Using Meteorological Data Towards Horse Racing Prediction

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Acknowledgements: Professor Jonathan Hanke, Sulin Liu

Overview

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2. Motivation
3. Prior Work
   a) Horse Racing
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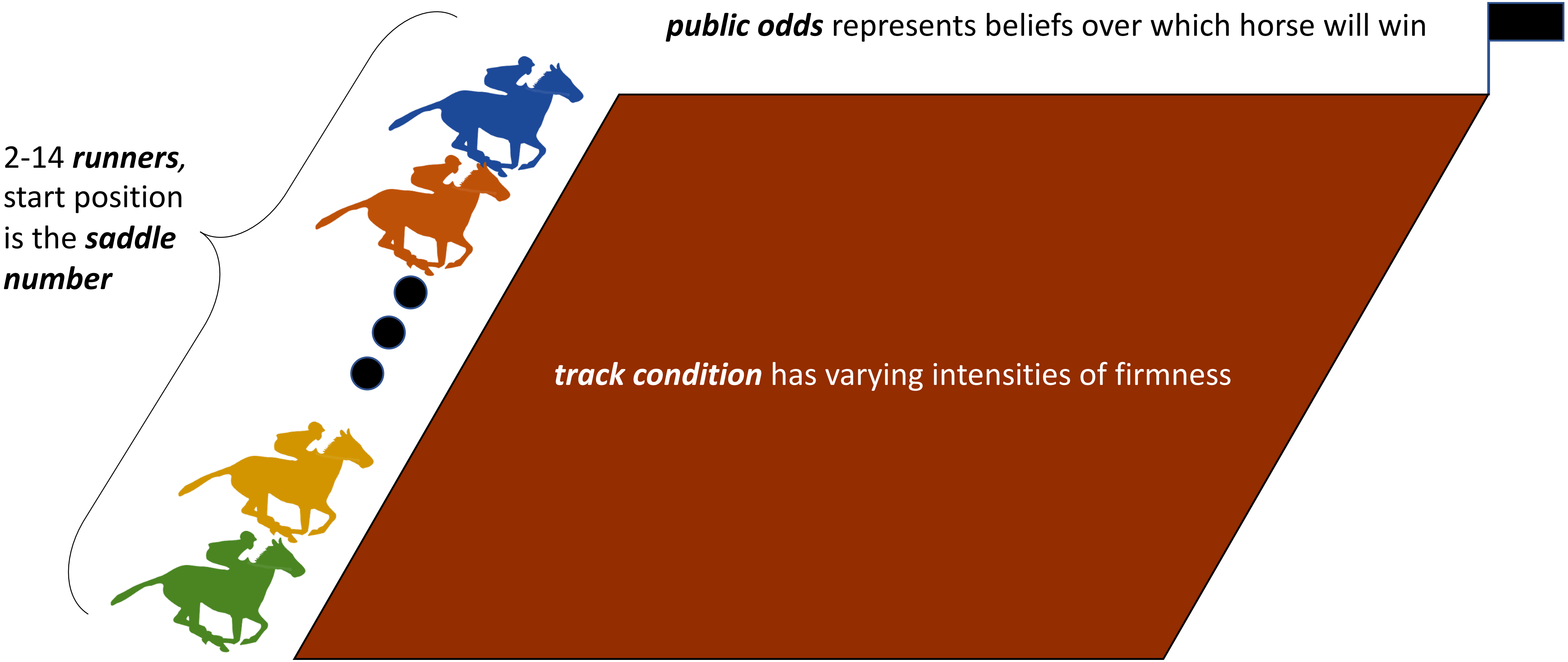
   c) Combining Data
5. Exploratory Data Analysis
6. Featurization
7. Analysis
8. Conclusion

Race Structure



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You get to be the machine learning model!

NO. FORM	HORSE	AGE	WGT OR	JOCKEY ALLOWANCE TRAINER RTF%	TS	RPR	ODDS↓
7 -25532	Enjoy D'allen › p 3 tips 12	6	12-0 118	J: Kevin Sexton › T: Peter Fahey › 56	59	124	15/8 PLACE BET 15/8 7/4 15/8 7/4
1 -01310	Basil's Boy › 19	6	12-0 -	J: Denis O'Regan › T: Liam P Cusack ›	-	-	7/2 PLACE BET 11/2 9/2 7/2 10/3
11 2234-3	Soldier At War › t D 21	6	12-0 -	J: Sean Flanagan › T: Gordon Elliott › 46	74	118	9/2 PLACE BET 11/2 6/1 13/2 5/1
6 2360-4	Ego Des Mottes › BF 73	6	12-0 -	J: Darragh O'Keeffe › T: 1 E Bolger ›	-	115	7/1 PLACE BET 17/2 8/1 6/1 13/2
9 43-548	Ingleby Mackenzie › t 60	6	12-0 119	J: Donagh Meyler › T: Eoin Doyle › 78	93	123	17/2 PLACE BET 15/2 8/1 17/2 8/1

Source: https://grandnational.fans

Constant Need for *Better* Models

Jockeys, trainers, and owners **(direct stake in performance of their horse)**

Racecourses **(bring customers out to the track)**

Bettors **(seek profitability at the racecourse)**

What are models missing?

Across the literature, models use:

- public odds
- track condition
- racecourse
- # of runners in the race
- average placement of horse
- average placement of jockey
- average placement of trainer
- past performance of a horse w/ certain conditions
- pedigree
- …

Personal Experience at Monmouth Park Racetrack

Does the rain inject more variance into the race?
Does the blue horse normally do well in the rain?

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- average placement of jockey
- average placement of trainer
- past performance of a horse w/ certain conditions
- pedigree
- …
- ***not weather!***

Can models benefit from weather data?

Claims About Weather in Horse Racing

Public opinion holds numerous ideas about weather in horse racing:

> “Barometric pressure, especially when it falls, can influence a horse both physically and emotionally… Other horses are not as affected and can handle pressure changes well.

> “If [the horse] performed consistently well under specific weather conditions, then it’s likely to keep doing so.

Source: https://skymetweather.com, https://horseracehandicappers.com

Research Question:

Can meteorological data improve predictions on a horse race?

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Davoodi and Khanteymoori (2010)

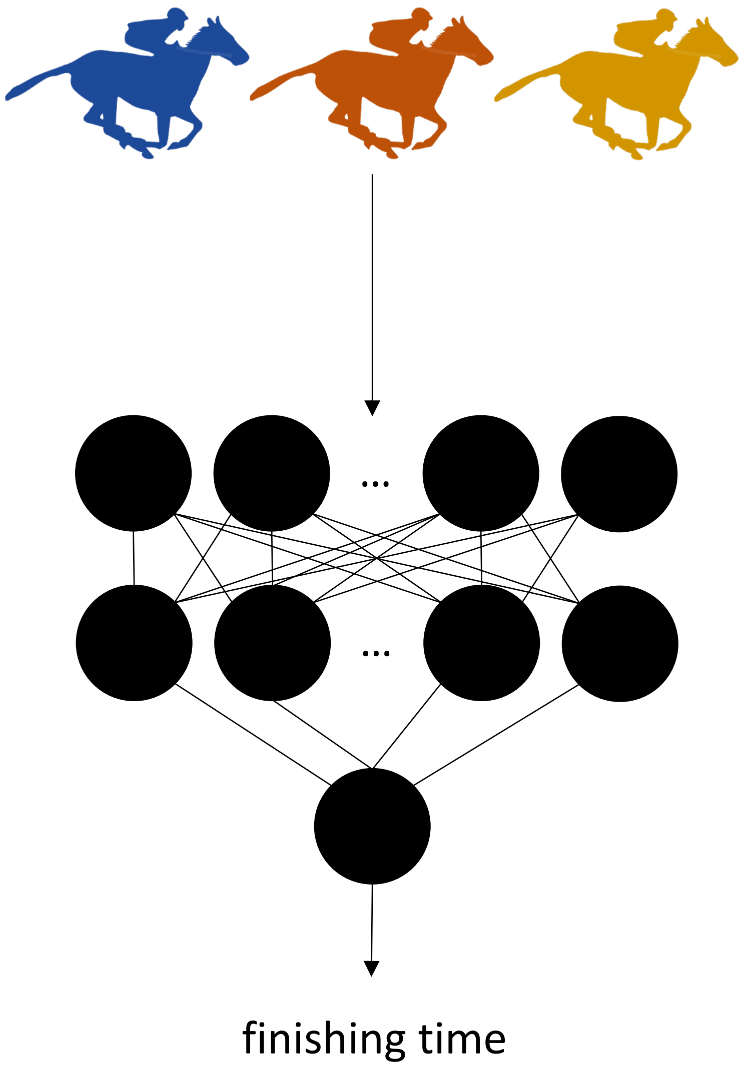
NN predicts finishing time of a **single** horse.

Weather, but a categorical variable:

- Clear
- Cloudy
- Showery

Achieves 77% accuracy on New York races.

Runner affinity for weather not considered.



Source: http://wseas.us/e-library/conferences/2010/Iasi/NNECFS/NNECFS-21.pdf

Torné (2021)

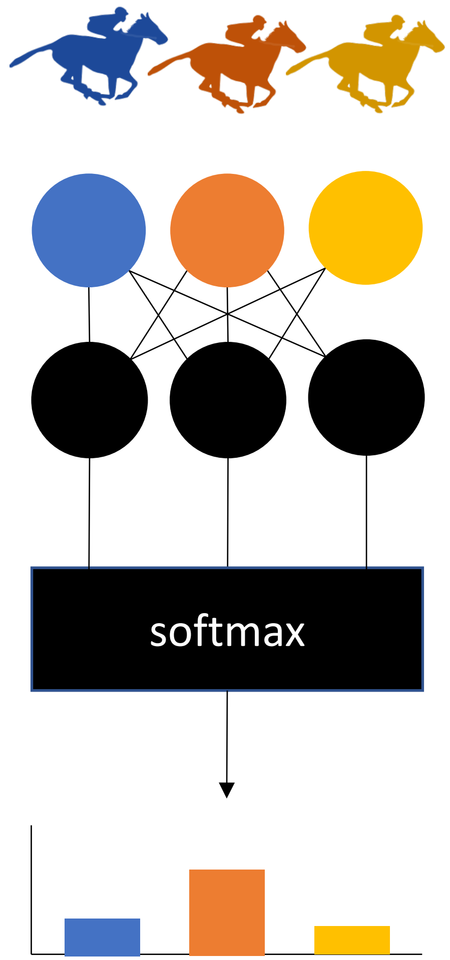
Neural network model accepts ***all*** runners in a race.

Features are past performance of horse, jockey, and trainer.

14% accuracy on **13,000** Hong Kong races.

Pads input to desired length with *UNK* tokens.

Some overfitting.



Source: http://cs230.stanford.edu/projects_winter_2021/reports/70738477.pdf

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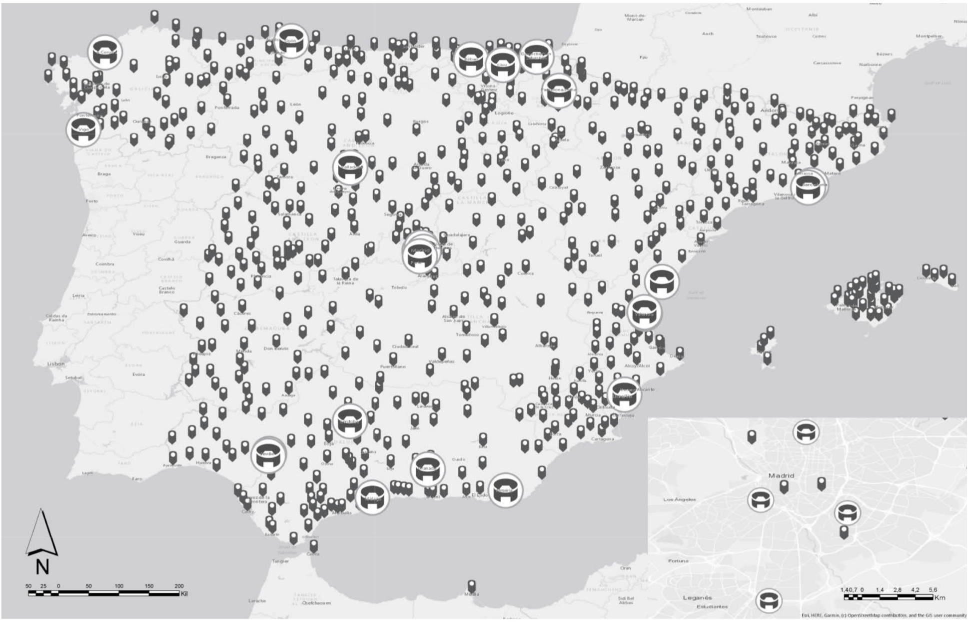
Iskandaryan et. al. (2020)

Determine if weather has effect on the outcome of a soccer match.

Weather significantly helps classification models.

*Method has **not** been applied to horse racing, allows us to fill this gap.*



Source: https://www.mdpi.com/2076-3417/10/19/6750/htm

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Kashavkin's Horse Racing Data

Contains > **400,000** races across the world from 1990 to 2020.

Most importantly, includes:

- Racetrack ⟶ *to find close weather stations*
- Date and time ⟶ *to get accurate weather readings*
- Finishing positions ⟶ *to serve as labels*
- Public odds ⟶ *to serve as baseline*

Needs *lots* of cleaning … (details omitted)

Source: https://www.kaggle.com/hwaitt/horse-racing

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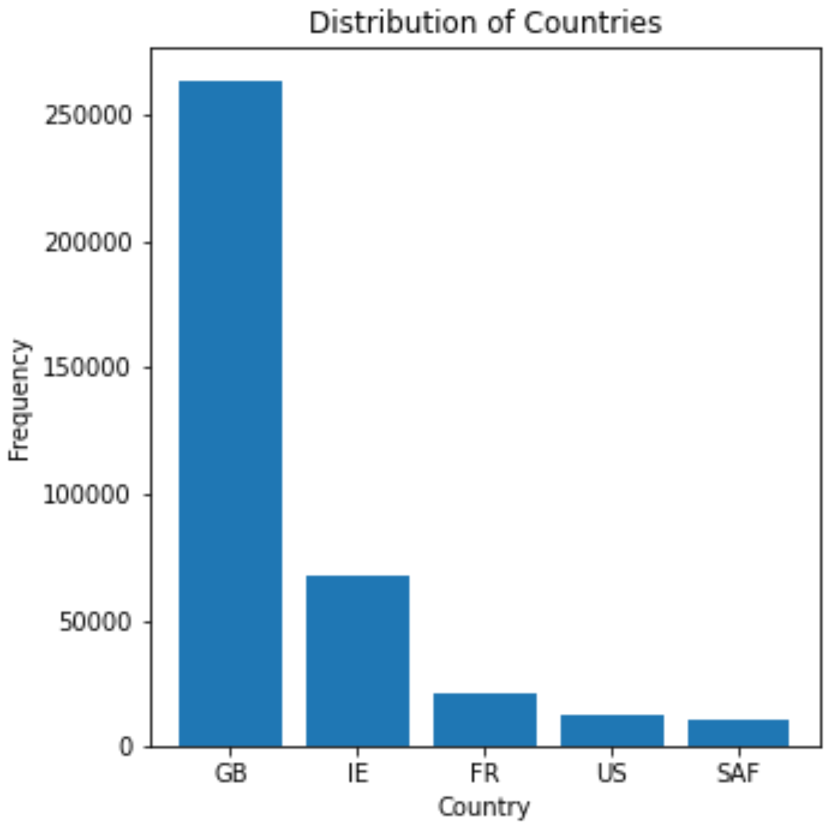
Meteorological Data

Focus on **one** country to avoid inconsistent weather practices.



Meteorological Data

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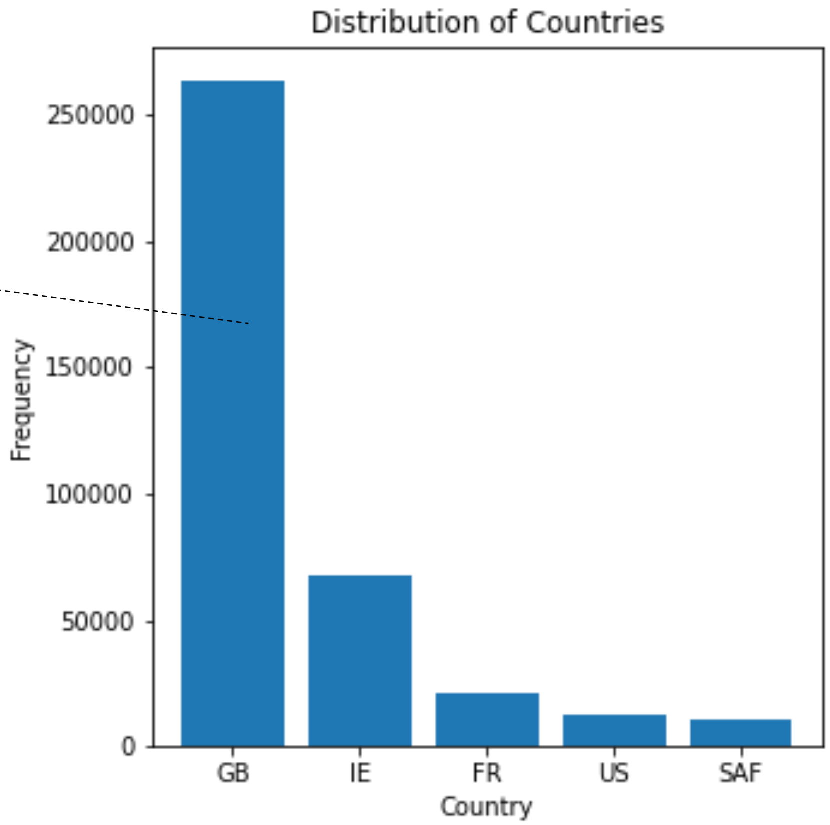
Doesn’t work...
See paper.



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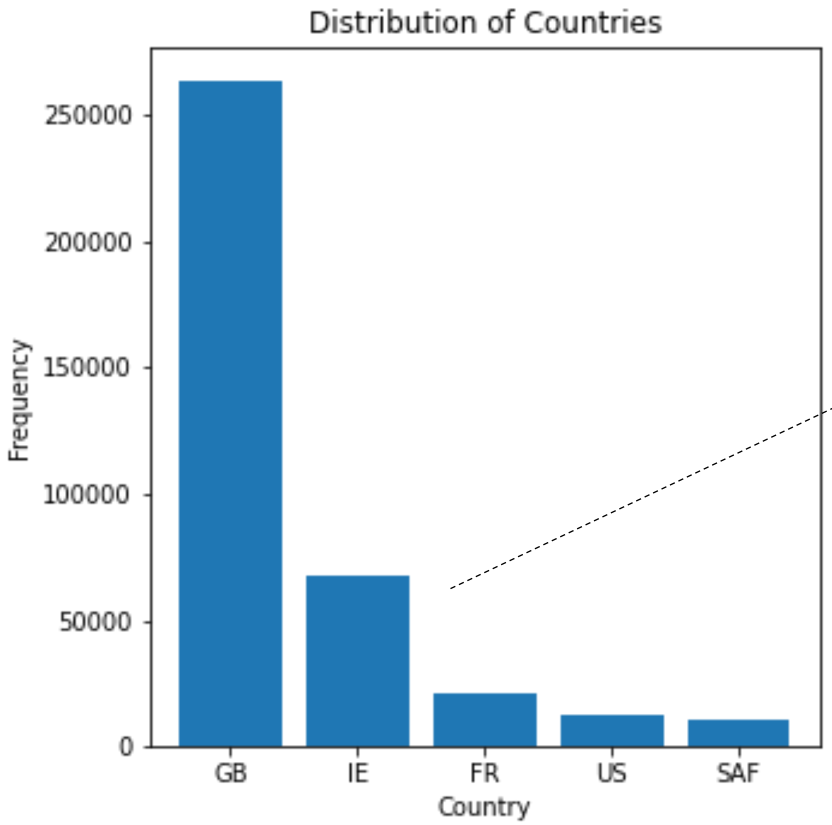


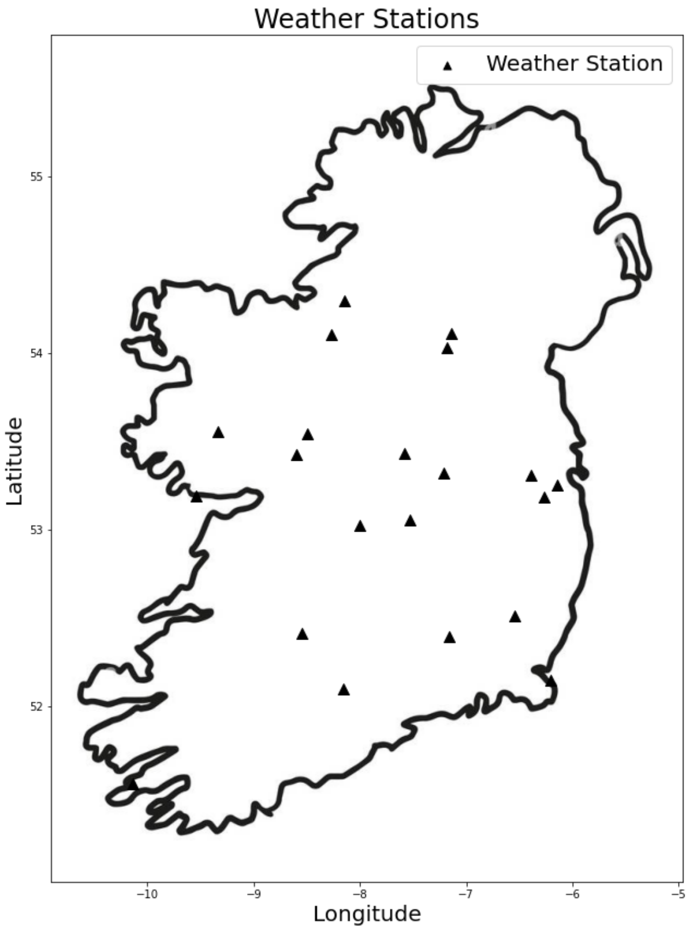
Met Eireann

- Clean data.
- Hourly readings.

