Austin Lowey

Predicting Survivor Winners with Machine Learning



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Predicting Survivor Winners with Machine Learning

Leveraged supervised learning techniques to predict the winner of the competition TV show, Survivor, based on historical performance data.

Part 1 - Data Engineering

Data ETL to build SQL database of contestant features for 45 Survivor seasons

Part 2 - Machine Learning

Trained multiple ML models using my database to predict contestant placements

Tools Used:

Python: scikit-learn, pandas, NumPy, psycopg2, Beautiful Soup/requests, OpenAI LLM API

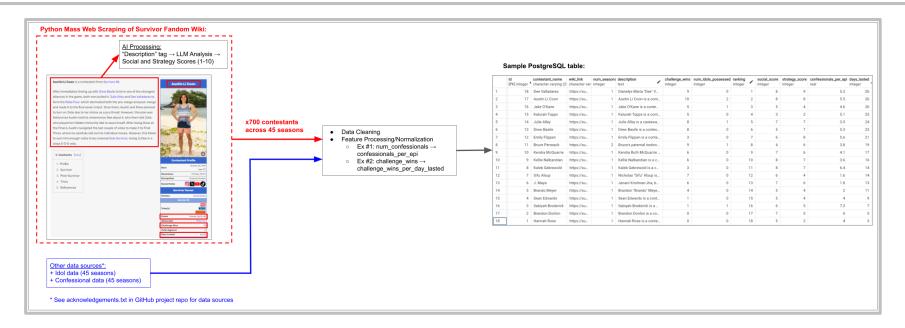
Databases: PostgreSQL, pgAdmin



Part 1: Data Engineering

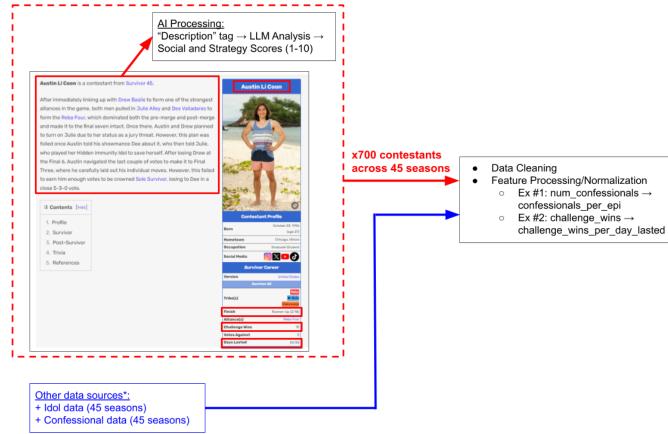
Populated a database with contestant data features for ML modeling.

- Planned ML model features and researched potential data sources
- Data ETL, including mass web scraping/parsing of the Survivor Wiki
- Integrated OpenAI's LLM API to conduct automated AI-analysis on contestant descriptions, generating social and strategy scores on pre-defined criteria



Part 1: Data Engineering

Python Mass Web Scraping of Survivor Fandom Wiki:



Sample PostgreSQL table:

contestant_name character varying (2!	wiki_link character var	num_seasons integer	description text	challenge_wins integer	num_idols_possessed integer	ranking integer	social_score integer	strategy_score integer	confessionals_per_epi real	days_lasted integer
Dee Valladares	https://su	1	Dianelys Maria "Dee" V	9	0	1	8	9	5.2	26
Austin Li Coon	https://su	1	Austin Li Coon is a cont	10	2	2	8	8	5.5	26
Jake O'Kane	https://su	1	Jake O'Kane is a conte	5	1	3	5	4	4.6	26
Katurah Topps	https://su	1	Katurah Topps is a cont	5	0	4	3	2	5.1	25
Julie Alley	https://su	1	Julie Alley is a castawa	8	1	5	7	7	3.5	24
Drew Basile	https://su	1	Drew Basile is a contes	8	0	6	5	7	5.3	23
Emily Flippen	https://su	1	Emily Flippen is a conte	3	0	7	6	8	5.6	21
Bruce Perreault	https://su	2	Bruce's paternal instinc	9	1	8	4	6	3.8	19
Kendra McQuarrie	https://su	1	Kendra Ruth McQuarrie	6	0	9	7	6	4.1	17
Kellie Nalbandian	https://su	1	Kellie Nalbandian is a c	6	0	10	8	7	3.6	16
Kaleb Gebrewold	https://su	1	Kaleb Gebrewold is a c	3	0	11	8	7	6.4	14
Sifu Alsup	https://su	1	Nicholas "Sifu" Alsup is	7	0	12	6	4	1.6	14
J. Maya	https://su	1	Janani Krishnan-Jha, b	6	0	13	7	6	1.8	13
Brando Meyer	https://su	1	Brandon "Brando" Meye	4	0	14	5	4	2	11
Sean Edwards	https://su	1	Sean Edwards is a cont	1	0	15	5	4	4	9
Sabiyah Broderick	https://su	1	Sabiyah Broderick is a	1	1	16	6	5	7.3	7
Brandon Donlon	https://su	1	Brandon Donlon is a co	0	0	17	7	5	6	5
Hannah Rose	https://su	1	Hannah Rose is a conte	0	0	18	5	2	4	3

^{*} See acknowledgements.txt in GitHub project repo for data sources

Part 2: Machine Learning

Explored multiple ML and mathematical modeling techniques, with Random Forest Regression ML model yielding great results.

