Springboard Data Science Career Track Capstone Project #1: Recognizing Relevant Messages From a Fantasy Football Twitter Feed

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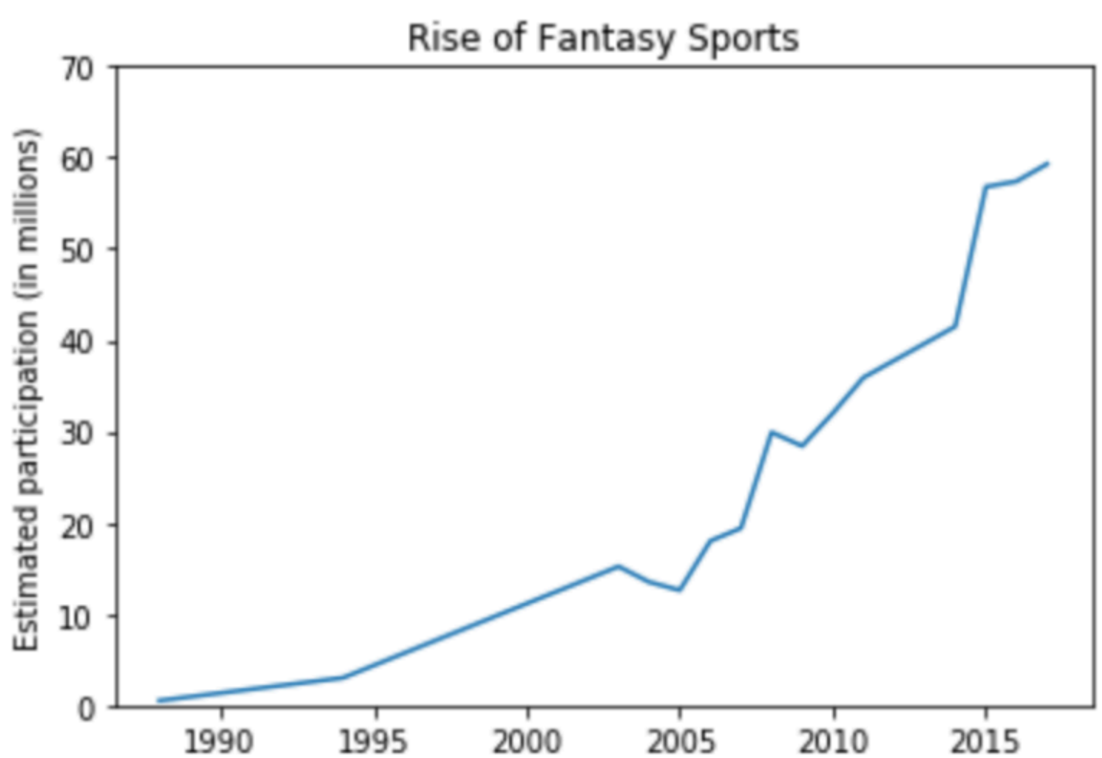
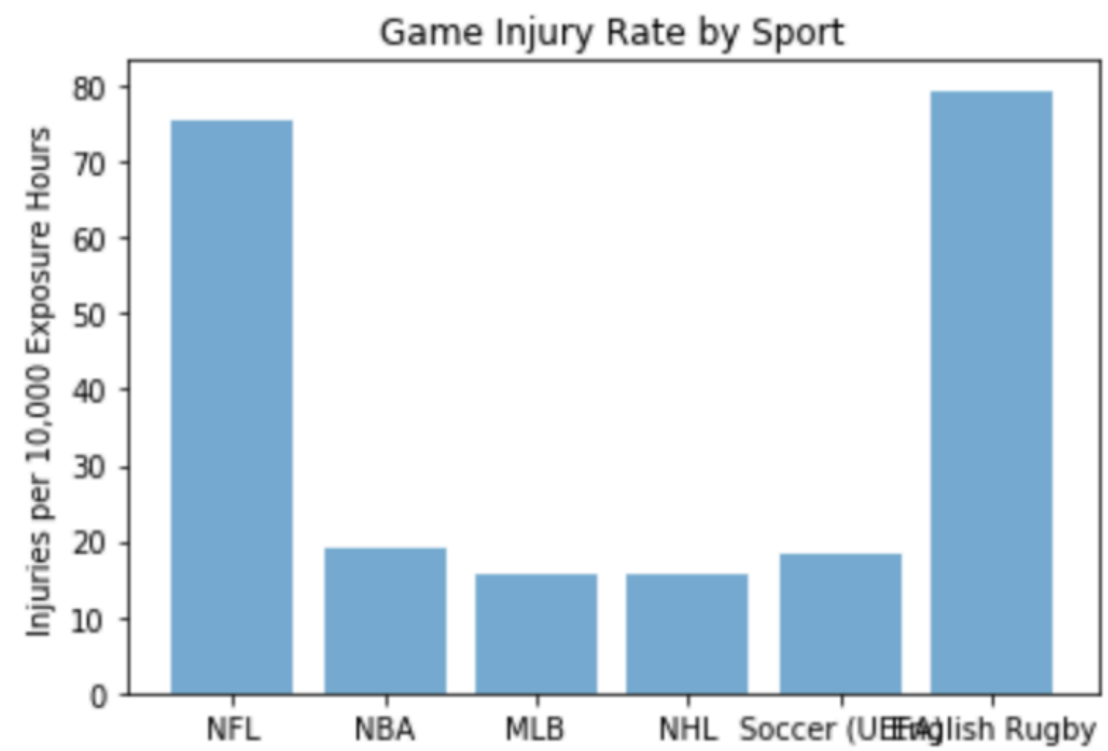
Introduction