Meteorological Data

Station readings include:

- Temperature
- Humidity
- Pressure
- Rainfall



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Locating Racecourses

Must locate the racecourses to match to weather stations.

Google's Geocoding API:

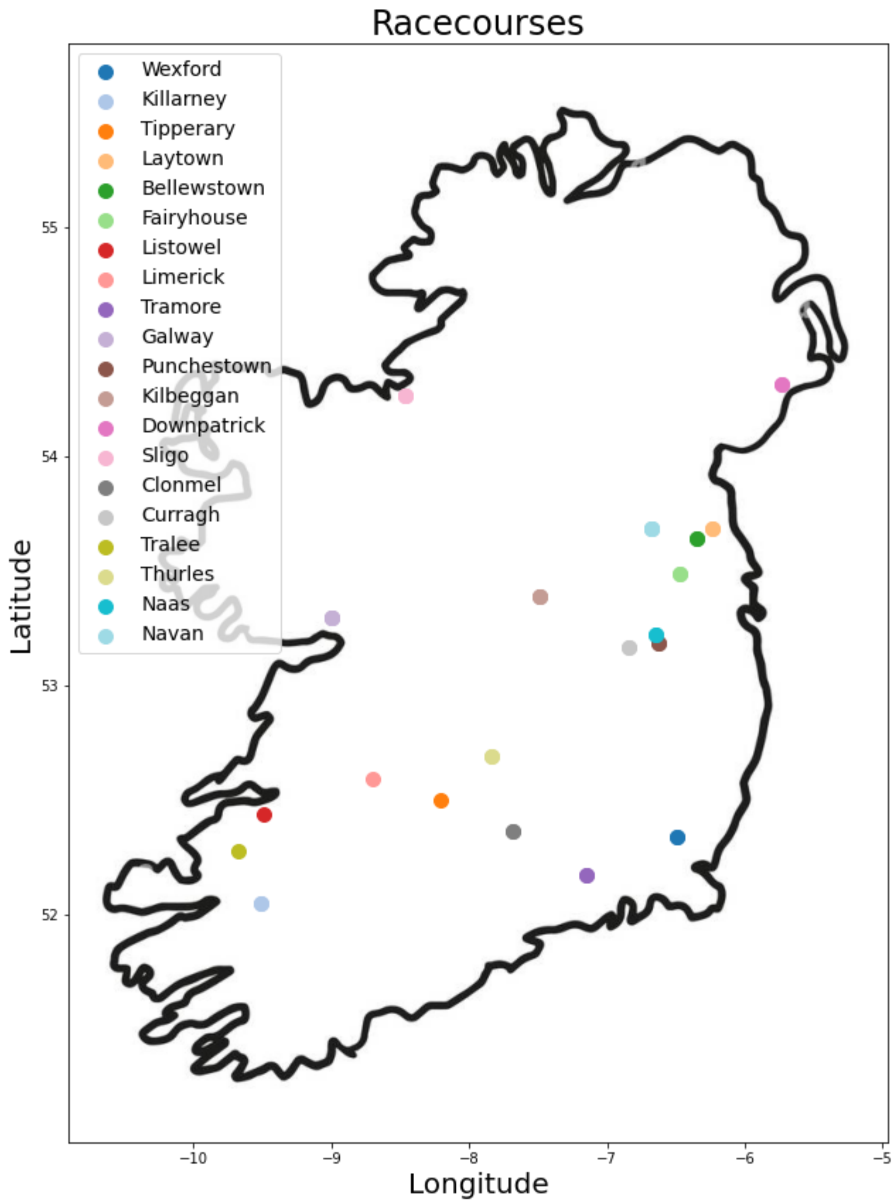
Tell me where is <racecourse name> racecourse in Ireland

<racecourse name> is at <coordinates>

Annotate Races w/ Weather

For each race:

1. Locate racecourse.
2. Find nearest open weather station.
3. Find most recent hourly weather reading.



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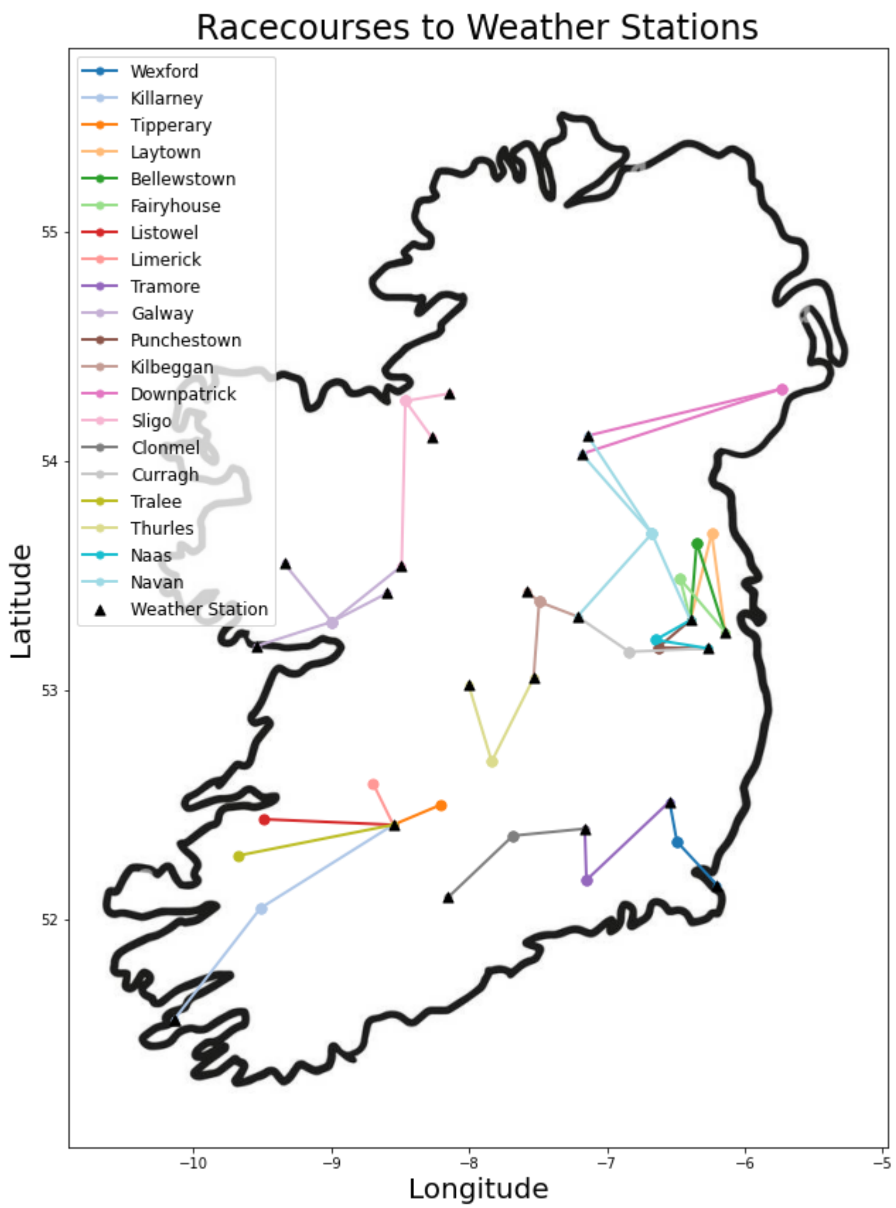

Summary of Data

Over 20,000 horse races from Ireland from 1990 to 2020 annotated with weather readings accurate to the half-hour which include:

- Temperature
- Humidity
- Pressure
- Rainfall

This dataset is a novelty of my project and made available on my GitHub.

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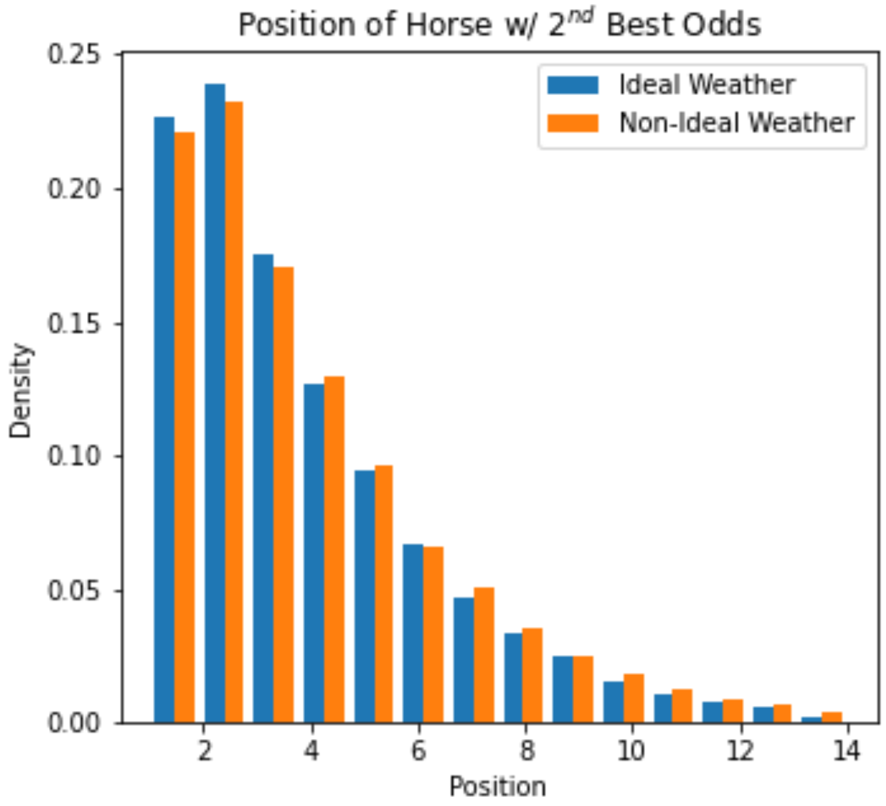
Projected Winners Place Higher in Ideal Weather

Position of projected winner is better during ideal weather condition.



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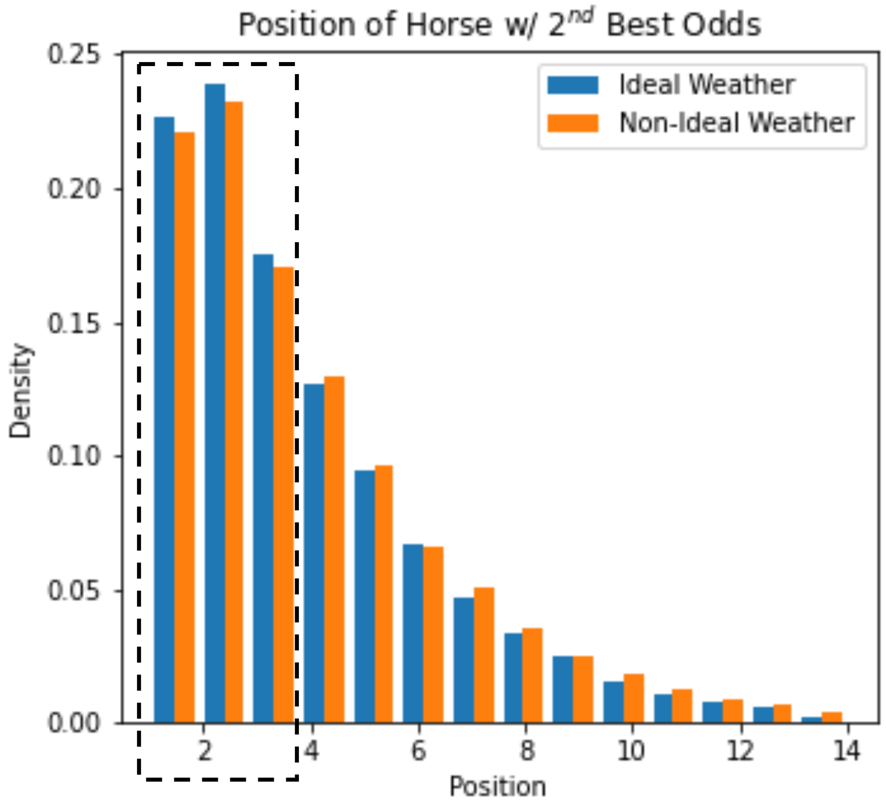

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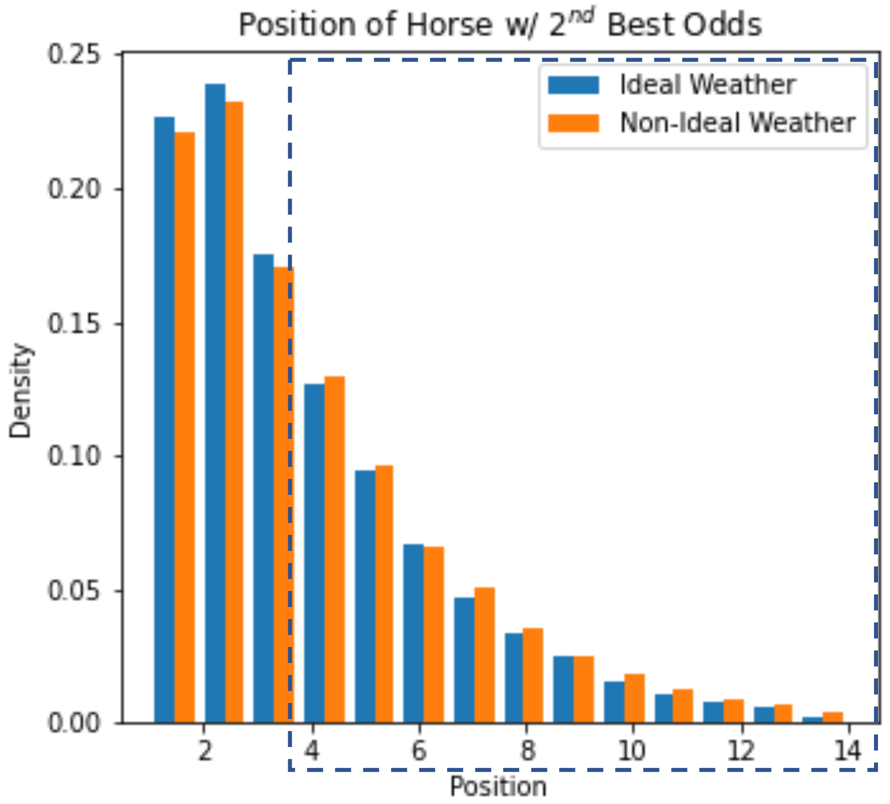

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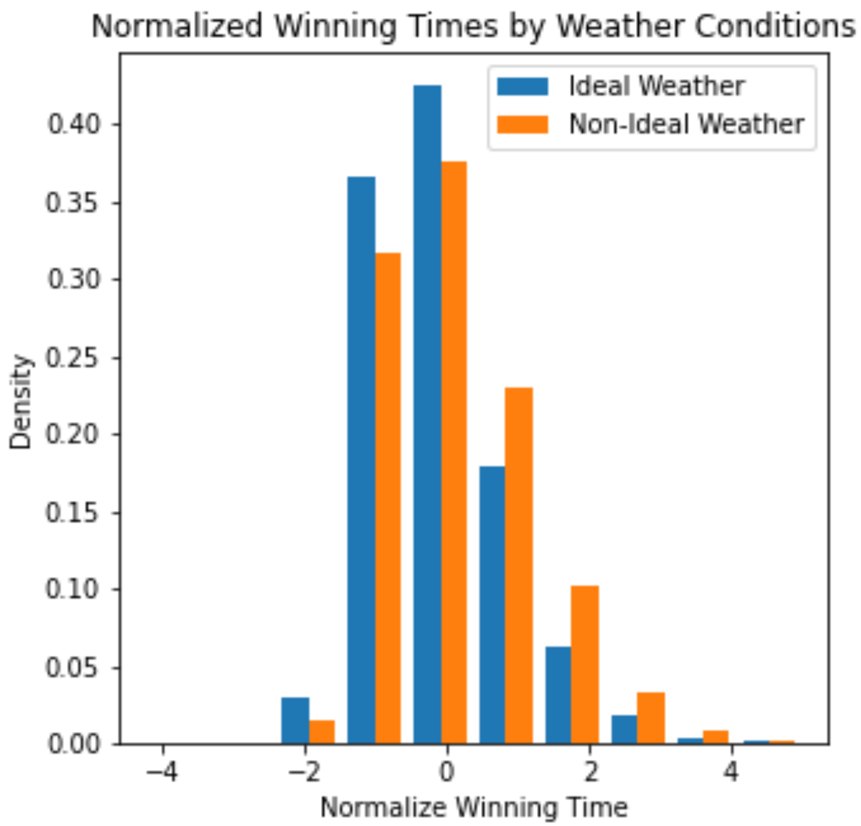
Winning Times are Lower in Ideal Weather

Horses run faster under ideal weather.

Normalized winning time is a way to account for varying distances across races.



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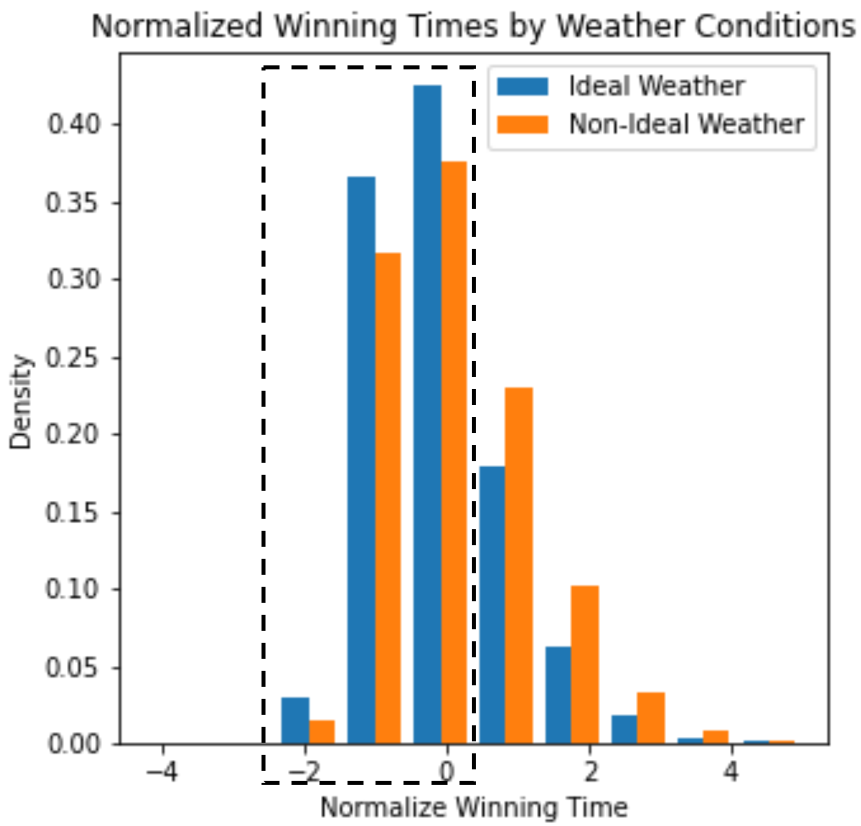

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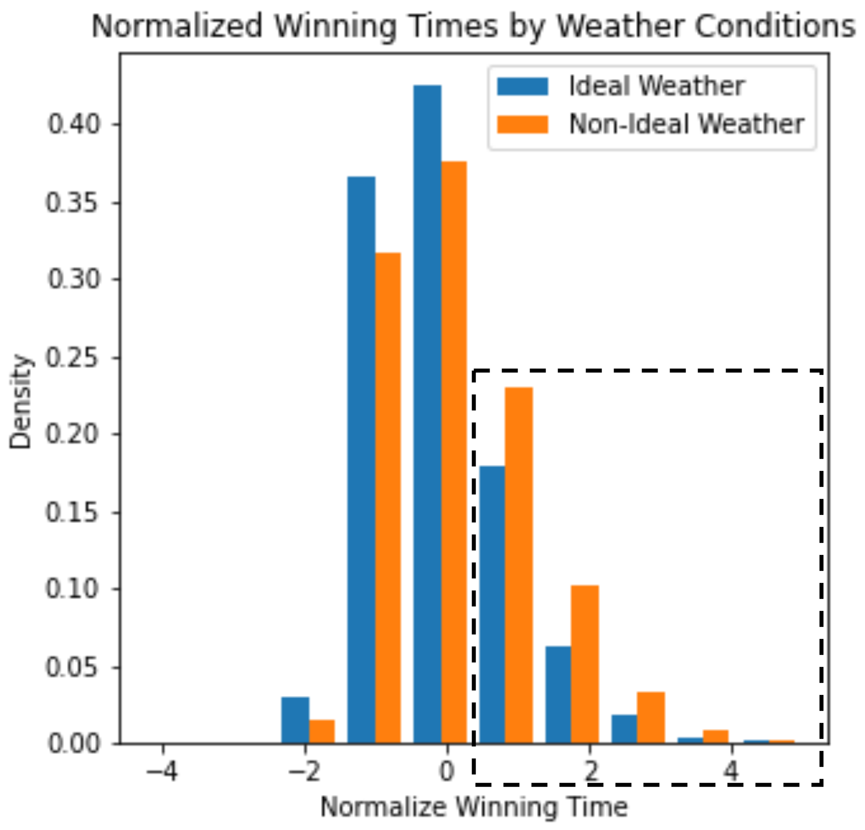

Summary of Exploratory Data Analysis

Able to support several intuitive hypotheses using our data.

