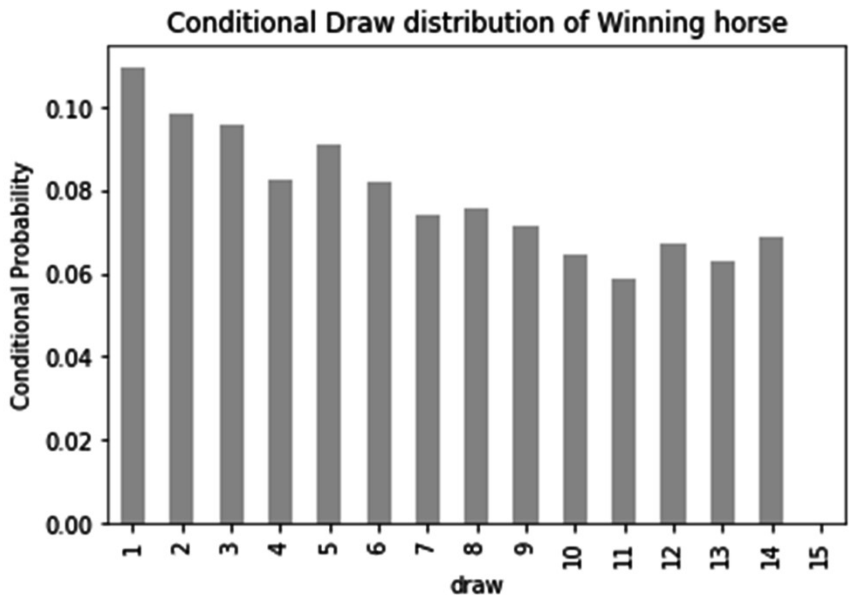
- The different hormones of different gender affects racing performance
- Rig and Horse are more likely to win than others



Colt: Young male under age 4
Filly: Young female under age 4
Gelding: Castrated male
Horse: Adult male
Mare: Adult female
Rig: Male with testicles concealed

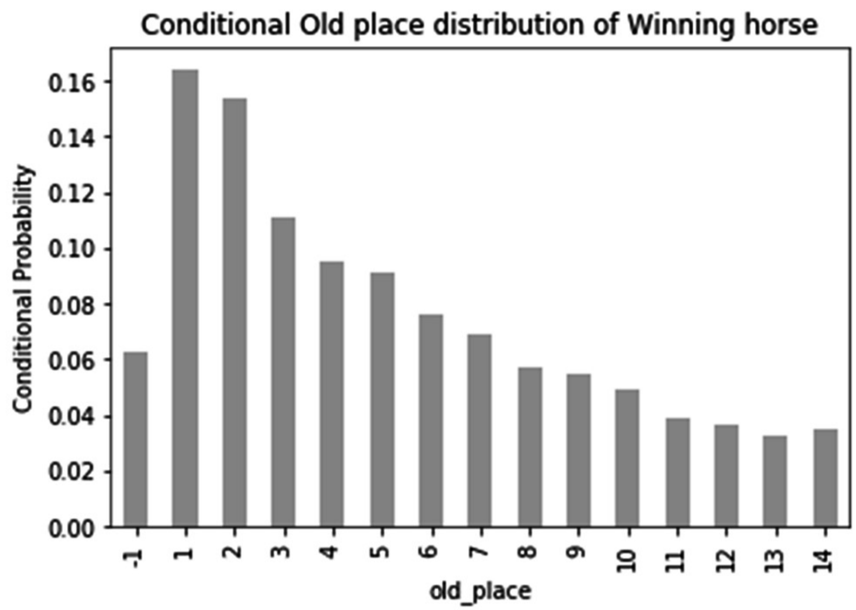
Feature Analysis – Draw

- Smaller draw number is closer to the inside of turn
- Larger draw number is further away from the inside of turn



Feature Analysis – Place in previous race

- Horses that wins in previous race are more likely to win
- -1 denotes no previous data



Feature Analysis – Additional Features

- The previous analysis only works for features that are different for horses in the same race
- How about features that are the same?
  - Location? Shatin and Happy Valley have very different tracks
  - Race courses? Race courses of the same location can also be different
  - Horse Class? Different horse class would favor different characteristics
  - Race Distance? Longer distance requires stamina; shorter distance requires acceleration
  - Going? (Soil Condition) Softer soil may favor some horses while harder soil favor others
  - Month of the race? The weather and temperature of each month may affect horse performance
- We decided to include all of the above

Feature Analysis – Non-Identity Features

- Horse Origin
- Horse Age
- Horse Color
- Horse Sex
- Horse Draw
- Horse Old place

- Race Location
- Race Course
- Horse Class (Race Class)
- Race Distance
- Course Going (Soil Condition)
- Race Month

Feature Analysis – Identity Features

- Identity features: horseid, jockeycode, trainercode, sire, dam, dam's sire
  - Many distinct values
  - Difficult to analyze
  - Leads to large input dimension
- Each individual horse is different
- The jockey in the race may also affect horse performance
- Different trainers results in better performance in particular tracks
- We split the input data into 3 groups
  - No identity features: input dimension of 71
  - Jockey and Trainer: input dimension of 277
  - All identity features: input dimension of 9113 (30x increase!)