Left: Fantasy Sports and Gaming Association. (n.d.). Industry Demographics. Retrieved from https://thefsga.org/industry-demographics/

Right: Binney, Z. (2017, June 7). Just How Dangerous IS the NFL vs. Other Sports? Retrieved from https://nflinjuryanalytics.com/2017/06/06/just-how-dangerous-is-the-nfl-vs-other-sports/

So, fantasy football can be seen as a game of information access.

But there are two problems…

1. Sometimes you need access before your competition
    - I.e., Nick Chubb in 2018

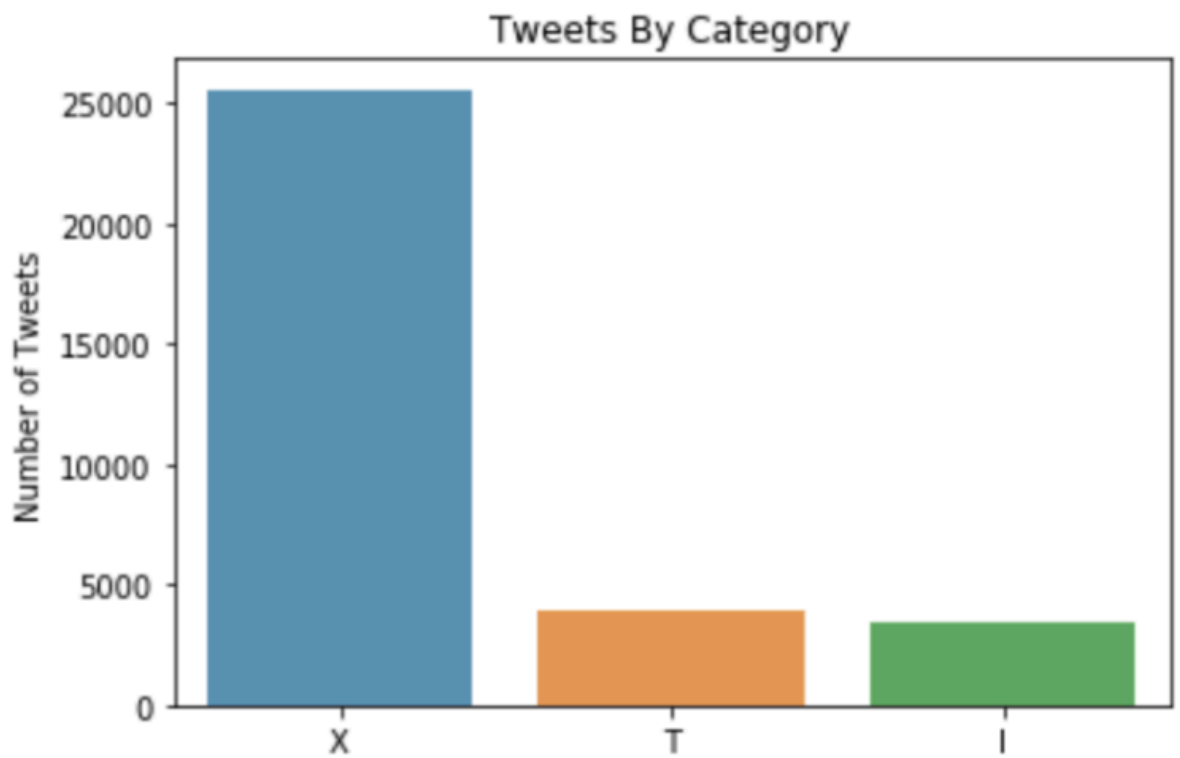
2. NFL teams have no incentive to provide accurate updates in real time

