Modeling International Figure Skating Scores

Statistics 98

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2022/05/03

Intro to the Research Topic

My final project seeks to analyze figure skating competition data from the past Olympic cycle in order to predict the 2022 World Championship results and assess potential judging bias.

Research Question

- What are the most significant predictors that determine a skater's total score and rank, and how can we use this to predict the 2022 World Championships?
- Do skaters receive a home-town advantage in scores when competing in their home country?

Data Collection Process

I scraped data from the past Olympic cycle using the rvest package from skatingscores.com, which uploads scoring protocols from all international and major domestic competitions under the IJS (International Judging System).

- I chose skaters who earned the top 15 free skate scores at the past two senior world championships (2022 and 2021).
- Selected skaters who competed at the world championships because oftentimes large countries like Russia will have several top scoring skaters, but each country can only send a maximum of three skaters to the world championships.
- Due to the volatile nature of the sport and short-lived seasons of skaters, I chose skaters who have been performing well in the past two years.

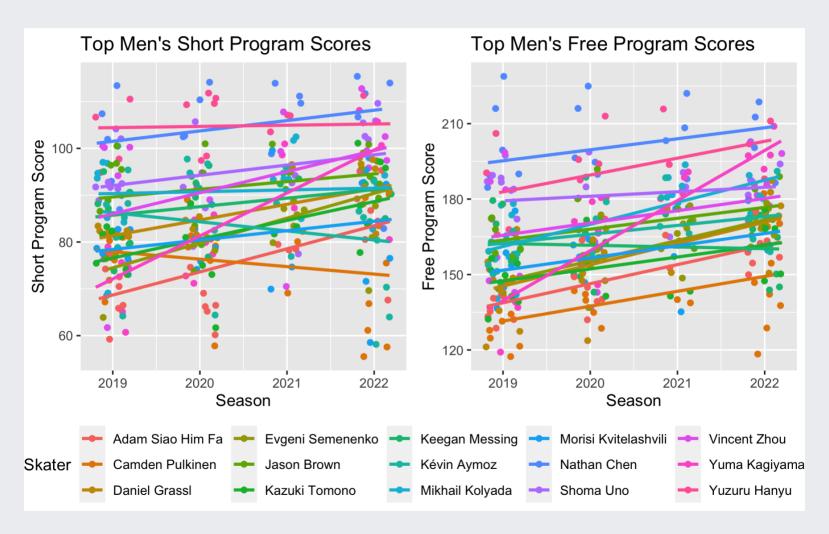
Due to the Russia-Ukraine conflict in recent months, the International Skating Union banned Russian athletes from participating in any international figure skating competitions on or after March 1, 2022, including the 2022 World Championships.