- Data split into 60/20/20% Train/Validation/Test
- Mathematical modeling: Continuous probability transformation function of contestant placement – Linear vs. Exponential Decay
- Linear Regression baseline model (v1)
- Random Forest Regression successor model (v2)
 - Good at handling noisy data
 - Captures non-linear feature relationships
 - Feature importance values useful for model interpretability

			Expected i	ideal α rang	ge	
rank	P(α=0.5)	P(α=0.4)	P(α=0.3)	P(α=0.2)	P(α=0.1)	
1	1	1.00	1.00	1.00	1.00	
2	0.61	0.67	0.74	0.82	0.90	
3	0.37	0.45	0.55	0.67	0.82	Desirable weighting
4	0.22	0.30	0.41	0.55	0.74	spread for top players
5	0.14	0.20	0.30	0.45	0.67	
6	0.08	0.14	0.22	0.37	0.61	
7	0.05	0.09	0.17	0.30	0.55	
8	0.03	0.06	0.12	0.25	0.50	
9	0.02	0.04	0.09	0.20	0.45	
10	0.01	0.03	0.07	0.17	0.41	
11	0.01	0.02	0.05	0.14	0.37	
12	0.00	0.01	0.04	0.11	0.33	
13	0.00	0.01	0.03	0.09	0.30	
14	0.00	0.01	0.02	0.07	0.27	
15	0.00	0.00	0.01	0.06	0.25	Decay is appropriate for N=16
16	0.00	0.00	0.01	0.05	0.22	
17	0.00	0.00	0.01	0.04	0.20	through N=20 (range for number
18	0.00	0.00	0.01	0.03	0.18	of contestants for each season)
19	0.00	0.00	0.00	0.03	0.17	
20	0.00	0.00	0.00	0.02	0.15	

Model Performance: Test Dataset

- 29% of placement predictions were exact or off by 1.
- 57% were within 3 places.

Model Predictions on Test Dataset (25/165 rows; full data on GitHub)
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contestant_name	actual_probability_from_placement	predicted_probability	placement	predicted_placement	season_total_contestants	season
Kelly Wiglesworth	0.82	0.56	2	4	16	1
Rudy Boesch	0.67	0.55	3	4	16	1
Sean Kenniff	0.45	0.44	5	5	16	1
Dirk Been	0.11	0.13	12	11	16	1
Colby Donaldson	0.82	0.50	2	4	16	2
Amber Brkich	0.37	0.28	6	7	16	2
Jerri Manthey	0.25	0.26	8	8	16	2
Kimmi Kappenberg	0.11	0.40	12	6	16	2
Kelly Goldsmith	0.20	0.52	9	4	16	3
Diane Ogden	0.05	0.05	16	16	16	3
Rob Mariano	0.17	0.70	10	3	16	4
Patricia Jackson	0.06	0.05	15	16	16	4
Peter Harkey	0.05	0.05	16	16	16	4
Helen Glover	0.55	0.36	4	6	16	5
Penny Ramsey	0.30	0.18	7	10	16	5
Erin Collins	0.20	0.28	9	7	16	5
Robb Zbacnik	0.14	0.07	11	14	16	5
Stephanie Dill	0.11	0.13	12	11	16	5
Tanya Vance	0.06	0.11	15	12	16	5
John Raymond	0.05	0.04	16	16	16	5
Rob Cesternino	0.67	0.60	3	4	16	6
Daniel Lue	0.07	0.16	14	10	16	6
Janet Koth	0.06	0.08	15	14	16	6
Sandra Diaz-Twine	1.00	0.54	1	4	16	7
Jon Dalton	0.67	0.49	3	5	16	7

Model Performance: S46 Week-to-Week Predictions

- Consistently forecasted top contestants, especially the top 2.
- Predicted Charlie (<u>very</u> close 2nd place) as 1st place winner as early as Week 5, and never predicted him to place higher than 3rd.