Increased confidence in the **cleanliness** of our data and **accuracy** of weather readings.

Already, we can show some ways in which weather affects a horse race!

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Preserving Horse Identity

Hoping that our model can learn that certain runners perform well under certain conditions.

Abbott

Age: 4

Weight: 400

Saddle: 2

Loves: Cold, rainy weather.

Costello

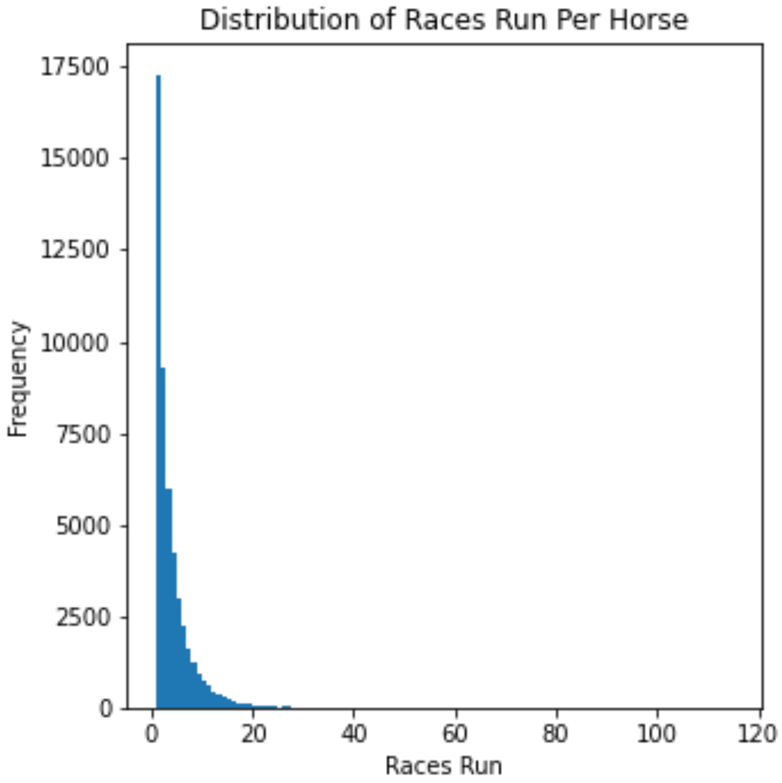
Age: 2

Weight: 500

Saddle: 3

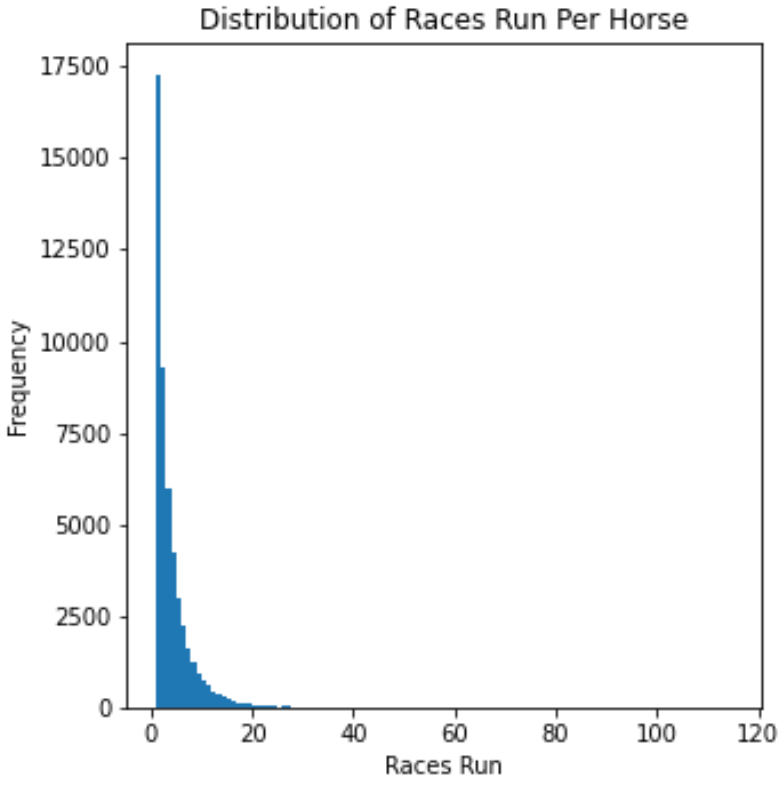
Loves: Hot, humid weather.

Preserving Horse Identity



50,291 unique horses

Preserving Horse Identity



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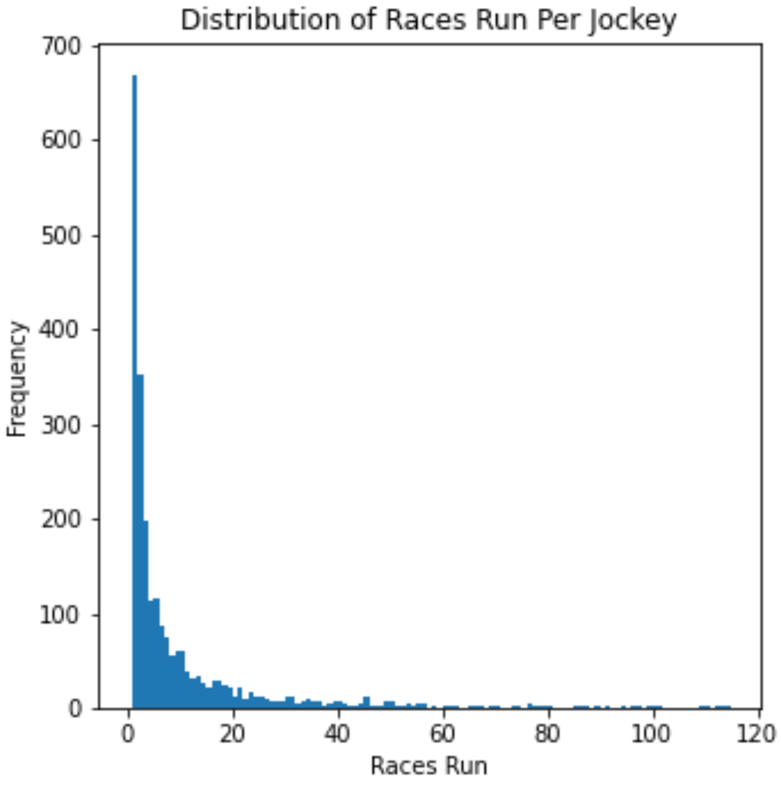


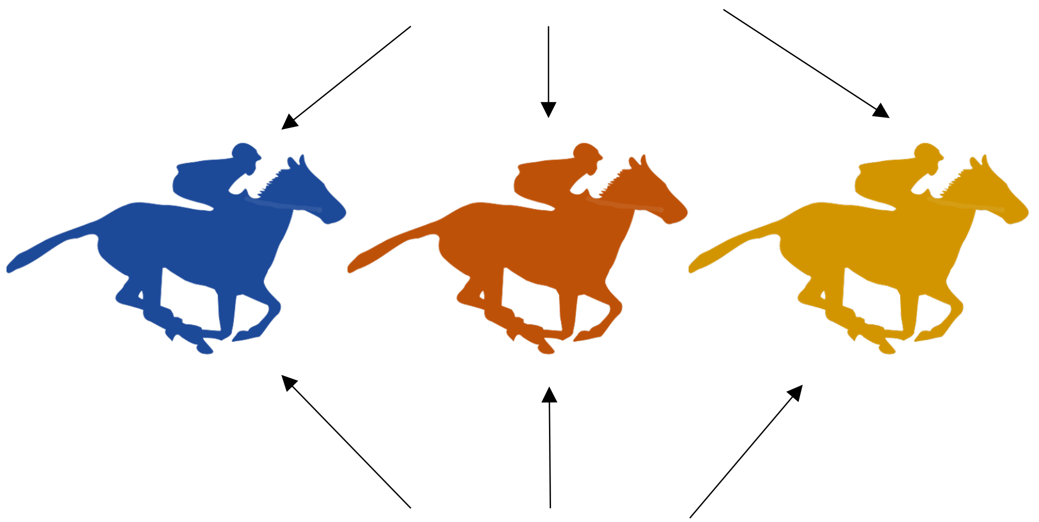
2,660 unique jockeys

Preserving Horse Identity

Use the past performance of a jockey as a proxy for horse identity.

<u>Assumption</u>:

same jockey



similar horses
(same training regiment, same diet, same lodging, **same affinity for weather**)

Features: Jockey Past Performance

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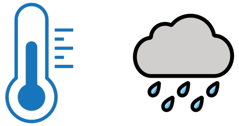
Today's weather: 

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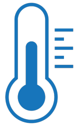
Today's weather:  

Feature Vector

Past performance under temperature.

Past performance under rainfall.

Group	Recency	Value
temp	1	
temp	2	
rain	1	
rain	2	

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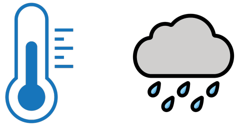
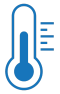
Today's weather: 

Jockey's Race History (leftmost is *most* recent)

temp					…
rain					…
position	1	3	2	5	…

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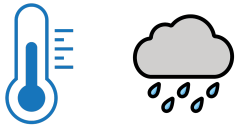
Today's weather: 

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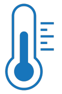
temp					…
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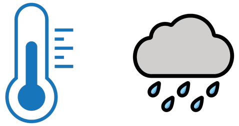
Today’s weather: 

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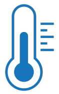
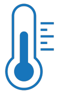
temp					…
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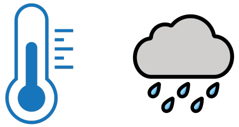
Today's weather: 

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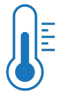
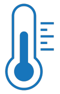
temp					…
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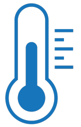
Today's weather:  

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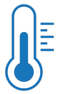
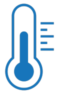
temp					…
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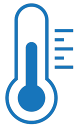
Today's weather:  

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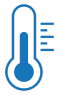
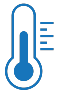
temp					…
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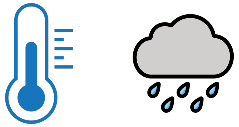
Today's weather: 

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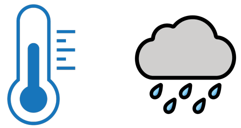
Today's weather: 

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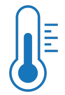
temp					…
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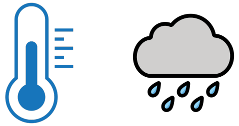
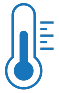
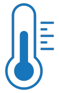
Past performance under rainfall.

Features: Jockey Past Performance

Today's weather: 

Jockey's Race History (leftmost is *most* recent)

temp					…
rain					…
position	1	3	2	5	…

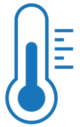
Feature Vector

Group	Recency	Value
temp	1	1
temp	2	3
rain	1	3
rain	2	

Past performance under temperature.

Past performance under rainfall.

Features: Jockey Past Performance

Today's weather:  

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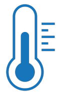
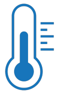
temp					…
rain					…
position	1	3	2	5	…

Feature Vector

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Past performance under temperature.	temp	1	1
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Past performance under rainfall.	rain	1	3
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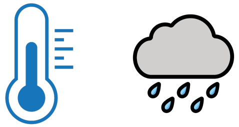
Today's weather: 

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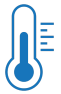
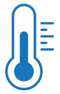
temp					…
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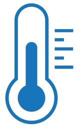
Past performance under temperature.

Past performance under rainfall.

Features: Jockey Past Performance

Today's weather:  

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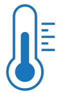
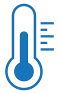
temp					…
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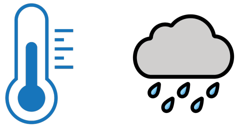
Today's weather: 

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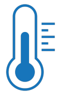
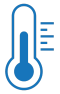
temp					…
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Past performance under temperature.

Past performance under rainfall.

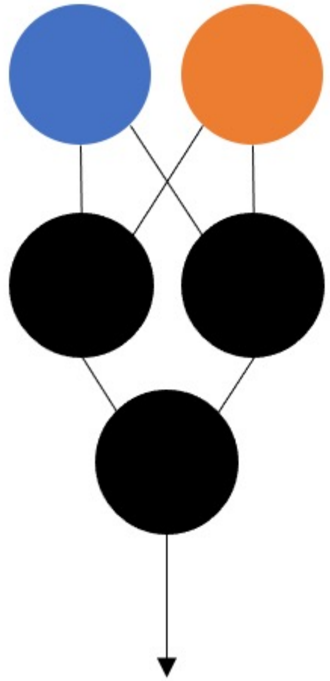
Prediction Target

Approach (*new!*):

Predict the earlier finisher over a pair of horses.

Pros:

- Simple binary classification problem.
- Handles missing data well.
- Narrow fixed-length input vectors.
- Quadratic data augmentation, $\binom{n}{2}$.



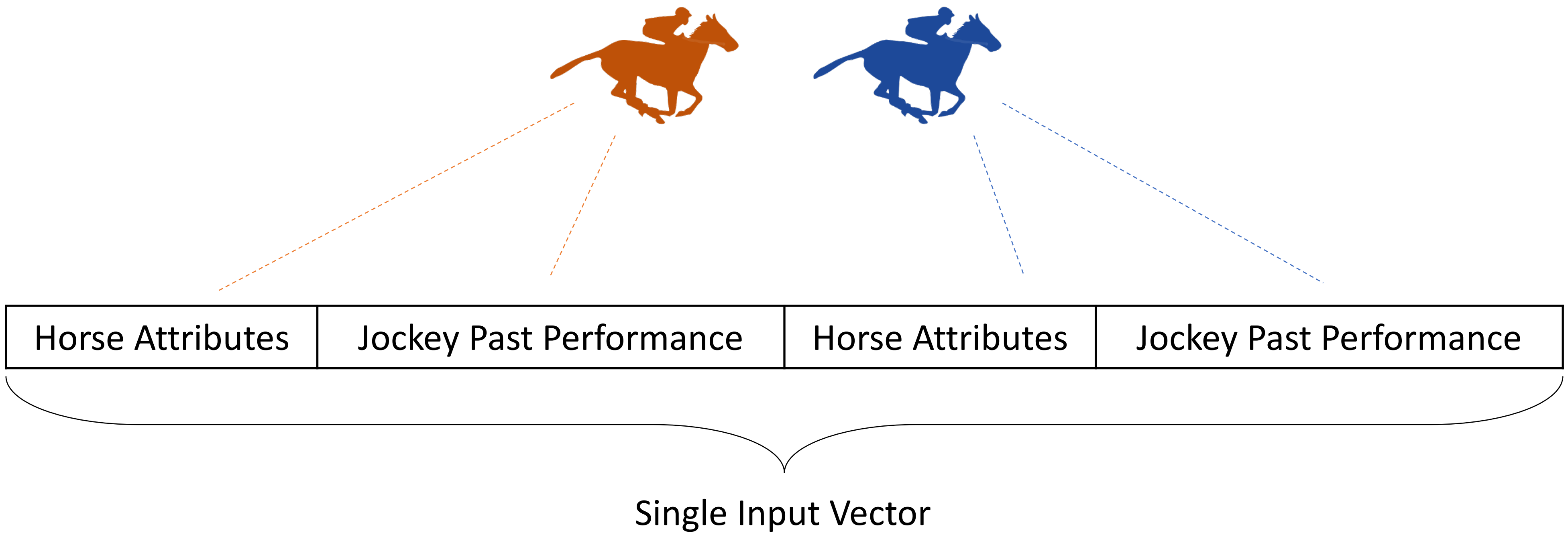
Cons:

- Independence assumption, but not as strong as considering horses in isolation.

Prediction Target

<u>Approach (*new!*)</u>:

Predict the earlier finisher over a pair of horses.



Summary of Featurization

1,143,824 ordered pairs of runners across **18,591** unique races.

Input has **144** features; **72** features for each runner in the pair.

Overview

1. Horse Racing
2. Motivation
3. Prior Work
   a) Horse Racing
   b) Weather in Sports
4. Data
   a) Horse Racing Data
   b) Meteorological Data
   c) Combining Data
5. Exploratory Data Analysis
6. Featurization
7. **Analysis**
8. Conclusion

Model Evaluation

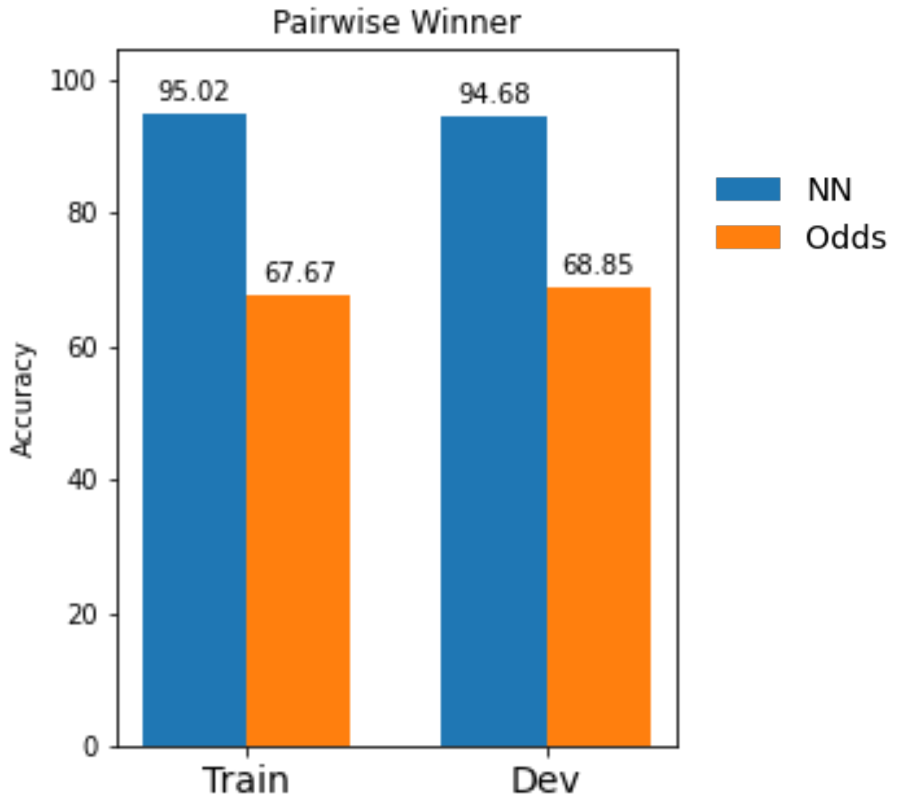
Can a model do well in general?

Give our ***best effort*** with a neural network, traditionally does well in the literature.

Pairwise Winner Accuracy

Hyperparameter	Value
Epochs	25
Batch Size	256
Learning Rate	0.02
Optimizer	Adam
# Hidden Layers	1
# Hidden Nodes / Layer	150

Neural network architecture is still reasonably simple.



Model Evaluation

Can we use this model towards downstream tasks?

- *Predict the **race winner**?*
- *Predict the **top two finishers**?*
- *Predict the **top three finishers**?*

Need a way to aggregate pairwise winner predictions.