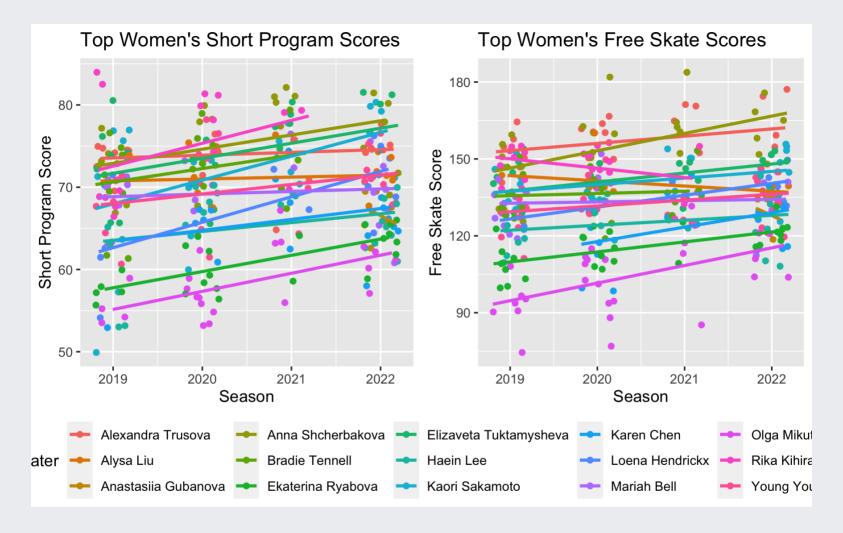
ank	Name					OC ode	Starti Numl		Total Segment Score	E	Total lement Score	Ó	Total Processing Total		Total Deductions
1	CHEN Nathan				US	SA		28	113.97		65.98			47.99	0.00
#	Executed Elements	Info	Base Value	GOE	J1	J2	J3	J4	J5	J6	J7	J8	J9	Ref	Scores of Pane
1	4F		11.00	4.40	4	4	5	4	4	4	4	4	4		15.40
2	3A		8.00	2.29	3	3	3	3	4	2	2	2	4		10.2
3	CCSp4		3.20	1.05	4	4	3	4	3	3	3	3	3		4.2
4	4Lz+3T		17.27 x	3.94	4	4	4	3	4	2	2	3	4		21.2
5	StSq4		3.90	1.95	5	5	5	5	5	5	4	5	5		5.8
6	FSSp4		3.00	1.03	3	4	4	3	4	3	3	3	4		4.0
7	CCoSp4		3.50	1.45	4	4	4	5	4	4	4	5	4		4.9
	·		49.87												65.9
	Program Components			Factor											
	Skating Skills			1.00	9.75	9.25	9.50	9.75	9.50	9.75	9.50	9.50	9.50		9.5
	Transitions			1.00	9.75	9.25	9.25	9.50	9.50	9.50	9.25	9.00	9.50		9.3
	Performance			1.00	10.00	9.50	9.75	10.00	9.50	9.75	9.50	9.50	10.00		9.7
	Composition			1.00	9.75	9.50	10.00	9.75	9.75	9.75	9.25	9.50	9.75		9.6
	Interpretation of the Music			1.00	10.00	9.75	10.00	9.75	9.50	9.50	9.50	9.50	9.50		9.6

Data Cleaning

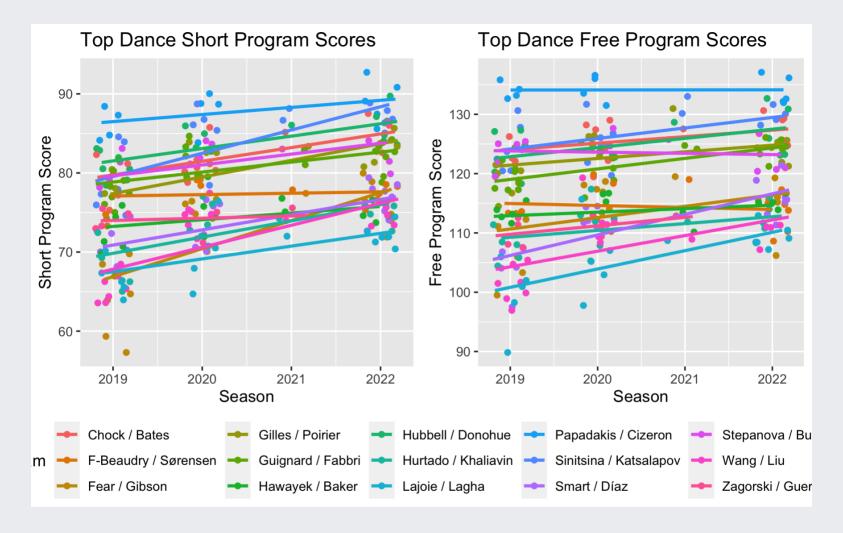
- all_men: 646 obs of 13 var
- all_women: 618 obs of 13 var
- all_pairs: 448 obs of 13 var
- all_dance: 495 obs of 13 var
- added random jitter to the seasons when conducting EDA