		Actual	w	eek 4	We	eek 5	W	eek 6	w	eek 7	w	eek 8	W	eek 9	We	ek 10	We	ek 11	We	eek 12	Actual
Con	ntestant	Placement	Predicted Placement	Predicted Win Probability	Placement																
Ken	nzie Petty	1	5	8.4%	6	6.6%	5	9.6%	3	12.9%	2	17.0%	2	21.9%	2	19.1%	2	20.8%	2	20.8%	1
Cha	arlie Davis	2	3	12.4%	1	15.3%	3	13.5%	2	14.8%	1	23.8%	1	23.8%	1	24.6%	1	28.3%	1	40.0%	2
Ben	ı Katzman	3	8	5.3%	8	5.9%	7	7.5%	6	9.8%	4	11.7%	4	12.0%	4	14.6%	3	20.6%	4	14.2%	3
Liz \	Wilcox	4	12	3.5%	10	3.8%	10	3.1%	9	4.6%	8	4.2%	6	8.3%	6	5.5%	6	5.1%	5	6.7%	4
Mari	ria Shrime Gonzalez	5	6	8.1%	5	8.7%	8	6.9%	4	10.9%	6	8.5%	5	10.4%	3	18.7%	4	17.5%	3	18.3%	5
QB	urdette	6	2	12.6%	2	15.2%	1	16.2%	5	10.2%	7	4.7%	7	4.2%	5	14.2%	5	7.7%	6	0%	6
Ven	us Vafa	7	14	2.1%	11	3.5%	12	2.0%	10	2.4%	9	2.6%	8	3.00%	7	3.3%	7	0%	7	0%	7
Tiffa	any Nicole Ervin	8	1	15.0%	3	13.6%	2	15.0%	1	17.4%	3	16.6%	3	16.4%	8	0%	8	0%	8	0%	8
Hun	nter McKnight	9	10	3.8%	7	6.1%	4	10.7%	7	9.1%	5	11.0%	9	0%	9	0%	9	0%	9	0%	9
Tevi	in Davis	10	4	9.4%	4	11.0%	6	9.3%	8	8.0%	10	0%	10	0%	10	0%	10	0%	10	0%	10
Sod	la Thompson	11	9	5.1%	9	4.1%	9	3.5%	11	0%	11	0%	11	0%	11	0%	11	0%	11	0%	11
Tim	Spicer	12	13	3.3%	13	3.0%	11	2.9%	12	0%	12	0%	12	0%	12	0%	12	0%	12	0%	12
Mori	riah Gaynor	13	11	3.6%	12	3.1%	13	0%	13	0%	13	0%	13	0%	13	0%	13	0%	13	0%	13
Jem	nila Hussain-Adams	14	7	7.6%	14	0%	14	0%	14	0%	14	0%	14	0%	14	0%	14	0%	14	0%	14
Bha	nu Gopal	15	15	0%	15	0%	15	0%	15	0%	15	0%	15	0%	15	0%	15	0%	15	0%	15
Ran	nden Montalvo	16	16	0%	16	0%	16	0%	16	0%	16	0%	16	0%	16	0%	16	0%	16	0%	16
Jess	sica "Jess" Chong	17	17	0%	17	0%	17	0%	17	0%	17	0%	17	0%	17	0%	17	0%	17	0%	17
Dav	vid Jelinsky	18	18	0%	18	0%	18	0%	18	0%	18	0%	18	0%	18	0%	18	0%	18	0%	18

ML Model Improvement Opportunities

v3 roadmap plan with areas for potential improvement

- 1. GridSearchCV hyperparameter tuning (Random Forest params, α , etc.)
- 2. Week-to-week predictions, as opposed to entire season
 - Pro: Better at handling varying strategies in early vs. mid vs. late game
 - Pro: Better approach to identify "goats" (i.e., less "threatening" players)
 - Con: Requires ~15x more data
- 3. Explore other features (ex: highest education level and/or profession)
- 4. Explore other ML model types

Supplemental Slides

Automated LLM-Analysis: Social & Strategy Scores

<u>Social Score Criteria:</u> Assesses the contestant's interpersonal skills, likability, and ability to navigate and influence social dynamics.

- Alliance Formation and Maintenance: The ability to create and maintain alliances that further the contestant's game.
- Social Integration: Effectiveness in becoming a key member of the group, avoiding social isolation.
- Jury Management: Skill in managing relationships with eventual jury members, crucial for securing votes in the final.
- Conflict Resolution: Competence in resolving disputes in a way that does not jeopardize their standing in the game.

<u>Strategy Score Criteria:</u> Assesses the contestant's game planning, tactical moves, and adaptability to changing dynamics.

- Strategic Planning: The ability to devise and implement plans that enhance their position in the game.
- Adaptability: Quick adjustment to new developments and ability to pivot strategies as the game evolves.
- Game-Changing Moves: Successfully executing moves that significantly alter the course of the game, including blindsides and effective use of immunity idols.

ML Model Feature Importances & Continuous Probability Transformation Functions

v2 Random Forest model feature importances

num_idols_possessed: 0.077

social_score: 0.090

strategy_score: 0.239

challenge_wins_per_day_lasted: 0.285

confessionals_per_epi: 0.308

Exponential Decay:

$$P(win) = e^{-lpha imes (rank-1)}$$

Where:

- ullet P(win) is the probability of winning.
- * lpha is a parameter that controls the rate of decay, with higher values making the curve steeper.
- rank is the contestant's final ranking.

Linear:

$$P(win) = rac{N-rank+1}{N}$$

Where:

- ullet P(win) is the probability of winning.
- \bullet N is the total number of contestants in the season.
- \bullet rank is the final ranking of the contestant.

Machine Learning Model Performances