Aggregate Likelihood

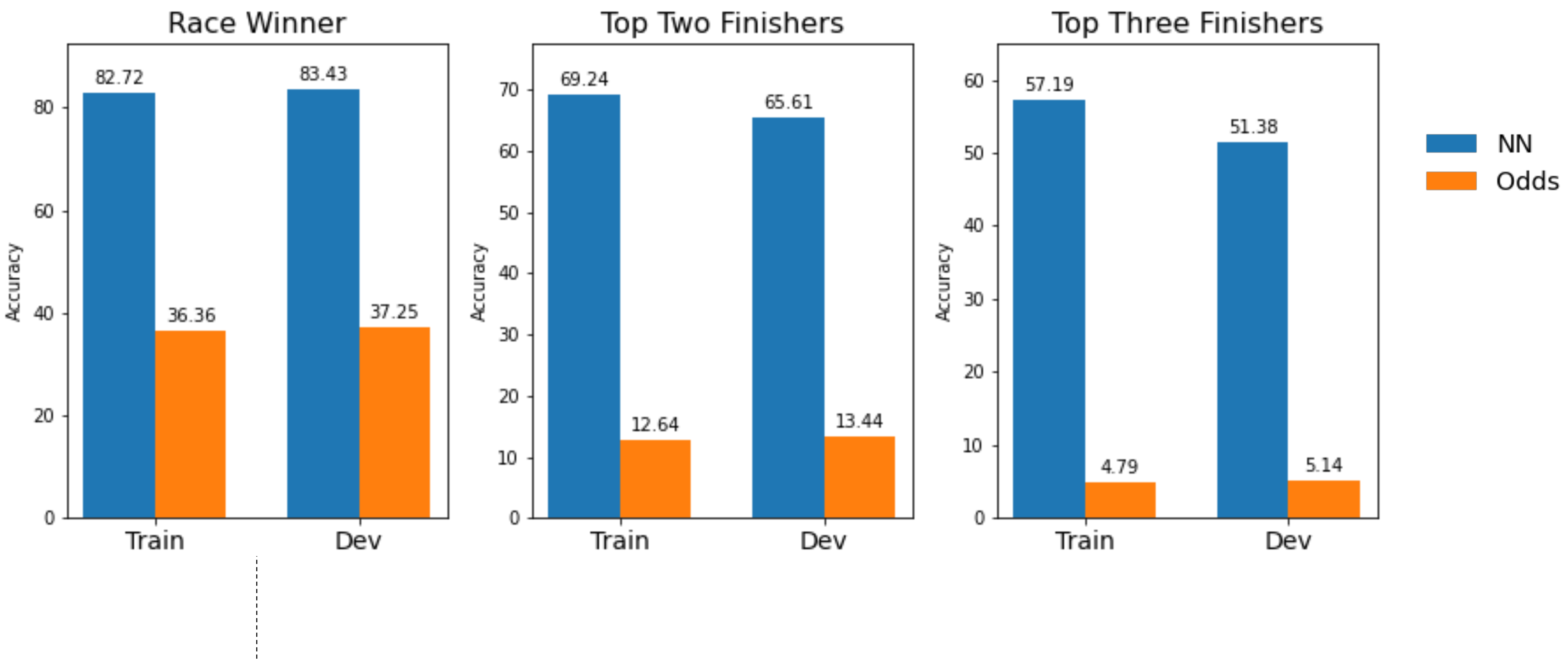
Runners: 

Aggregate likelihood of  : $f($  $) + f($  $)$

To get predicted race ordering, sort horses by aggregate likelihood.

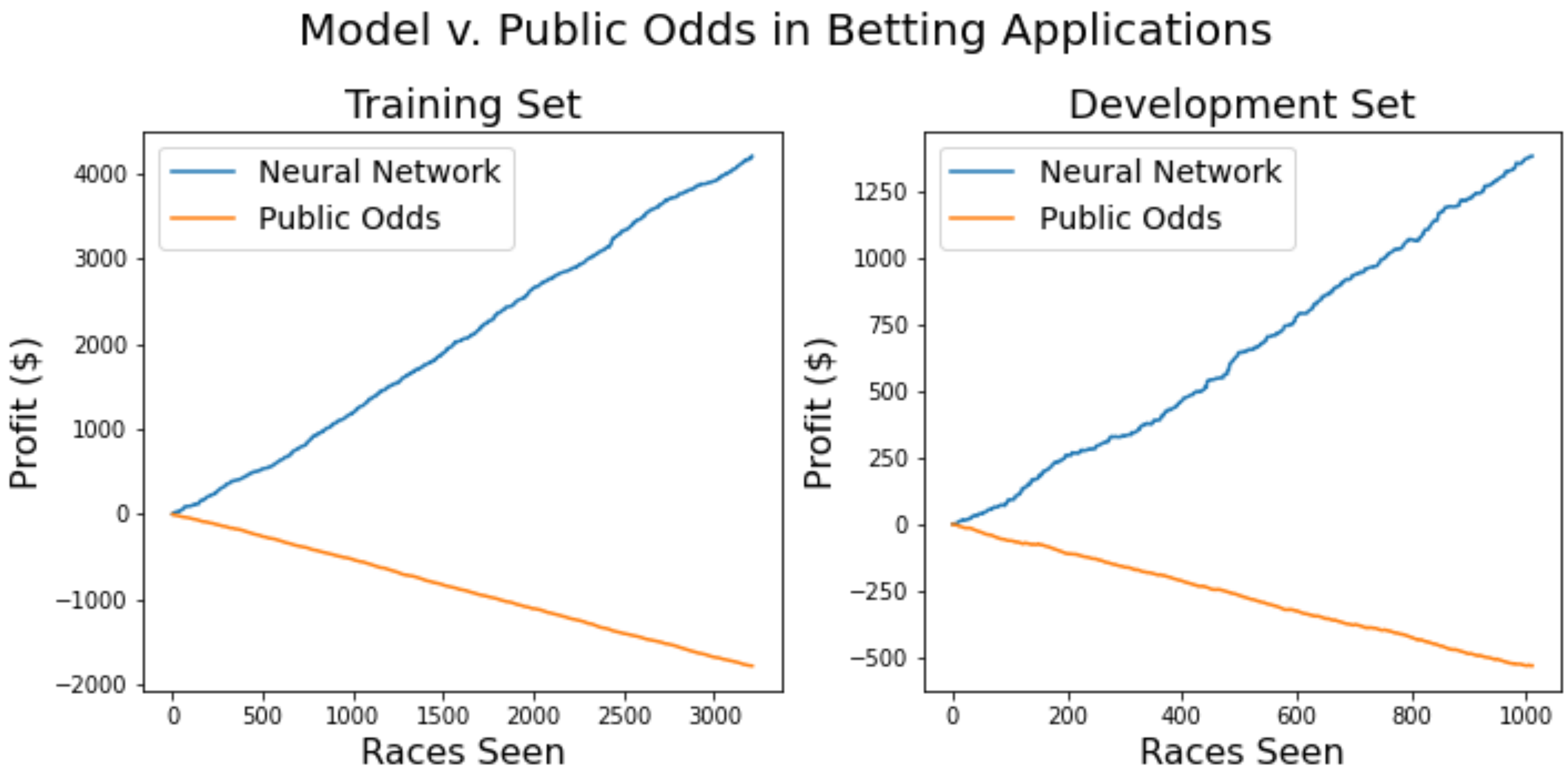
* f is the function the neural network computes

Downstream Tasks



Highest in the literature was 77%, although on a different dataset.

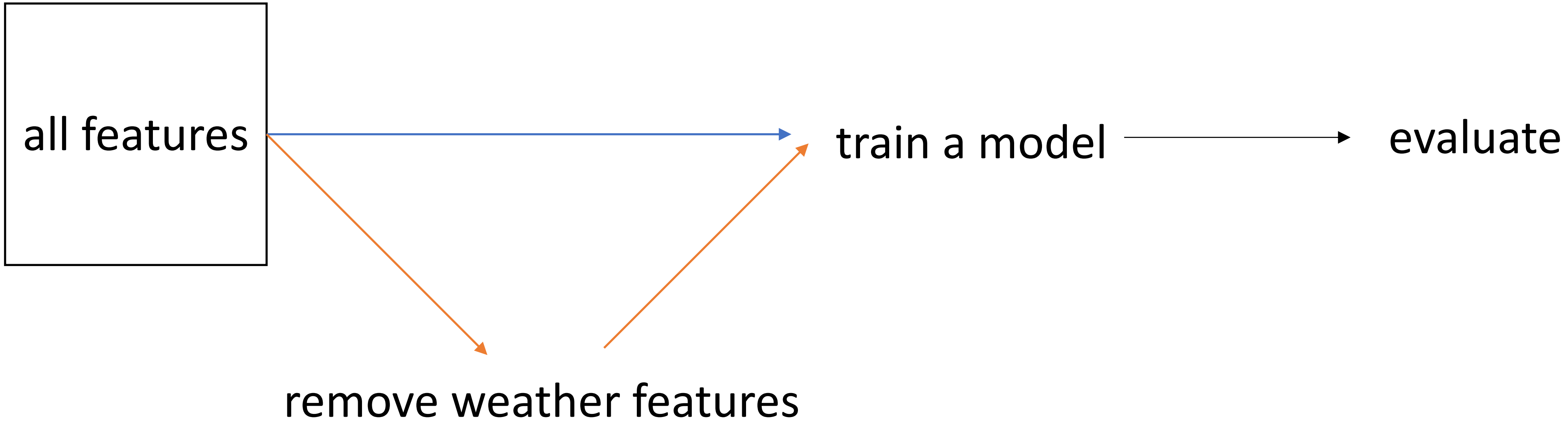
Betting Applications



Ablation Experiment

Is the high performance due to the inclusion of meteorological data?

Follow method by *Iskandaryan et. al. (2020)*:



Ablation Experiment

		w/o Weather			w/ Weather		
Model	**Hyperparameters**	**Opt**	**Train**	**Dev**	**Opt**	**Train**	**Dev**
NN	*	*	95.28	95.13	*	95.02	94.68
LR	solver penalty C	lbfgs none 100	94.55	94.31	lbfgs l2 100	94.55	94.31

Neural Networks

w/o Weather			w/ Weather		
Opt	Train	Dev	Opt	Train	Dev
*	95.28	95.13	*	95.02	94.68

Neural Networks

w/o Weather			w/ Weather		
Opt	$\boxed{\text{Train}}$	Dev	Opt	$\boxed{\text{Train}}$	Dev
*	$\boxed{95.28}$	95.13	*	$\boxed{95.02}$	94.68

Neural Networks

w/o Weather			w/ Weather		
Opt	**Train**	**Dev**	**Opt**	**Train**	**Dev**
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Neural Networks

w/o Weather			w/ Weather		
Opt	Train	Dev	Opt	Train	Dev
*	95.28	95.13	*	95.02	94.68

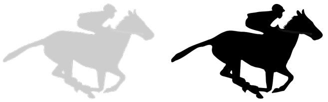
How is the neural network using weather features?

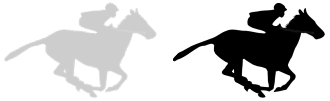
Observing weights is difficult for a neural network of this size.

Instead, will feed it **hand-crafted input** and inspect the result.

Hand-Crafted Input

Start with **logically equivalent horses**: 

Change **one feature** to make one horse more favorable: 

Measure change in output: $f($  $) - f($  $)$

Feature importance ∝ change in output.

Neural Networks

	NN w/o Weather			NN w/ Weather		
	Avg Diff in Output (x100)			Avg Diff in Output (x100)		
Group	**Small Mod**	**Large Mod**	**Avg Rank**	**Small Mod**	**Large Mod**	**Avg Rank**
Horse Attributes	40.8	40.8	1.0	38.2	38.3	1.0
Past Perf, Unconditioned	1.66	2.01	4.5	1.19	1.48	7.0
Past Perf w/ Course	1.47	2.10	5.5	0.90	1.13	10.0
Past Perf w/ Distance	1.42	2.52	5.0	1.12	1.30	8.5
Past Perf w/ Track Condition	1.61	1.95	5.5	0.83	0.84	11.0
Past Perf w/ Runners	1.94	2.22	3.0	1.52	1.65	5.0
Past Perf w/ Month	1.55	2.80	3.5	1.56	2.07	3.0
Past Perf w/ Temperature	-	-	-	1.22	1.66	5.5
Past Perf w/ Pressure	-	-	-	1.36	2.83	3.0
Past Perf w/ Rain	-	-	-	0.98	1.83	7.0
Past Perf w/ Humidity	-	-	-	1.18	2.10	5.0

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Low average rank corresponds to most important features.

Neural Networks

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horse attributes,

(in order of importance)

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horse attributes, runners and month,

(in order of importance)

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horse attributes, runners and month, general performance and distance,

(in order of importance)

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horse attributes, runners and month, general performance and distance, course and track condition

pressure,

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Past Perf w/ Humidity	-	-	-	1.18	2.10	5.0

horse attributes, runners and month, general performance and distance, course and track condition

pressure, temperature and humidity,

Neural Networks

	NN w/o Weather			NN w/ Weather		
	Avg Diff in Output (x100)			Avg Diff in Output (x100)		
Group	**Small Mod**	**Large Mod**	**Avg Rank**	**Small Mod**	**Large Mod**	**Avg Rank**
Horse Attributes	40.8	40.8	1.0	38.2	38.3	1.0
Past Perf, Unconditioned	1.66	2.01	4.5	1.19	1.48	7.0
Past Perf w/ Course	1.47	2.10	5.5	0.90	1.13	10.0
Past Perf w/ Distance	1.42	2.52	5.0	1.12	1.30	8.5
Past Perf w/ Track Condition	1.61	1.95	5.5	0.83	0.84	11.0
Past Perf w/ Runners	1.94	2.22	3.0	1.52	1.65	5.0
Past Perf w/ Month	1.55	2.80	3.5	1.56	2.07	3.0
Past Perf w/ Temperature	-	-	-	1.22	1.66	5.5
Past Perf w/ Pressure	-	-	-	1.36	2.83	3.0
Past Perf w/ Rain	-	-	-	0.98	1.83	7.0
Past Perf w/ Humidity	-	-	-	1.18	2.10	5.0

horse attributes, runners and month, general performance and distance, course and track condition

pressure, temperature and humidity, rainfall

Neural Networks

	NN w/o Weather			**NN w/ Weather**		
	Avg Diff in Output (x100)			**Avg Diff in Output (x100)**		
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Past Perf w/ Humidity	-	-	-	1.18	2.10	5.0

horse attributes, runners and month, general performance and distance, course and track condition

pressure, temperature and humidity, rainfall

Neural Networks

non-weather

horse attributes, runners and month, general performance and distance, course and track condition

pressure, temperature and humidity, rainfall

weather

more important

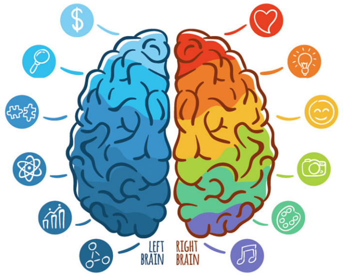
Neural Networks

NN w/ weather meaningfully use **pressure**, **temperature** and **humidity**.

Uses weather features more heavily than non-weather features.

NN w/ weather and NN w/o weather have **disjoint knowledge**.

Future work may try to combine these models.



Logistic Regression Models

w/o Weather			w/ Weather		
Opt	Train	Dev	Opt	Train	Dev
lbfgs none 100	94.55	94.31	lbfgs l2 100	94.55	94.31

Logistic Regression Models

w/o Weather			w/ Weather		
Opt	**Train**	**Dev**	**Opt**	**Train**	**Dev**
lbfgs none 100	94.55	94.31	lbfgs l2 100	94.55	94.31

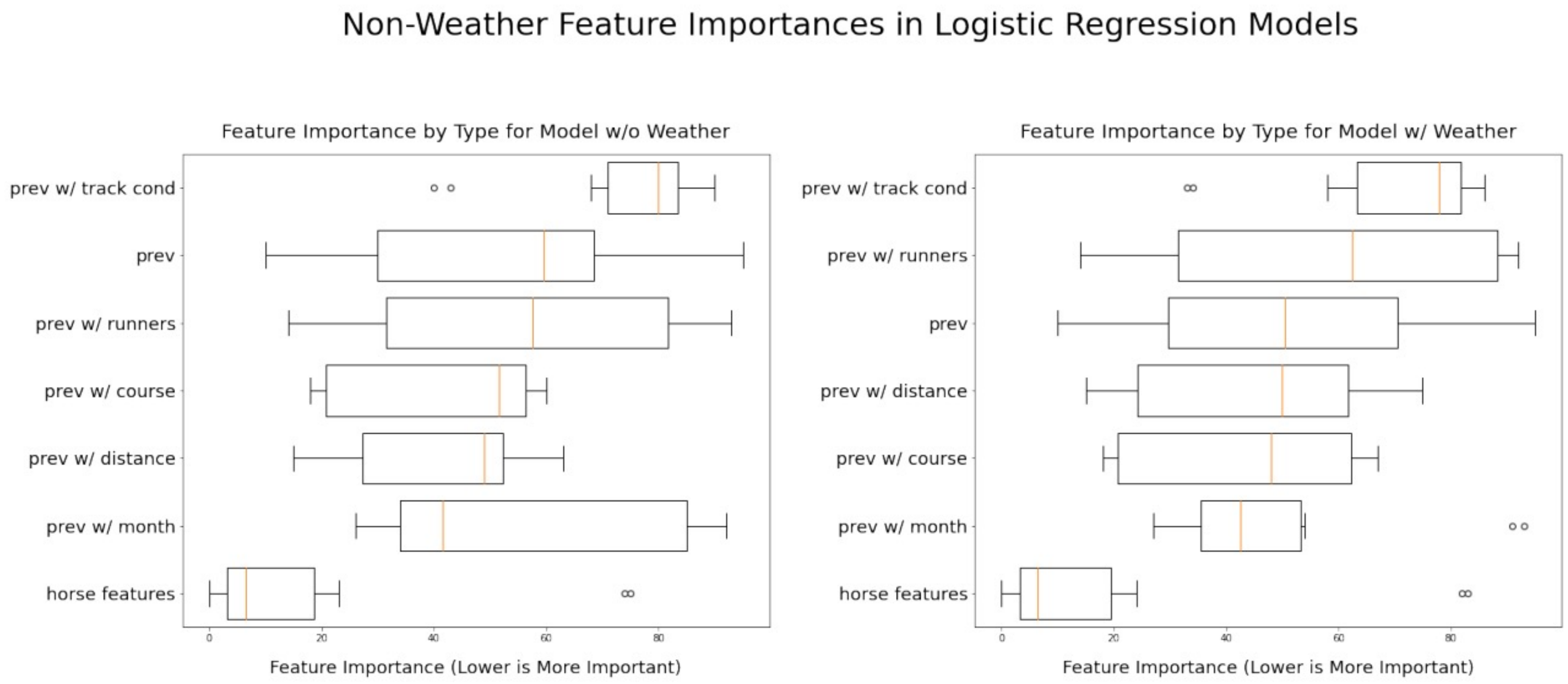
Logistic Regression Models

w/o Weather			w/ Weather		
Opt	**Train**	**Dev**	**Opt**	**Train**	**Dev**
lbfgs none 100	94.55	94.31	lbfgs l2 100	94.55	94.31

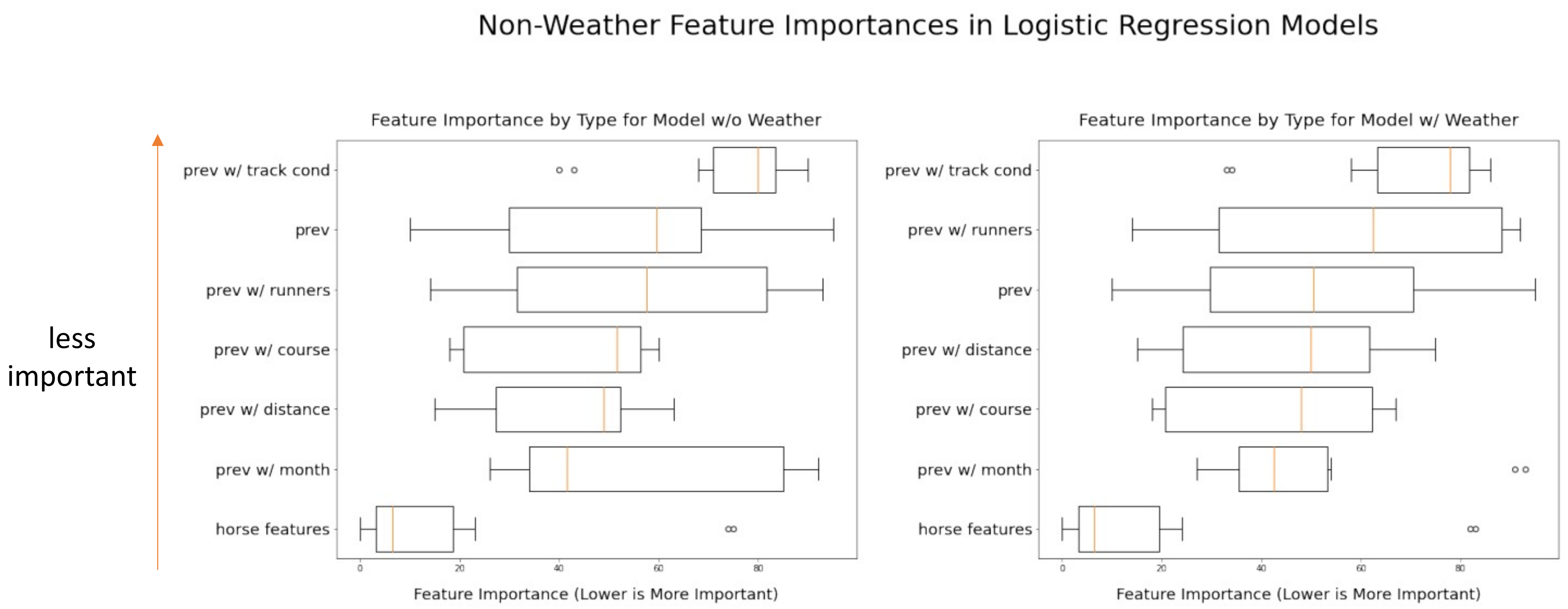
How is the logistic regression model using weather features?

We can observe the weight vector $\overrightarrow{w}$.