Initial EDA

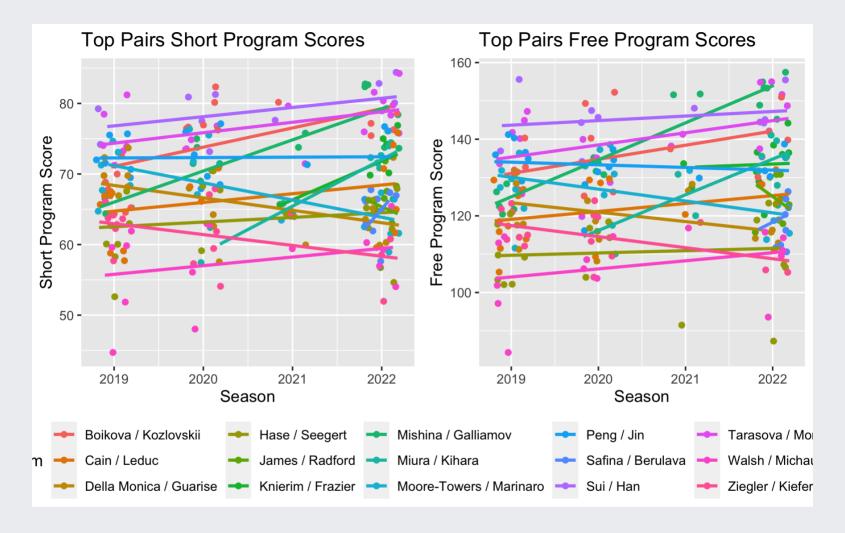




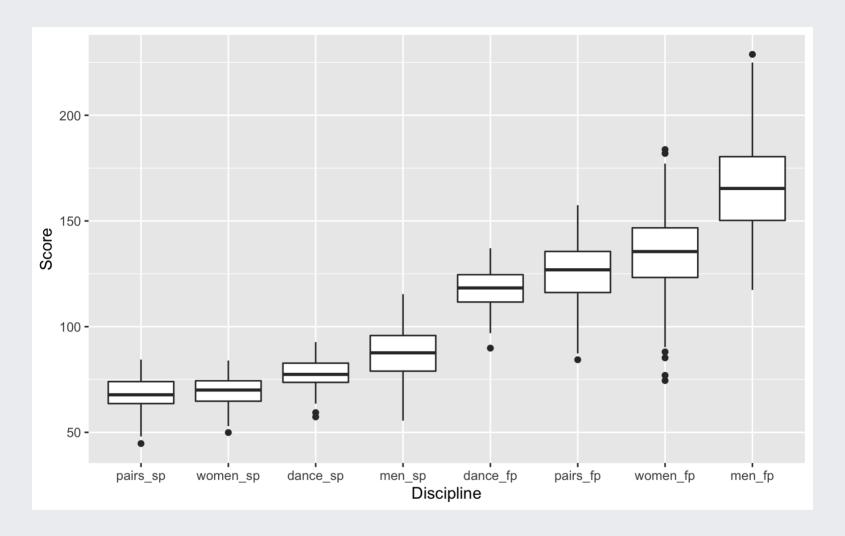
- Chen and Hanyu dominate in the men's discipline
- Women's discipline has less consistent champions
- We see many intersecting lines and much movement across seasons



- Much more consistent rankings across seasons and teams
- Smaller range of scores
- Differences between scores diminish in recent years



- Fewer data points during the 2021 season due to COVID
- Generally consistent rankings across seasons



- Dance scores have lower variance than other discplines
- Men's scores are higher and consist of more outliers

Modeling Plan

Prediction

 OLS: outcome is the final score, predictors: mean GOE mark, mean PCS mark Each segment is normally distributed based on the predictors, previous personal best (\$h_{short}\$), mean GOE (\$\text{goe}_i\$), and mean PCS (\$\text{pcs}_i\$). *Note PB is not included yet

• Mixed effects model: incorporate home-town advantage, starting order

Judging Bias

- Use Spearman's Rank Correlation to assess how judges' rankings line up with the final skater rankings
- Bayesian generalized linear model (stan_glm) to check for a correlation between competing in home country and final score: $y = f(\beta_0 + \beta_1 * \text{home})$