Results

- Use neural network with 4 layers, each with 16 neurons
- Train models over 800, 000 iterations over the training dataset
- Adam optimizer with an initial learning rate of 0.001
- Sample 100 different neural network from model and take average

Results – Betting

- A horse is bet on if it has the highest place 1 score
- For example, the following tables shows the place 1 score outputted by the neural network
- In this case, we bet on horse 3, because it has the highest score

Horse	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Place1 Score	0.1	0.15	0.2	0.1	0.05	0.1	0.1	0.1	0.1	0	0	0	0	0

Results – Identity Features

- Using Jockey and Trainer have the best performance

Model	Public Odds	No Identity	Jockey Trainer	All Identity
Accuracy_{win}	0.2614	0.1840	0.1798	0.1830
Accuracy_{place}	0.5709	0.4513	0.4479	0.4551
Net gain	-224.90	-184.68	-177.45	-220.29
Return/Bet For Win Bet	-0.2637	-0.2165	-0.2080	-0.2583

Results – Win Odds

- Win Odds offers the input from public intelligence
- Marginal improvement

Model	Public Odds	No Identity	+Odds	Jockey Trainer	+Odds	All Identity	+Odds
Accuracy_{win}	0.2614	0.1840	0.2576	0.1798	0.2592	0.1830	0.2634
Accuracy_{place}	0.5709	0.4513	0.5695	0.4479	0.5774	0.4551	0.5816
Net gain	-224.90	-184.68	-184.5	-177.45	-164.65	-220.29	-188.06
Return/Bet	-0.2637	-0.2165	-0.2163 (0.0002)	-0.2080	-0.2009 (0.0071)	-0.2583	-0.2205 (0.0378)

Results

- Currently, if we bet on all races, we are still unable to obtain a net gain
- Yet to achieve the original objective
- Can we obtain a net gain if we only bet on specific classes?

Results – Training performance by class

- Even with in training, there is no net gain in classes other than Class 1 and Group 3
- No reason to bet on other classes

Training performance of model Jockey Trainer by class

Class	Class 1	Class 2	Class 3	Class 4	Class 5	Group 1	Group 2	Group 3
$Accuracy_{win}$	0.2536	0.2522	0.2254	0.2120	0.2168	0.2558	0.2302	0.3349
$Accuracy_{place}$	0.5199	0.5456	0.4987	0.5027	0.4476	0.5626	0.5721	0.5952
Net gain	1.69	-54.45	-254.67	-304.50	-19.43	-18.80	-8.32	10.86
Return/Bet	0.0123	-0.1224	-0.1677	-0.1762	-0.0278	-0.2089	-0.1935	0.1448

Results – Testing performance by class

- Betting only on Class 1 and Group3, we can achieve the following performance:

Class	Class 1	Group 3	Overall
$Accuracy_{win}$	0.2771	0.2825	0.2796
$Accuracy_{place}$	0.4979	0.6117	0.5504
Net gain	2.45	7.89	10.34
Return/Bet	0.1753	0.6573	0.3977

Testing performance of model Jockey Trainer by class

Class	Class 1	Class 2	Class 3	Class 4	Class 5	Group 1	Group 2	Group 3
$Accuracy_{win}$	0.2771	0.2756	0.1741	0.1552	0.1407	0.2142	0.4311	0.2825
$Accuracy_{place}$	0.4979	0.5372	0.4566	0.4191	0.3686	0.7867	0.5489	0.6117
Net gain	2.45	-15.57	-59.41	-81.17	-31.70	-1.64	1.69	7.89
Return/Bet	0.1753	-0.1730	-0.2077	-0.2569	-0.2780	-0.1363	0.1879	0.6573

Conclusion

- Currently, if we bet on all races, we are still unable to obtain a net gain
- We have yet to achieve the original objective
- We can obtain a net gain of ~40% if we only bet on specific classes

Future work

- Current model has 4 layers with 16 neurons per layer
- May be too small to fully utilize the large input size
- Explore different hyper parameters

- Current model will be bet on a horse if it has the highest score
- Even if the score is low (as low as 0.1, i.e., 10% chance to win)
  - If winodds is smaller than 10, then there is an expected loss
- Adjust to betting only if probability > (1/winodds)

Future work

- Current model takes entry input one by one
- Fails to take performance of other horses into consideration
- Build a model which takes all horses in the same races for input

- Current model give equal importance to all training data
- However, correctly predicting horses of high win odds is more important because this results in higher return
- Duplicate training data according to win odds
- Reinforcement learning

Thank you!