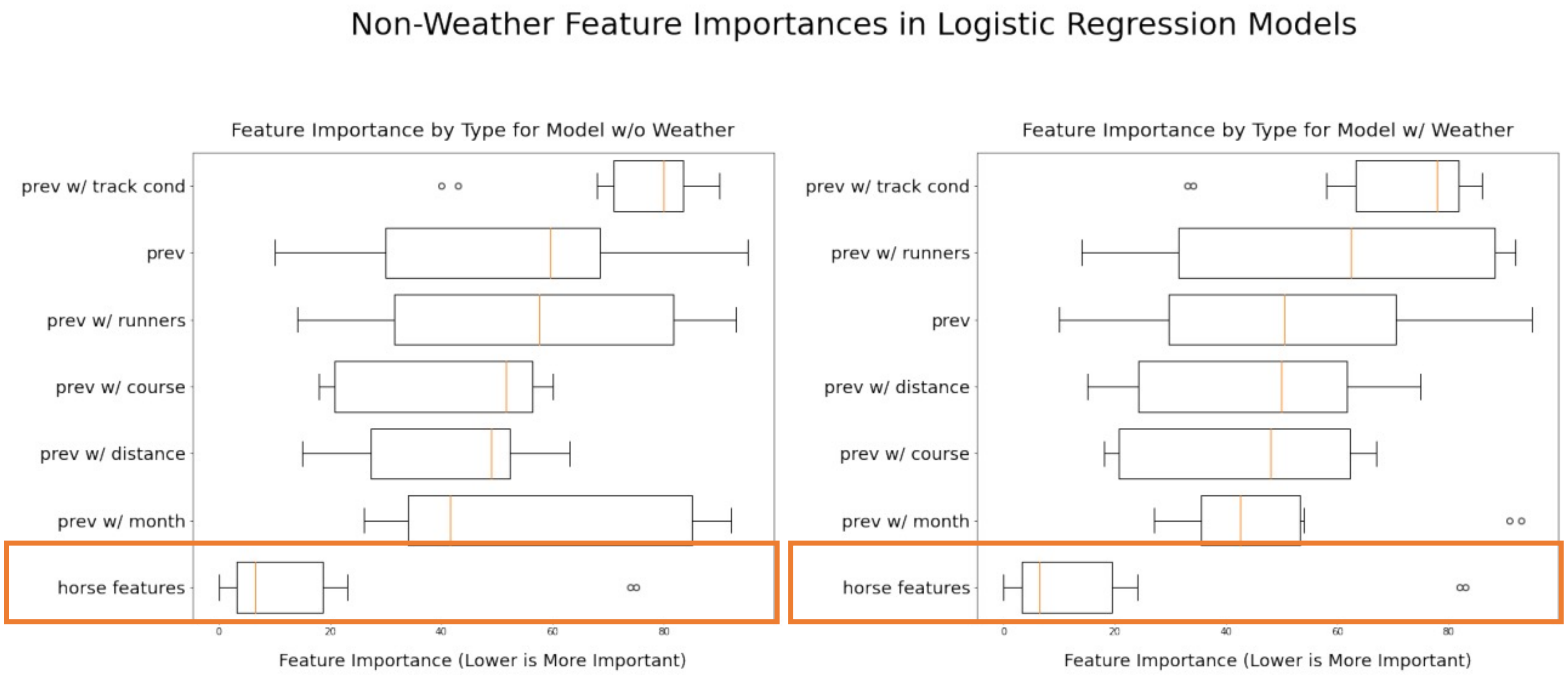
Logistic Regression Models



Logistic Regression Models

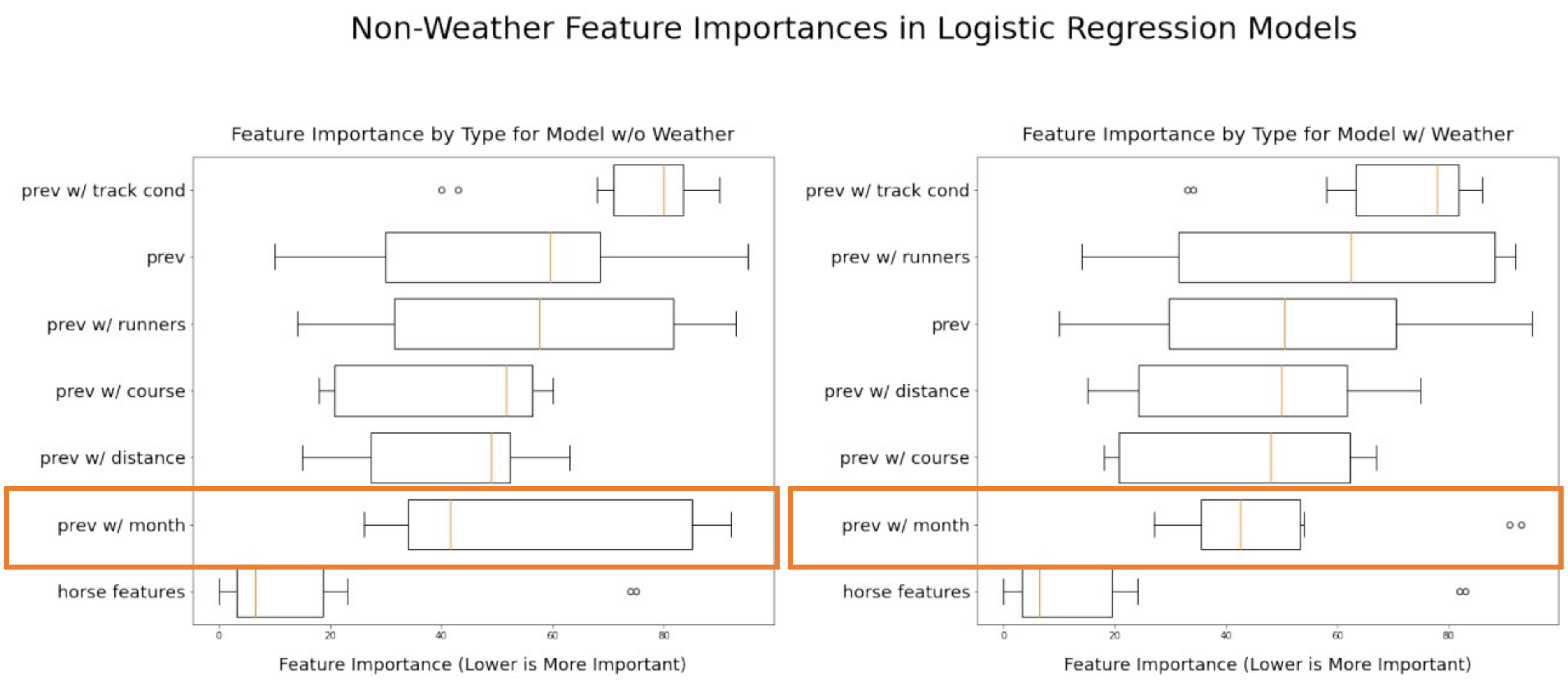


Logistic Regression Models



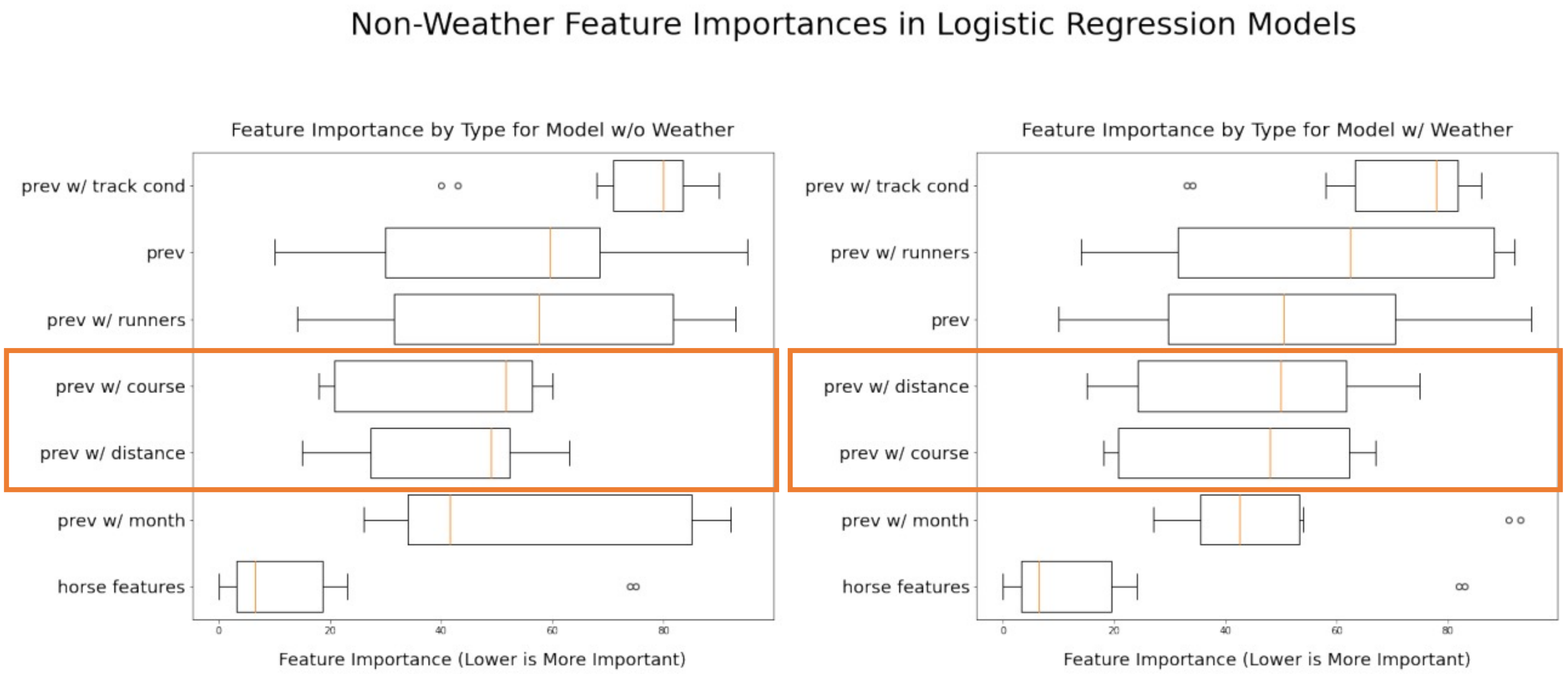
horse attributes,

Logistic Regression Models



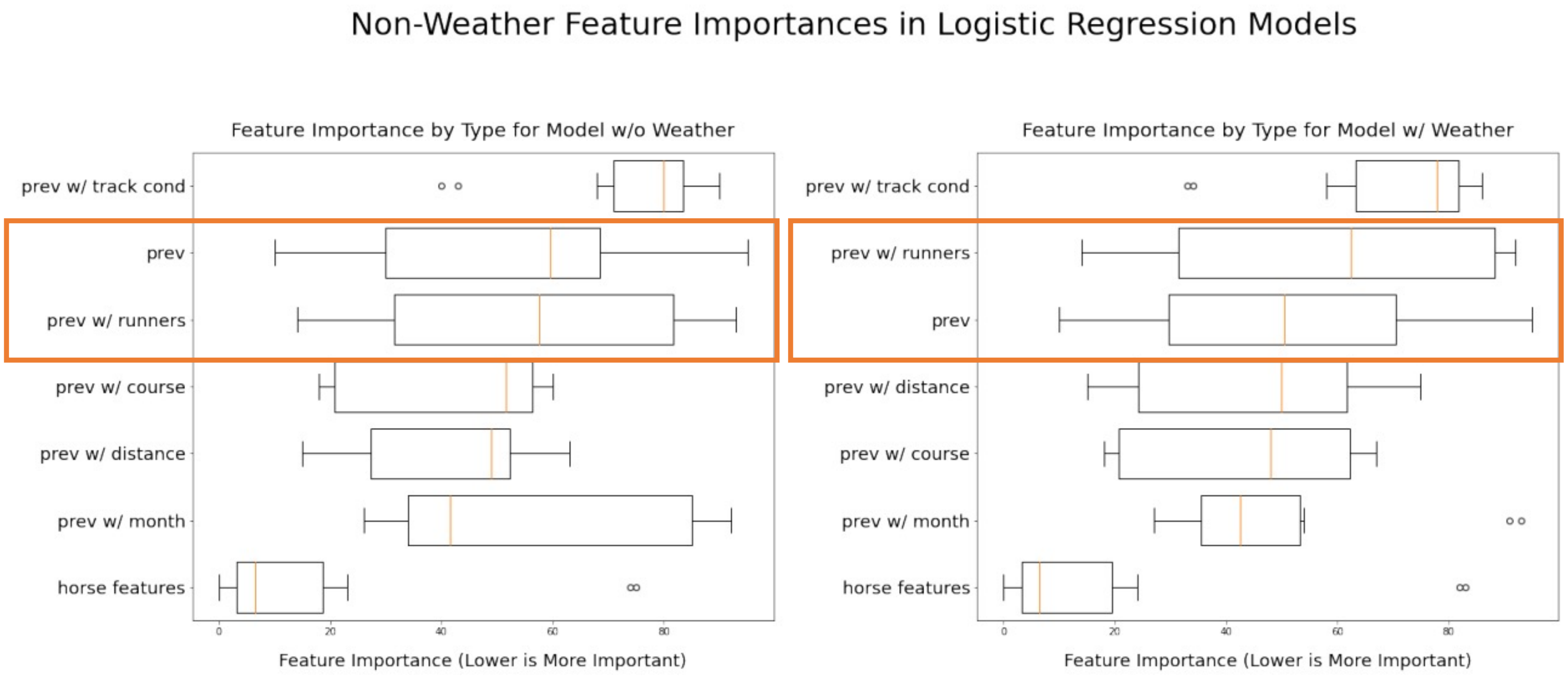
horse attributes, month,

Logistic Regression Models



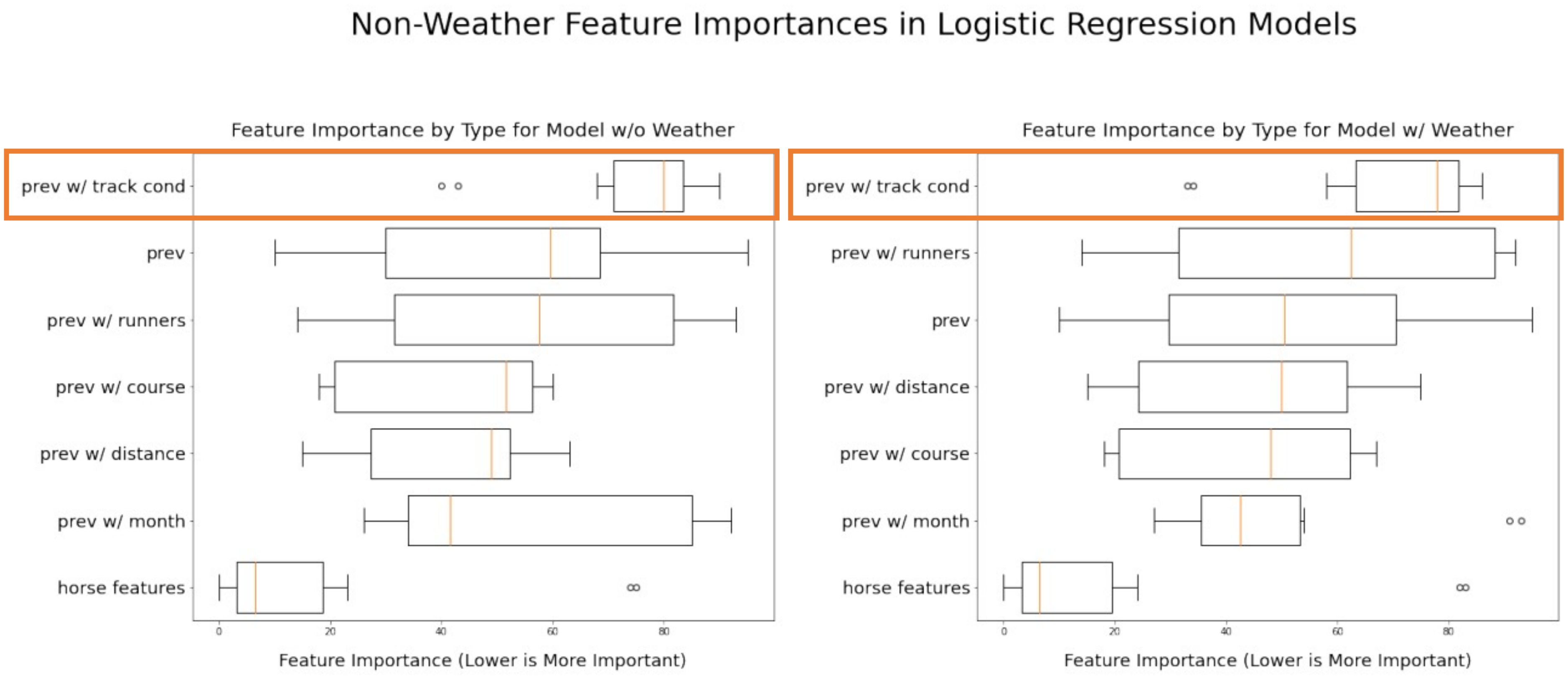
horse attributes, month, course and distance,

Logistic Regression Models



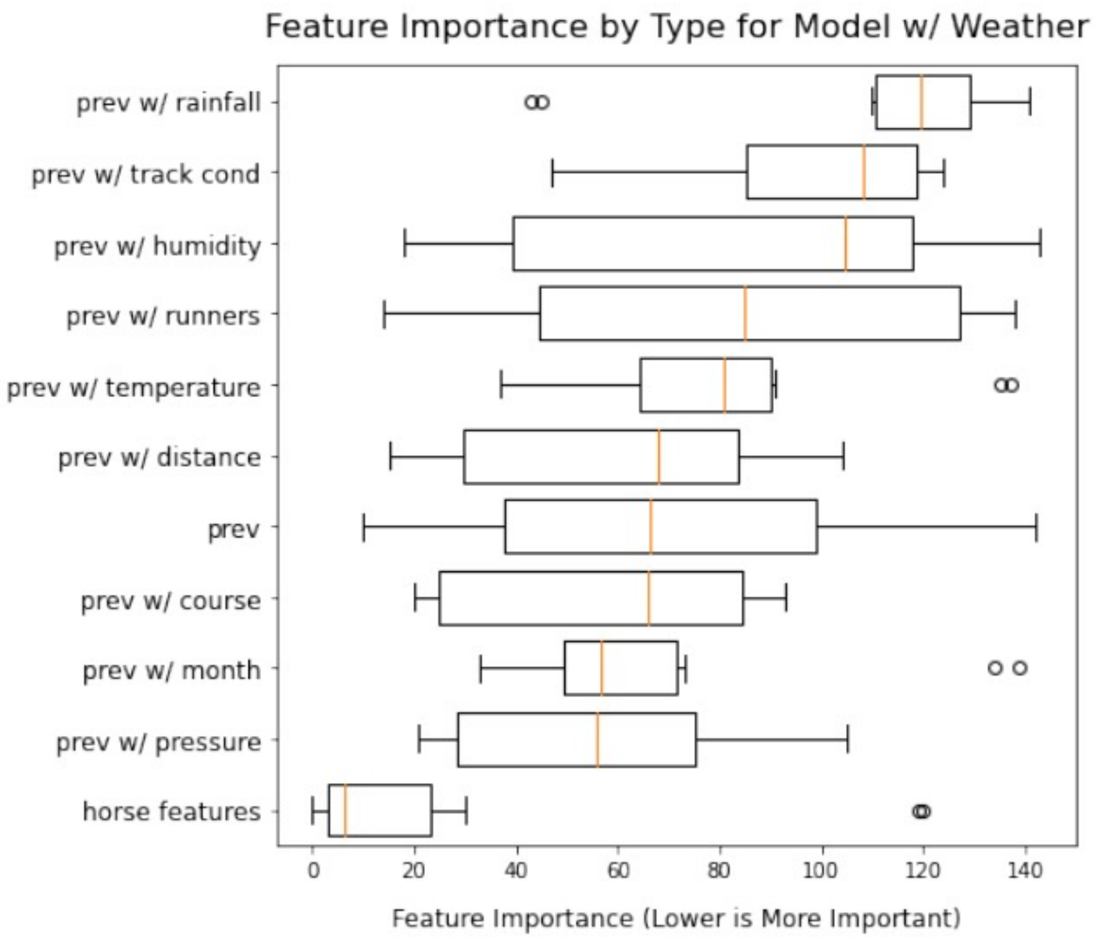
horse attributes, month, course and distance, general performance and runners,