Results

```
summary(lm(TES ~ MeanGOE.Mark + MeanPCS.Mark, data = fp_men))
##
## Call:
## lm(formula = TES ~ MeanGOE.Mark + MeanPCS.Mark, data = fp men)
##
## Residuals:
##
       Min 1Q Median 3Q
                                         Max
## -26.1184 -6.5738 0.4681 6.6633 27.1024
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
                       7.2009 4.495 9.70e-06 ***
## (Intercept) 32.3652
## MeanGOE.Mark 7.0387 0.8011 8.786 < 2e-16 ***
## MeanPCS.Mark 4.9022 0.9744 5.031 8.07e-07 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.641 on 326 degrees of freedom
## Multiple R-squared: 0.5472, Adjusted R-squared: 0.5444
## F-statistic: 197 on 2 and 326 DF, p-value: < 2.2e-16
```

```
summary(lm(TES ~ MeanGOE.Mark + MeanPCS.Mark, data = sp_men))
##
## Call:
## lm(formula = TES ~ MeanGOE.Mark + MeanPCS.Mark, data = sp_men)
##
## Residuals:
## Min 10 Median 30 Max
## -16.6297 -3.0178 0.2811 4.3390 9.5421
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 16.9989
                       3.6978 4.597 6.22e-06 ***
## MeanGOE.Mark 4.6288 0.3697 12.519 < 2e-16 ***
## MeanPCS.Mark 2.3832 0.5077 4.694 4.00e-06 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.383 on 314 degrees of freedom
## Multiple R-squared: 0.641, Adjusted R-squared: 0.6388
## F-statistic: 280.4 on 2 and 314 DF, p-value: < 2.2e-16
```

Spearman rank correlations

X final	_placement Skater	natio	n CAN	EST	SWE:	ITA	TUR	AUT I	FRA	AZE	KAZ
2	1 Shoma UNO	•									1
3	2 Yuma KAGIYAMA	0									2
4	3 Camden PULKINEN										5
5	4 Vincent ZHOU										4
6	5 Morisi KVITELASHVILI	88									3
7	6 Adam SIAO HIM FA	11									6
10	7 Daniel GRASSL	III								11	9
11	8 Kazuki TOMONO	0							11		7
12	9 Roman SADOVSKY	9				11		11			11
13	10 Matteo RIZZO	•		11			11				10

The high correlations indicate that judges generally agree with each other, but we note that the Italian judge has the lowest correlation.

In the final paper I will test for whether this statistic is significantly lower than the correlations of the other judges.

countries_men <chr></chr>	corr_men <dbl></dbl>
CAN	0.9871542
EST	0.9812253
SWE	0.9871542
ITA	0.9792490
TUR	0.9871542
AUT	0.9802372
FRA	0.9832016
AZE	0.9812253
KAZ	0.9832016

Home Country Advantage

Regression of Host Country

How Competing in Their Home Country Affects Mens' Scores

Characteristic	Beta	95% CI ¹
(Intercept)	218	214, 222
Home	21	7.5, 34
¹ CI = Confidence Interval		

Regression of Host Country

How Competing in Their Home Country Affects Ladies Scores

Characteristic	Beta	95% CI ¹
(Intercept)	162	159, 165
Home	22	11, 34
¹ CI = Confidence Interval		

Confidence interval does not contain 0

Regression of Host Country

How Competing in Their Home Country Affects Pairs Scores

Characteristic	Beta	95% CI ¹
(Intercept)	176	172, 180
Home	8.9	-4.3, 22
¹ CI = Confidence Interval		

Regression of Host Country

How Competing in Their Home Country Affects Dance Scores

Characteristic	Beta	95% CI ¹
(Intercept)	164	161, 166
Home	9.3	-0.73, 20
¹ CI = Confidence Interval		

Confidence interval contains 0

Discussion & Limitations

Prediction

- Grade of Execution and Program
 Component Scores are strong
 indicators of final score, although
 GOE holds a stronger weight (beta
 coefficient = 4.63 for GOE vs. 2.38
 for PCS)
- These beta coefficients are highly significant

Bias

- There is a strong indication of advantage for skaters competing in their hometown, but this may be conflated with the fact that countries with top skaters are more likely to host competitions
- Judges have generally high agreeability, but we should look further into whether low correlations are significant results