We therefore must rely upon the media to access most information…

…and something that could instantly recognize relevant information would provide an advantage to anyone who plays fantasy football.

Approach

- Adam Schefter
- 30,000 tweets from January 2010 through April 2019
- Labeled:
    - T - any tweet relating to a transaction
    - I - any tweet relating to workload impediments
        - Injury, role change, etc
    - X - anything else



Class	Tweet
0	rt rank best kicker history top maybe top 3. f...
0	april least one trade made (but one waiting
1	giant re-signed restricted free agent guard kevin
0	@profootballtalk aaron retiring least trying g...
0	jimmy clausen scheduled fly washington spend s...

Baseline Modeling

1. A Bernoulli naive Bayes classifier (BNB)

2. A multinomial naive Bayes classifier (MNB)

3. A logistic regression classifier (LR)

Baseline Modeling

	BNB	BNB (tuned)	MNB	MNB (tuned)	LR	LR (tuned)	Ridge	Lasso
Training Accuracy	0.89	0.891	0.886	0.89	0.939	0.938	0.938	0.932
Test Accuracy	0.879	0.882	0.874	0.881	0.911	0.911	0.911	0.912
Training Precision (0)	0.963	0.947	0.965	0.947	0.949	0.949	0.949	0.944
Test Precision (0)	0.952	0.941	0.956	0.941	0.929	0.929	0.929	0.929
Training Precision (1)	0.705	0.726	0.692	0.726	0.896	0.896	0.896	0.883
Test Precision (1)	0.69	0.709	0.674	0.709	0.839	0.839	0.839	0.841
Training Recall (0)	0.892	0.909	0.884	0.909	0.972	0.972	0.972	0.969
Test Recall (0)	0.889	0.903	0.878	0.903	0.958	0.958	0.958	0.959
Training Recall (1)	0.882	0.825	0.89	0.825	0.822	0.822	0.822	0.804
Test Recall (1)	0.848	0.807	0.861	0.807	0.749	0.749	0.749	0.751
Training F1 score (0)	0.926	0.928	0.923	0.928	0.961	0.961	0.961	0.956
Test F1 score (0)	0.919	0.922	0.915	0.91	0.922	0.943	0.943	0.943
Training F1 score (1)	0.783	0.772	0.778	0.772	0.857	0.857	0.857	0.842
Test F1 score (1)	0.761	0.755	0.756	0.755	0.791	0.791	0.791	0.793
Count - Training (0)	19185							
Count - Training (1)	5595							
Count - Test (0)	6391							
Count - Test (1)	1870							