Logistic Regression Models

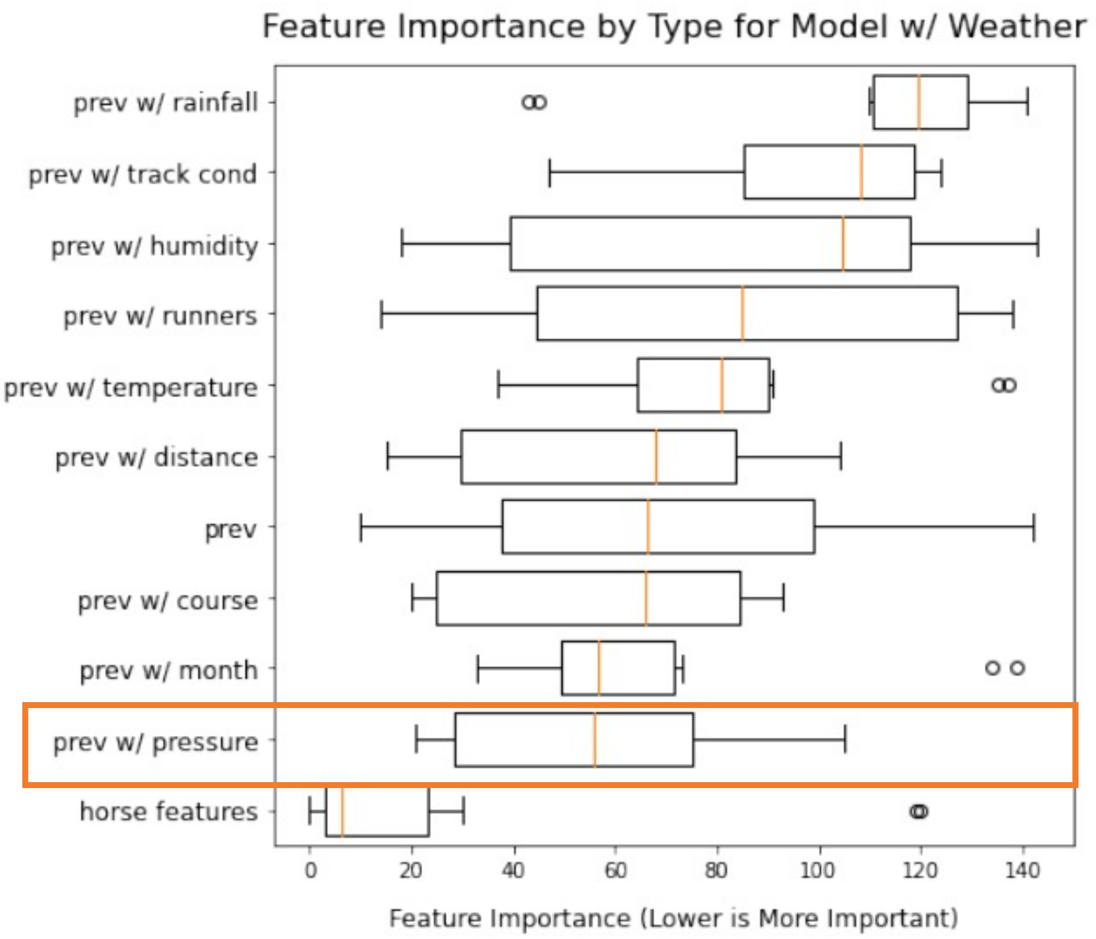


horse attributes, month, course and distance, general performance and runners, track condition

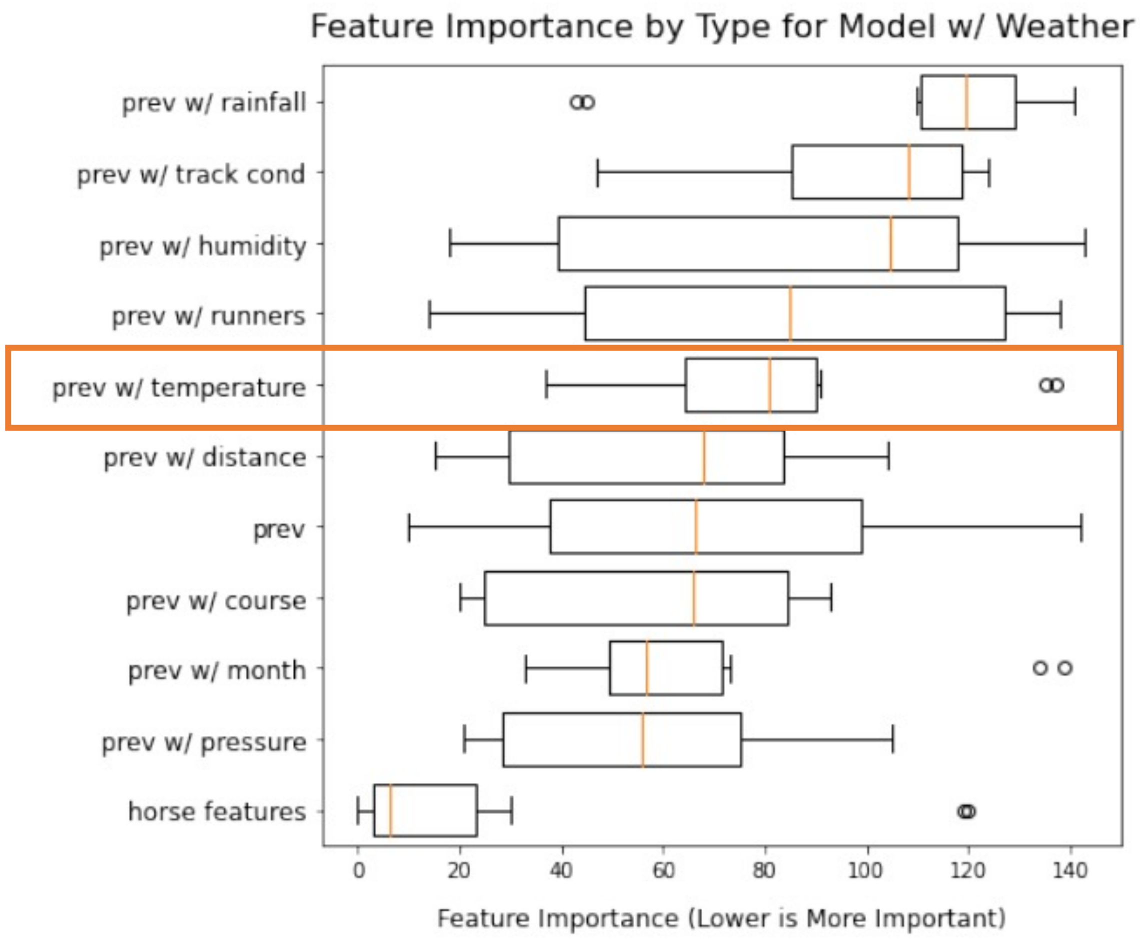
Logistic Regression Models



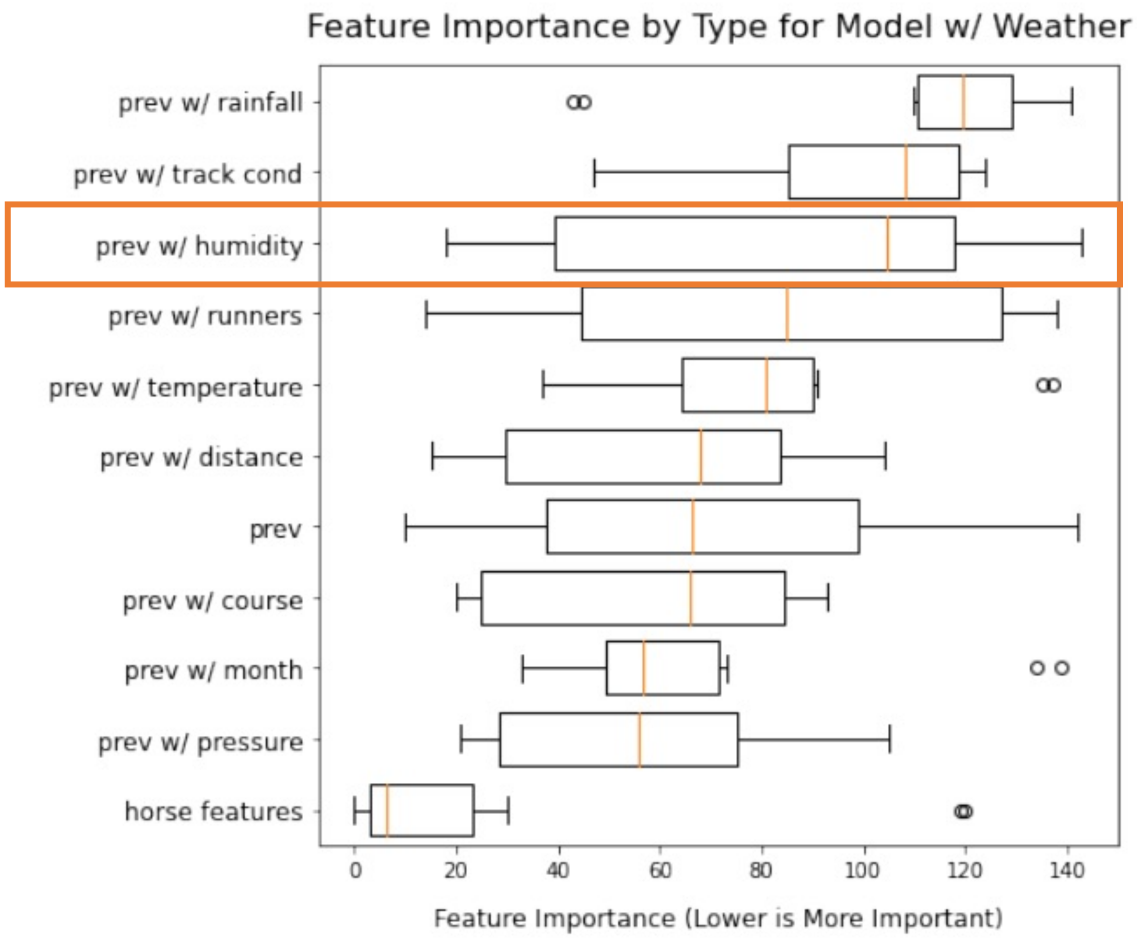
Logistic Regression Models



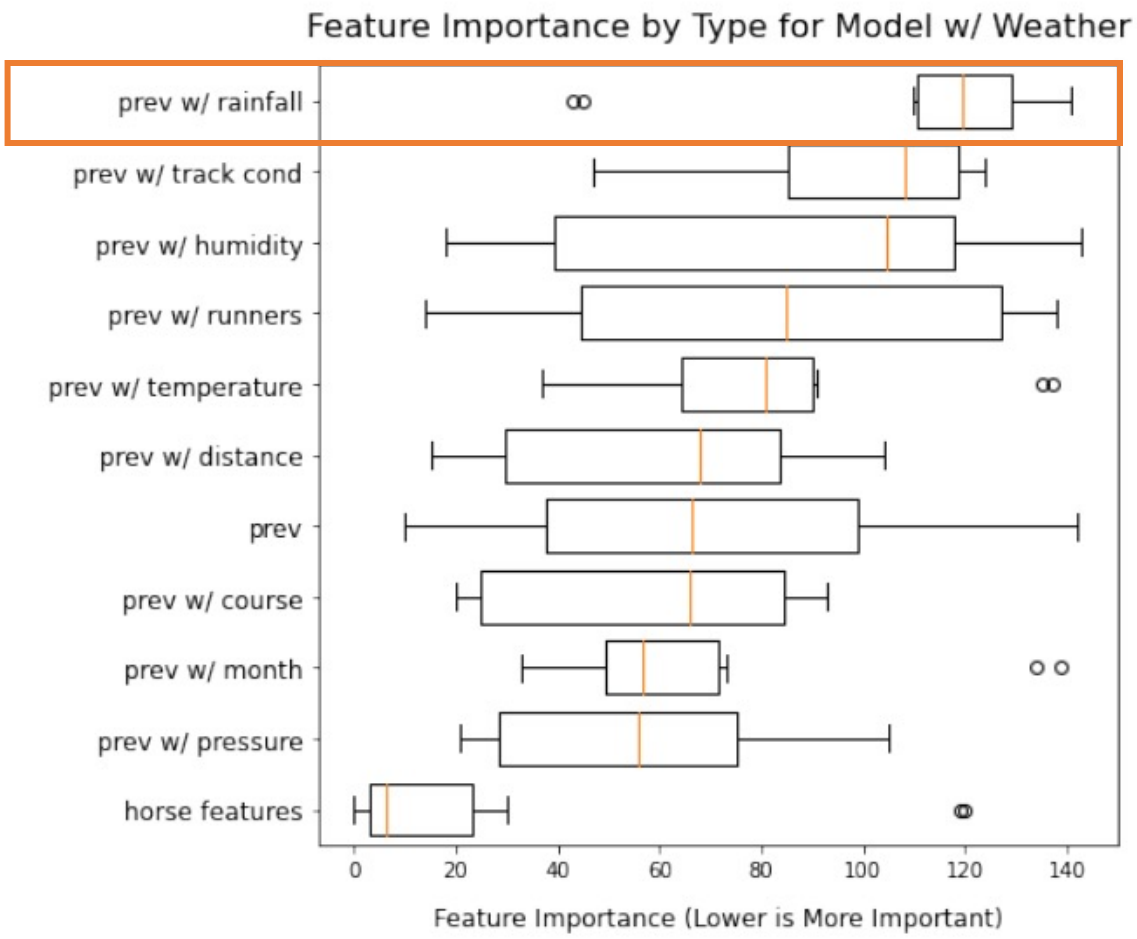
Logistic Regression Models



Logistic Regression Models



Logistic Regression Models



Logistic Regression Models

Logistic regression model w/ weather meaningfully uses **pressure** and *possibly* **temperature** towards prediction.

Future work may use results for feature selection.

Summary of Analysis

Models seem to meaningfully leverage **pressure** and **temperature.**

But, unable to leverage the full feature space to outperform models w/o weather.

Inclusion of weather features alone cannot explain the success of our models, so we conclude that this is owed to our **featurization** and **pairwise prediction approach**.

Overview

1. Horse Racing
2. Motivation
3. Prior Work
    a) Horse Racing
    b) Weather in Sports
4. Data
    a) Horse Racing Data
    b) Meteorological Data
    c) Combining Data
5. Exploratory Data Analysis
6. Featurization
7. Analysis
8. **Conclusion**

Conclusion

Can meteorological data improve predictions on a horse race?

We are unable to show this quantitatively…

but, some evidence for this after opening the models

and EDA shows that weather injects variance, so still room for improvement

Contributions to the Literature

Over 20,000 Irish horse races annotated with weather information.

The "pairwise winner" approach to the prediction problem.

Use of *Iskandaryan et. al. (2020)*'s method in the context of horse racing.

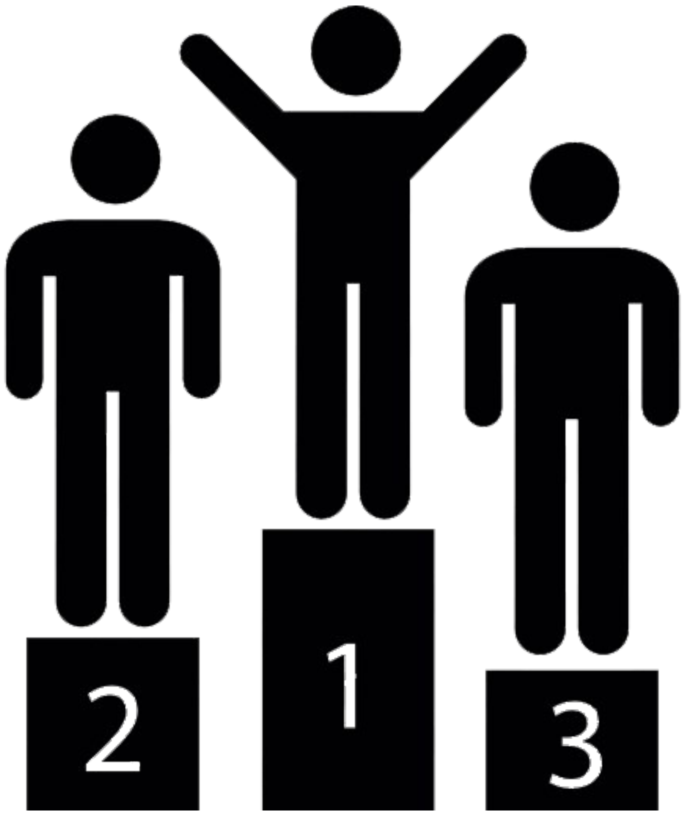
Some evidence that pressure and temperature can help models.

Future Work

Explicit comparison between pairwise prediction and other methods.

Application of pairwise prediction to other disciplines, such as:

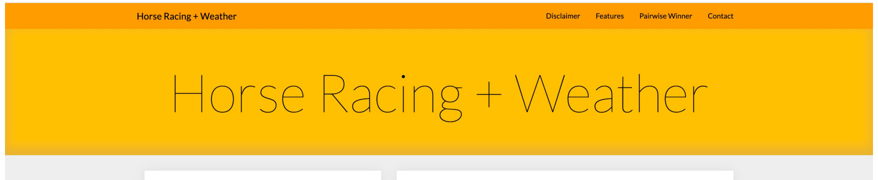
- auto racing
- track and field
- political elections
- *anything involving a synchronous competition between +2 participants*

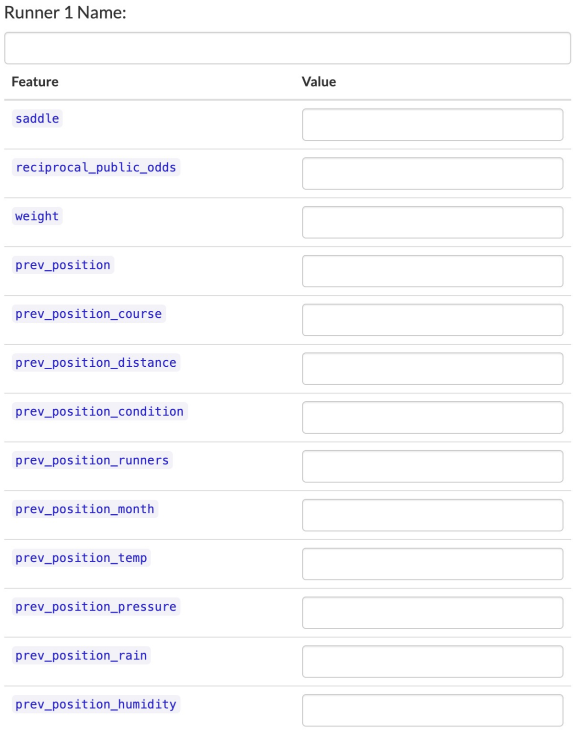


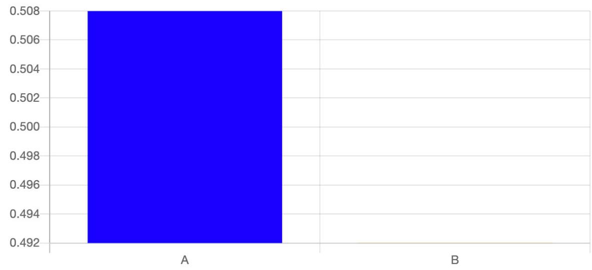
Code Availability

GitHub: https://github.com/AnthonyHein/SML310Project

Web App: http://horseracing.anthonyhein.com







Questions?

Also, feel free to email anhein@princeton.edu.

Monmouth park racetrack.

Extra Slides (Not Presented)

Technical details, definitions, more prior literature.

Horse Racing

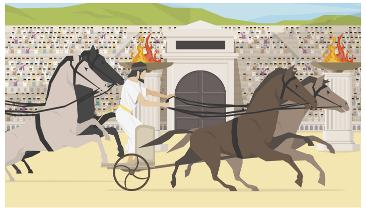
History

700 BCE

1000

1800

Ancient Greek Olympic Games



Norse mythology

British royalty

Source: https://www.britannica.com/sports/horse-racing

Prevalence

Horse racings occurs all over the world:

United States horse racing industry generates 102 billion dollars annually.

Hong Kong Jockey Club is the city's largest taxpayer and benefactor.

Source: https://www.statista.com, https://www.hkjc.com, https://eqgroup.com

Horse Race Wagering

Horse	$1 Bets	Public Odds	Payout
	99 bets	0.999	$1.01
	1 bets	0.001	$100.00

Horse Race Wagering

Most commonly bet on a horse to ***win*** the race.

Payout determined by the ***public odds,*** public's beliefs about who will win.

Example 1:

Horse	$1 Bets	Public Odds	Payout
	50 bets	0.5	$2.00
	50 bets	0.5	$2.00

Example 2:

Horse	$1 Bets	Public Odds	Payout
	99 bets	0.999	$1.01
	1 bets	0.001	$100.00

Horse Racing Controversy

Pressure to perform has led to mistreatment.

THOROUGHBRED
RETIREMENT
FOUNDATION

I do not condone these practices and have made a donation to the Thoroughbred Retirement Foundation.

Source: https://trfinc.org

Motivation

Claims About Weather in Horse Racing

Non-academic sources (i.e. blog posts by horse racing enthusiasts) make numerous claims about weather in horse racing:

> “Barometric pressure, especially when it falls, can influence a horse both physically and emotionally… Other horses are not as affected and can handle pressure changes well.

> “Many people who give tips on horse racing, will agree that rain can have a significant affect on a horse's performance.

> “Humid weather slows down the ability to shed heat from the body and horses can often struggle to sweat enough to stay ahead of the heat buildup in their body.

> “If [the horse] performed consistently well under specific weather conditions, then it’s likely to keep doing so.

Source: https://skymetweather.com, https://punter2pro.com, https://horseracehandicappers.com, https://horseracingkills.com

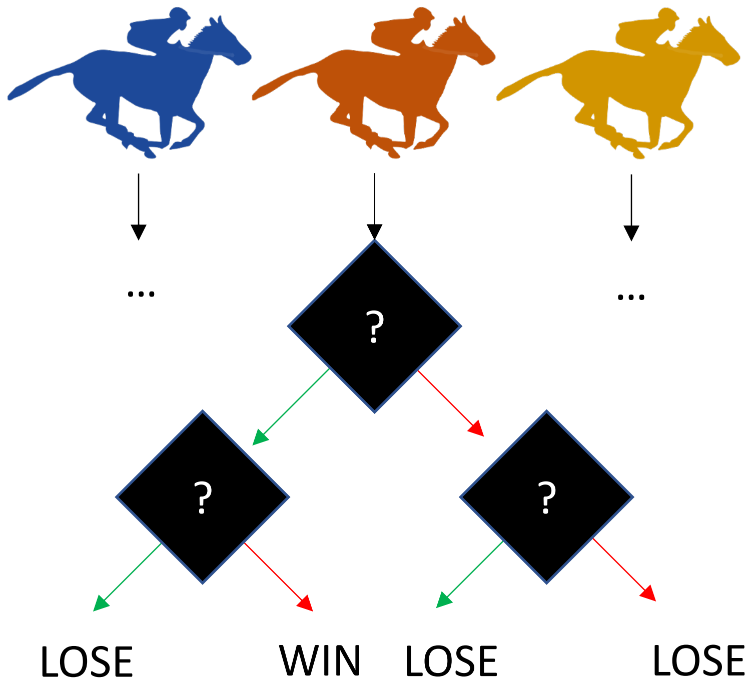
Additional Literature

Vergin (1977s)

Surveyed ***decision rules***, ad hoc decision trees based on anecdotal evidence.

Showed such rules to yield substantial losses in practice.

e.g. “Bet on a horse which had a race within the last ***fifteen*** days at a distance within ***one*** furlong of today's distance and was ***first*** at the stretch call and won the race by at least ***one and a half*** lengths.”



Source: https://pubsonline.informs.org/doi/pdf/10.1287/inte.8.1.34

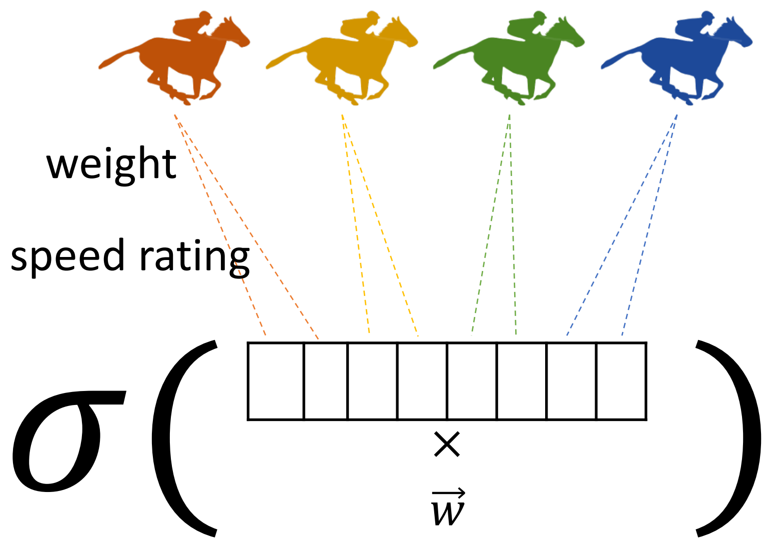
Bolton and Chapman (1986)

Multinomial logistic regression model.

No assumption that runners run independently.

Extremely small dataset (~200 U.S. races).

Focus on betting; do not report accuracy.



Source: https://www.researchgate.net/publication/292145708_Searching_for_Positive_Returns_at_the_Track

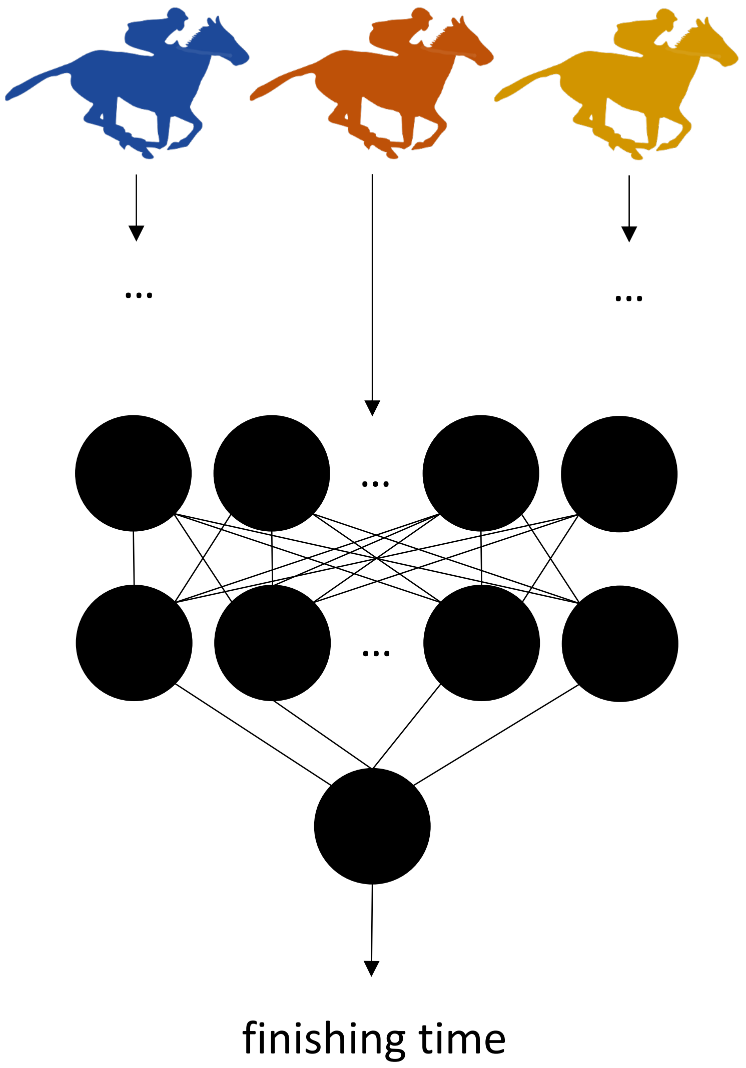
Williams and Li (2008)

Neural network model.

Predict finishing time of a **single** horse.

Achieves 74% accuracy on Jamaican races.

Extremely small dataset (~100 races).



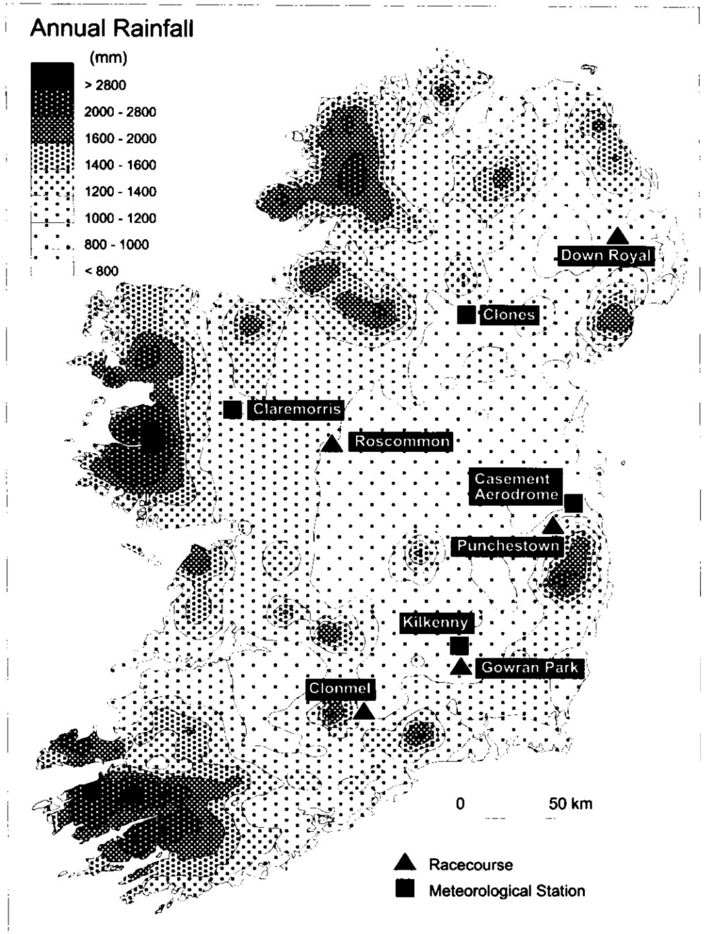
Source: https://eprints.usq.edu.au/4300/

Sheridan and Sweeney (2001)

Use weather to predict the *track condition* for races in Ireland.

Track condition can "explain the difference between a horse winning and losing a race".

*Seems plausible that weather may have a more **explicit** effect.*



Source: http://mural.maynoothuniversity.ie/9963/1/JS-Weather-2001.pdf

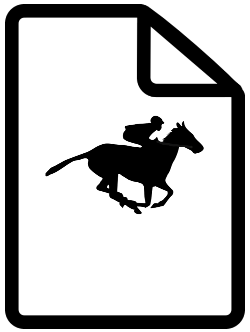
Data Cleaning

No Existing Datasets

No horse racing datasets with suitable weather annotations exist.

Therefore, we need to make our own, will need to separately get:

- Horse racing data.
- Meteorological data.



Horse Racing Data

United States:

Data is guarded behind a paywall.

Hong Kong:

Data does not have the start time of the races;
daily weather readings may be too coarse grained.

Inferring the Finishing Time

Does not include the **finishing time** of horses.

We can estimate the finishing time of each horse in a race using the **winning time** and the **distance of a horse to its predecessor**.

Cleaning Horse Racing Data

Dataset did not include the ***finishing time*** of a horse.

Infer this value using race distance, winning time, and length from predecessor:

$$\gamma \; seconds \; per \; length = \frac{winning \; time}{race \; distance} \times average \; length \; of \; horse$$

$$finishing \; time = winning \; time + lengths \; behind \; winner \times \gamma$$

Cleaning Horse Racing Data

Non-positive age:

1. Look for the same horse in another race.
2. See if the horse has an age in another race.
3. Calculate the age using the time between races.

Non-positive saddle number:

1. Look at all horses in this race.
2. Determine if there is a *single* missing saddle number.
3. Fill in the value.

Cleaning Horse Racing Data

Drop if the following conditions are true (cannot be inferred):

- non-positive winning time for a race
- non-positive distance to predecessor
- null jockey or trainer name

Used to calculate the finishing time.

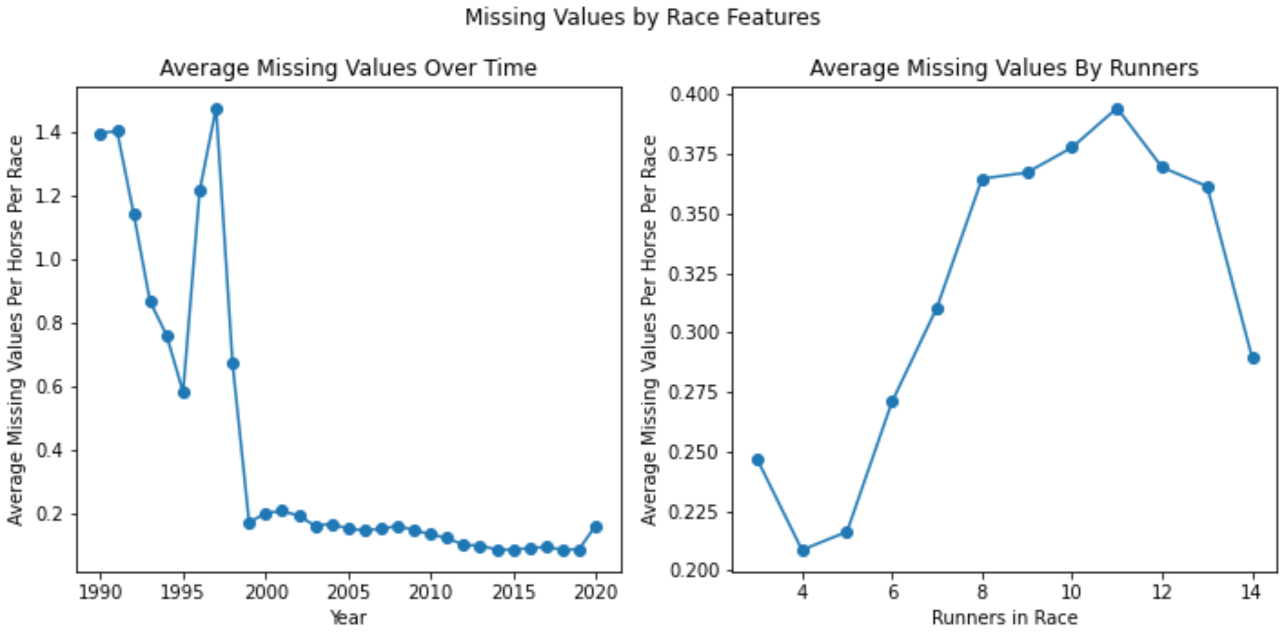
Cleaning Horse Racing Data

Have we injected bias into the dataset by dropping data?

Values missing because races are **old** or have **many runners**.

Not a problem:

- We care most about more recent races.
- Will evaluate against the public odds anyways.



"Goodness" of Weather Readings

Distribution of distances from a race to station.

25th %-ile = 21.5 km

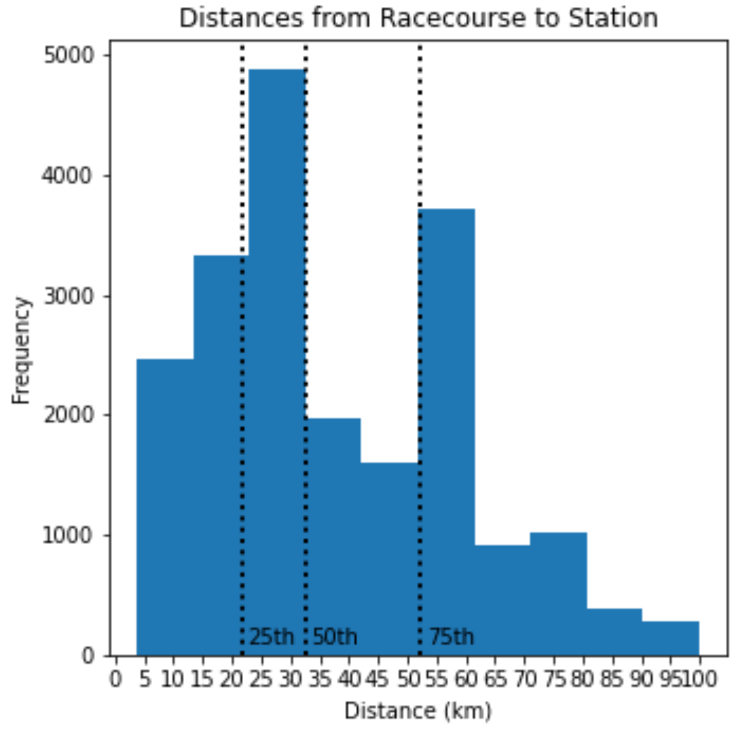
From Princeton to Edison.

50th %-ile = 32.5 km

From Princeton to Trenton and back.

75th %-ile = 52.5 km

From Princeton to Philadelphia.



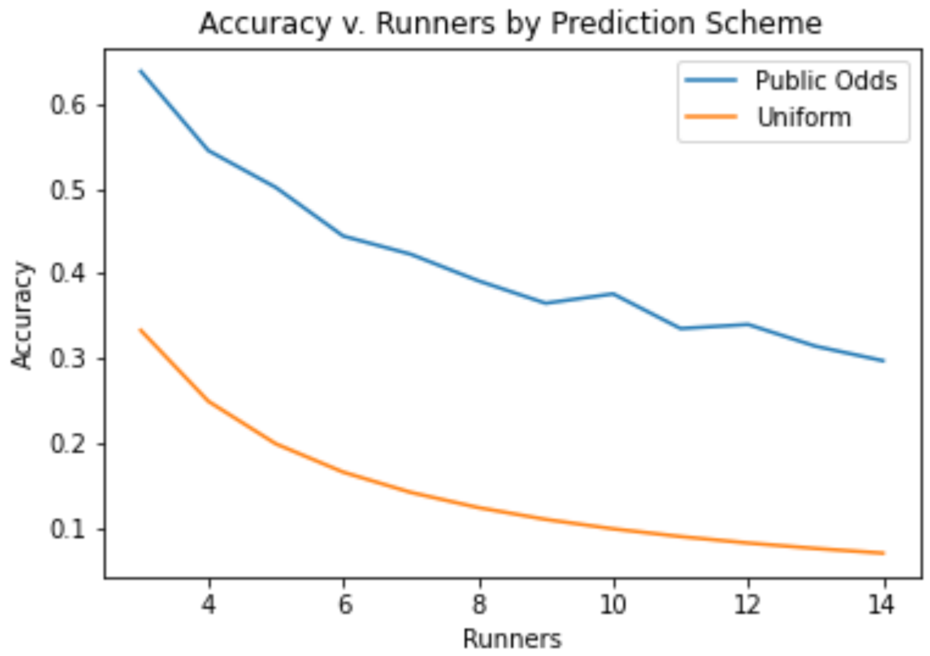
More Exploratory Data Analysis

Public Odds Decently Predict the Winner

37.1% accuracy across the entire dataset.

Larger accuracy over races w/ fewer runners.

Public odds can serve as a good baseline.



Dangerous Track Conditions Due to Rain

Track conditions:

increasing slipperiness

Firm

Good

Soft

Heavy

Dangerous Track Conditions Due to Rain

Track conditions:

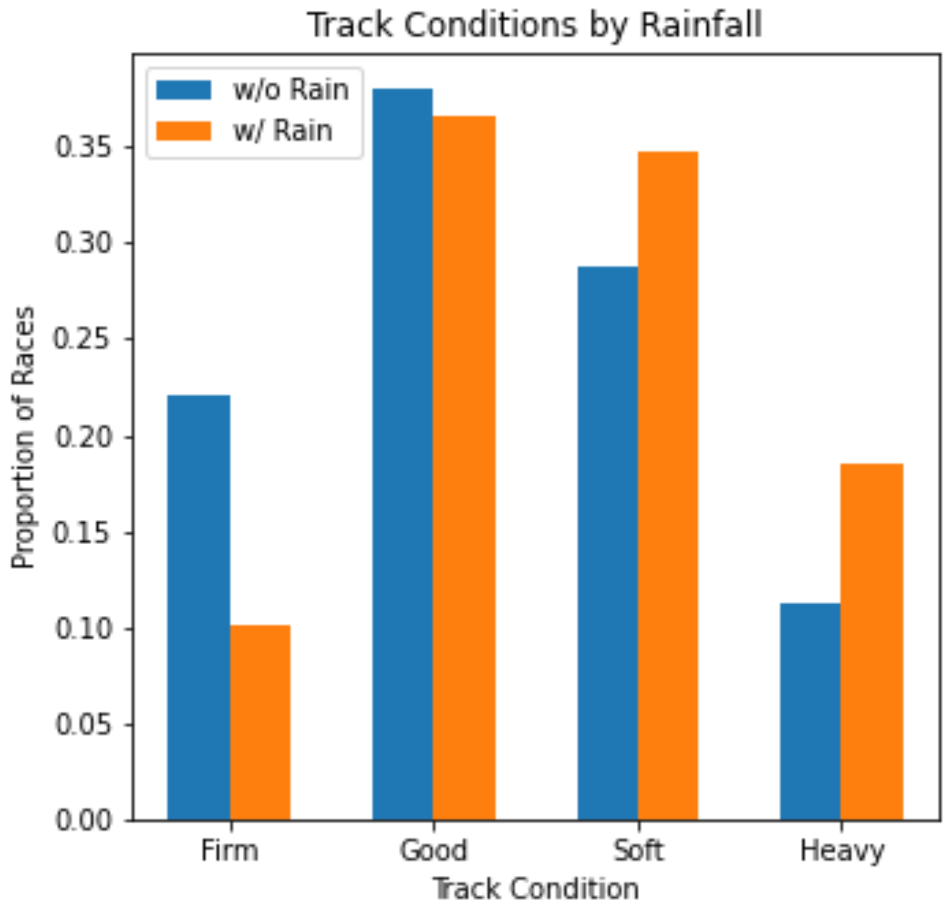
increasing slipperiness

Firm

Good

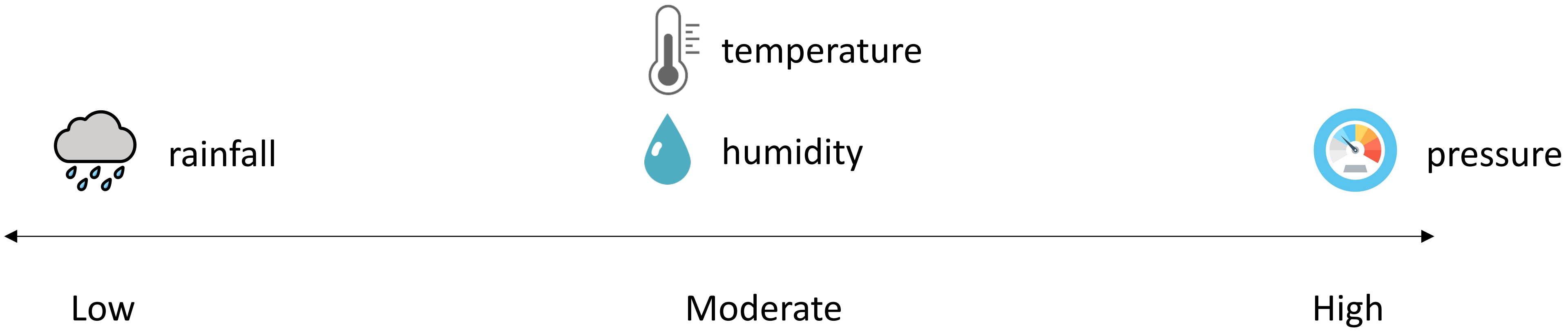
Soft

Heavy



Projected Winners Place Higher in Ideal Weather

What is ideal weather?



Less Failures Occur in Ideal Weather

A horse may not finish if they suffer an injury or if the jockey “pulls up”.

0.142 horses fail to finish per race during **ideal** weather

0.155 horses fail to finish per race during **non-ideal** weather

Fewer horses fail to finish during ideal weather, though these results are not statistically significant.*

* Possibly because jockeys may “pull up” when there is no change of winning, even if there is no imminent danger.

Featurization Details

Features: Horse Attributes

Feature	Description
`age`	age of the horse in years at the start of the race.
`saddle`	saddle number of the horse
`decimalPrice`	reciprocal of the public odds for a horse (larger means more favored to win).
`isFav`	whether the horse has the best public odds of all horses in the race.
`outHandicap`	amount of additional weight placed on the horse
`RPR`	rating by racecourse officials, similar to the public odds
`weight`	weight of horse

Features: Jockey Past Performance

For each:

x in {finishing position, finishing time ratio}

y in {1, 2, 3}

z in {ϵ, course, distance, condition, runners, month, temp, pressure, rain, humidity}

The feature:

`prev_x_y_z`, the *x* of the jockey in their *y*th most previous race on the same/similar *z*.

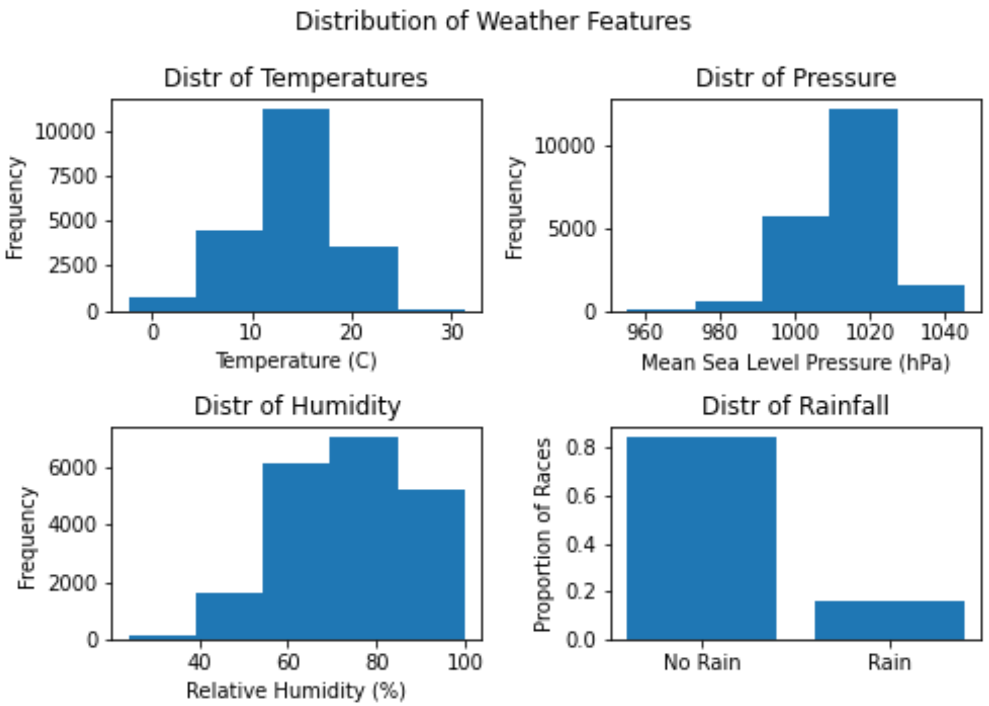
e.g., **`prev_finishing_position_2_course`**

Features: Jockey Past Performance

Similar weather means the same ***bin.***

5 bins used for temperature, pressure, and humidity.

Rainfall binarized.



Prediction Target

Approach 1:

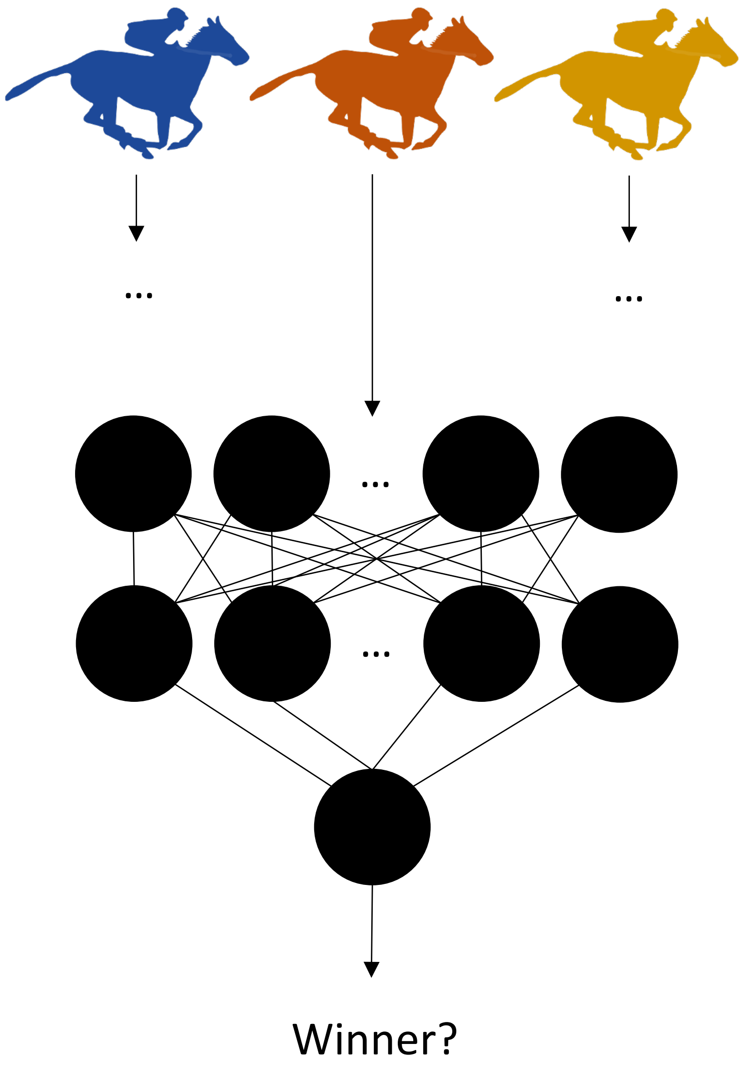
Predict whether a given horse will be a winner.

Pros:

- Simple binary classification problem.
- Handles missing data well.

Cons:

- Assumes horses run independently.
- Cannot adjust for the *skill level* of the race.



Prediction Target

Approach 2:

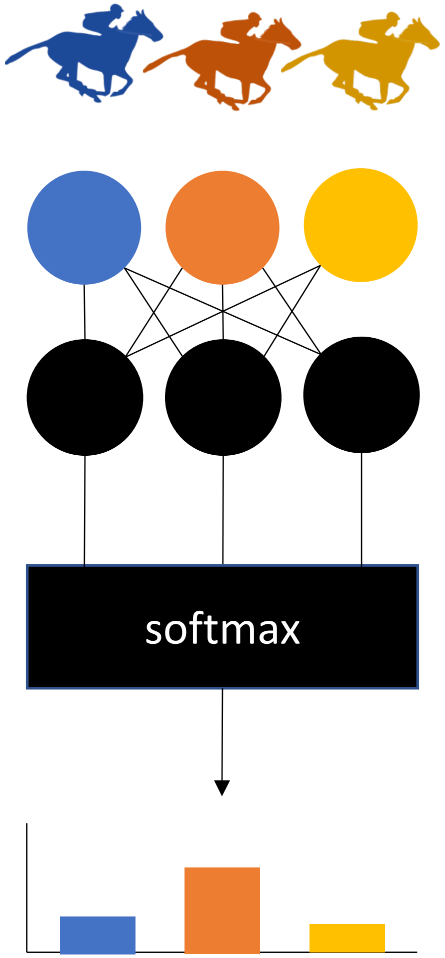
Predict the winner given an entire race.

Pros:

- Explicitly considers all runners in a race.

Cons:

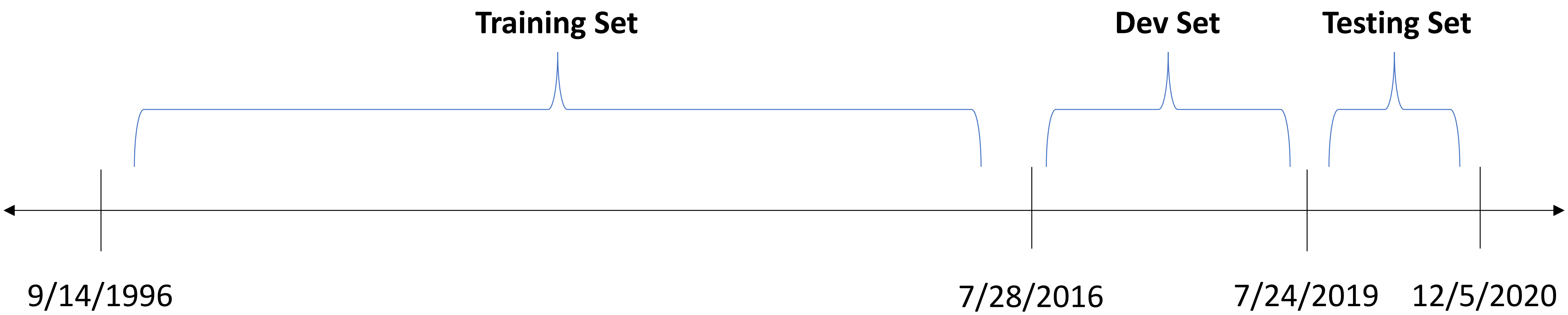
- Variable length inputs must be padded.
- Complicated architecture.
- Tradeoff between # of features and # of datapoints.



Analysis Details

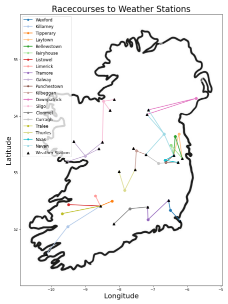
Train-Dev-Test Split

Since using past performance, must split the dataset chronologically.

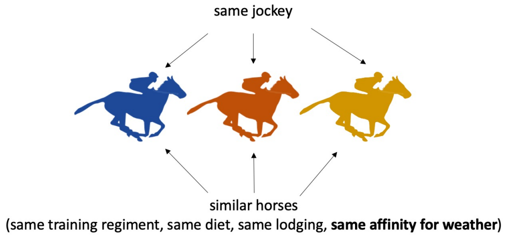


Model Assumptions

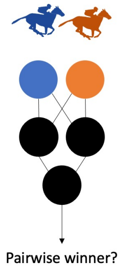
Weather readings are accurate over some distance.



Jockey past performance is a proxy for horse identity.



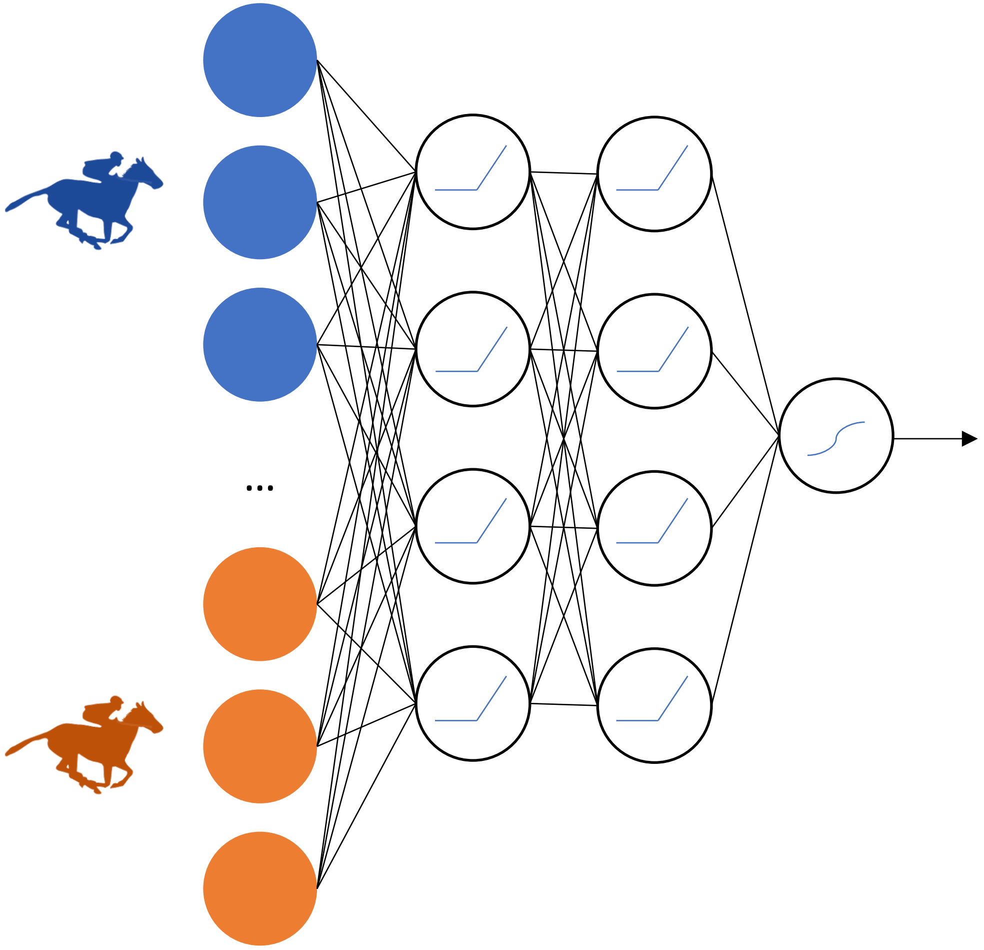
The pairwise winner approach is reasonable.



Model Parameters

Fix a few features of our neural network:

- Fully-connected feed-forward.
- ReLU activation at all hidden nodes.
- Sigmoid activation at the output node.
- Binary cross entropy loss.



Ablation Experiment

		w/o Weather			w/ Weather		
Model	**Hyperparameters**	**Opt**	**Train**	**Dev**	**Opt**	**Train**	**Dev**
NN	*	*	95.28	95.13	*	95.02	94.68
LR	solver penalty C	lbfgs none 100	94.55	94.31	lbfgs l2 100	94.55	94.31
RF	n_estimators max_features min_samples_leaf	200 sqrt 10	96.95	85.78	200 auto 5	99.34	84.76
ET	n_estimators max_features min_samples_leaf	200 sqrt 5	99.16	83.59	200 sqrt 5	99.59	82.89
DT	criterion splitter max_depth min_samples_split min_samples_leaf	gini best 10 5 8	92.55	90.44	gini best 10 10 4	92.56	90.48

Ablation Experiment

		w/o Weather			w/ Weather		
Model	**Hyperparameters**	**Opt**	**Train**	**Dev**	**Opt**	**Train**	**Dev**
NN	*	*	95.28	95.13	*	95.02	94.68
LR	solver penalty C	lbfgs none 100	94.55	94.31	lbfgs l2 100	94.55	94.31
RF	n_estimators max_features min_samples_leaf	200 sqrt 10	96.95	85.78	200 auto 5	99.34	84.76
ET	n_estimators max_features min_samples_leaf	200 sqrt 5	99.16	83.59	200 sqrt 5	99.59	82.89
DT	criterion splitter max_depth min_samples_split min_samples_leaf	gini best 10 5 8	92.55	90.44	gini best 10 10 4	92.56	90.48

Ablation Experiment

		w/o Weather			w/ Weather		
Model	**Hyperparameters**	**Opt**	**Train**	**Dev**	**Opt**	**Train**	**Dev**
NN	*	*	95.28	95.13	*	95.02	94.68
LR	solver	lbfgs	94.55	94.31	lbfgs	94.55	94.31
	penalty	none			l2		
	C	100			100		
RF	n_estimators	200	96.95	85.78	200	99.34	84.76
	max_features	sqrt			auto		
	min_samples_leaf	10			5		
ET	n_estimators	200	99.16	83.59	200	99.59	82.89
	max_features	sqrt			sqrt		
	min_samples_leaf	5			5		
DT	criterion	gini	92.55	90.44	gini	92.56	90.48
	splitter	best			best		
	max_depth	10			10		
	min_samples_split	5			10		
	min_samples_leaf	8			4		

Ablation Experiment

		w/o Weather			w/ Weather		
Model	**Hyperparameters**	**Opt**	**Train**	**Dev**	**Opt**	**Train**	**Dev**
NN	*	*	95.28	95.13	*	95.02	94.68
LR	solver penalty C	lbfgs none 100	94.55	94.31	lbfgs l2 100	94.55	94.31
RF	n_estimators max_features min_samples_leaf	200 sqrt 10	96.95	85.78	200 auto 5	99.34	84.76
ET	n_estimators max_features min_samples_leaf	200 sqrt 5	99.16	83.59	200 sqrt 5	99.59	82.89
DT	criterion splitter max_depth min_samples_split min_samples_leaf	gini best 10 5 8	92.55	90.44	gini best 10 10 4	92.56	90.48

Ablation Experiment

		w/o Weather			w/ Weather		
Model	**Hyperparameters**	**Opt**	**Train**	**Dev**	**Opt**	**Train**	**Dev**
NN	*	*	95.28	95.13	*	95.02	94.68
LR	solver penalty C	lbfgs none 100	94.55	94.31	lbfgs l2 100	94.55	94.31
RF	n_estimators max_features min_samples_leaf	200 sqrt 10	96.95	85.78	200 auto 5	99.34	84.76
ET	n_estimators max_features min_samples_leaf	200 sqrt 5	99.16	83.59	200 sqrt 5	99.59	82.89
DT	criterion splitter max_depth min_samples_split min_samples_leaf	gini best 10 5 8	92.55	90.44	gini best 10 10 4	92.56	90.48

Ablation Experiment

		w/o Weather			w/ Weather		
Model	**Hyperparameters**	**Opt**	**Train**	**Dev**	**Opt**	**Train**	**Dev**
NN	*	*	95.28	95.13	*	95.02	94.68
LR	solver penalty C	lbfgs none 100	94.55	94.31	lbfgs l2 100	94.55	94.31
RF	n_estimators max_features min_samples_leaf	200 sqrt 10	96.95	85.78	200 auto 5	99.34	84.76
ET	n_estimators max_features min_samples_leaf	200 sqrt 5	99.16	83.59	200 sqrt 5	99.59	82.89
DT	criterion splitter max_depth min_samples_split min_samples_leaf	gini best 10 5 8	92.55	90.44	gini best 10 10 4	92.56	90.48

Neural Networks

"Small" and "large" modification intensities.

	NN w/o Weather			NN w/ Weather		
	Avg Diff in Output (x100)			Avg Diff in Output (x100)		
Group	**Small Mod**	**Large Mod**	**Avg Rank**	**Small Mod**	**Large Mod**	**Avg Rank**
Horse Attributes	40.8	40.8	1.0	38.2	38.3	1.0
Past Perf, Unconditioned	1.66	2.01	4.5	1.19	1.48	7.0
Past Perf w/ Course	1.47	2.10	5.5	0.90	1.13	10.0
Past Perf w/ Distance	1.42	2.52	5.0	1.12	1.30	8.5
Past Perf w/ Track Condition	1.61	1.95	5.5	0.83	0.84	11.0
Past Perf w/ Runners	1.94	2.22	3.0	1.52	1.65	5.0
Past Perf w/ Month	1.55	2.80	3.5	1.56	2.07	3.0
Past Perf w/ Temperature	-	-	-	1.22	1.66	5.5
Past Perf w/ Pressure	-	-	-	1.36	2.83	3.0
Past Perf w/ Rain	-	-	-	0.98	1.83	7.0
Past Perf w/ Humidity	-	-	-	1.18	2.10	5.0

Neural Networks

	NN w/o Weather			NN w/ Weather		
	Avg Diff in Output (x100)			Avg Diff in Output (x100)		
Group	**Small Mod**	**Large Mod**	**Avg Rank**	**Small Mod**	**Large Mod**	**Avg Rank**
Horse Attributes	40.8	40.8	1.0	38.2	38.3	1.0
Past Perf, Unconditioned	1.66	2.01	4.5	1.19	1.48	7.0
Past Perf w/ Course	1.47	2.10	5.5	0.90	1.13	10.0
Past Perf w/ Distance	1.42	2.52	5.0	1.12	1.30	8.5
Past Perf w/ Track Condition	1.61	1.95	5.5	0.83	0.84	11.0
Past Perf w/ Runners	1.94	2.22	3.0	1.52	1.65	5.0
Past Perf w/ Month	1.55	2.80	3.5	1.56	2.07	3.0
Past Perf w/ Temperature	-	-	-	1.22	1.66	5.5
Past Perf w/ Pressure	-	-	-	1.36	2.83	3.0
Past Perf w/ Rain	-	-	-	0.98	1.83	7.0
Past Perf w/ Humidity	-	-	-	1.18	2.10	5.0

2 + 4 = 6 / 2 = 3

(40.8, **1.94**, 1.66, 1.61, 1.55, 1.47, 1.42) (40.8, 2.80, 2.52, **2.22**, 2.10, 2.01, 1.95)