Extended Modeling

	BNB	BNB (tuned)	MNB	MNB (tuned)	LR	LR (tuned)
Training Accuracy	0.893	0.892	0.903	0.905	0.923	0.929
Test Accuracy	0.882	0.885	0.891	0.89	0.909	0.911
Training Precision (0)	0.961	0.936	0.921	0.93	0.931	0.939
Test Precision (0)	0.952	0.93	0.912	0.916	0.919	0.924
Training Precision (1)	0.716	0.749	0.828	0.811	0.886	0.888
Test Precision (1)	0.697	0.738	0.805	0.788	0.864	0.855
Training Recall (0)	0.899	0.923	0.957	0.949	0.972	0.971
Test Recall (0)	0.893	0.921	0.951	0.945	0.967	0.964
Training Recall (1)	0.875	0.783	0.718	0.757	0.755	0.785
Test Recall (1)	0.845	0.763	0.684	0.702	0.709	0.728
Training F1 score (0)	0.929	0.93	0.938	0.939	0.951	0.955
Test F1 score (0)	0.921	0.925	0.931	0.93	0.943	0.943
Training F1 score (1)	0.787	0.766	0.769	0.783	0.815	0.833
Test F1 score (1)	0.764	0.75	0.74	0.743	0.779	0.786
Count - Training (0)	19185					
Count - Training (1)	5595					
Count - Test (0)	6391					
Count - Test (1)	1870					

Extended Modeling

	BNB (TF-IDF)	MNB (TF-IDF)	LR (TF-IDF)	BNB (Count)	MNB (Count)	LR (Count)
Training Accuracy	0.814	0.88	0.923	0.814	0.994	0.999
Test Accuracy	0.784	0.804	0.874	0.784	0.86	0.912
Training Precision (0)	0.806	0.866	0.913	0.806	0.999	0.999
Test Precision (0)	0.782	0.798	0.868	0.782	0.965	0.927
Training Precision (1)	1	0.988	0.976	1	0.977	1
Test Precision (1)	0.978	0.984	0.918	0.978	0.636	0.853
Training Recall (0)	1	1	0.995	1	0.993	1
Test Recall (0)	1	0.999	0.987	1	0.85	0.963
Training Recall (1)	0.177	0.467	0.676	0.177	0.996	0.996
Test Recall (1)	0.047	0.135	0.487	0.047	0.894	0.739
Training F1 score (0)	0.893	0.928	0.952	0.893	0.996	0.999
Test F1 score (0)	0.877	0.887	0.924	0.877	0.877	0.904
Training F1 score (1)	0.301	0.637	0.799	0.301	0.986	0.998
Test F1 score (1)	0.09	0.238	0.636	0.09	0.743	0.792
Count - Training (0)	19185					
Count - Training (1)	5595					
Count - Test (0)	6391					
Count - Test (1)	1870					

Findings and Analysis

- Accuracy, precision, or recall?
- Context of the problem
- False positives vs. false negatives

Extended Modeling, Revisited

	MNB (1,3)	MNB (1,4)	MNB (2,5)
Training Accuracy	0.978	0.99	0.996
Test Accuracy	0.879	0.87	0.508
Training Precision (0)	0.995	0.999	0.999
Test Precision (0)	0.951	0.959	0.969
Training Precision (1)	0.926	0.961	0.986
Test Precision (1)	0.691	0.661	0.31
Training Recall (0)	0.977	0.988	0.996
Test Recall (0)	0.889	0.869	0.376
Training Recall (1)	0.983	0.995	0.997
Test Recall (1)	0.845	0.874	0.959
Training F1 score (0)	0.986	0.993	0.997
Test F1 score (0)	0.919	0.912	0.542
Training F1 score (1)	0.954	0.978	0.991
Test F1 score (1)	0.76	0.753	0.469
Count - Training (0)	19185		
Count - Training (1)	5595		
Count - Test (0)	6391		
Count - Test (1)	1870		

Conclusion

Winner: multinomial Naive Bayes model that uses a count vectorizer and n-grams of range 2 through 5

	MNB (1,3)	MNB (1,4)	MNB (2,5)
Training Accuracy	0.978	0.99	0.996
Test Accuracy	0.879	0.87	0.508
Training Precision (0)	0.995	0.999	0.999
Test Precision (0)	0.951	0.959	0.969
Training Precision (1)	0.926	0.961	0.986
Test Precision (1)	0.691	0.661	0.31
Training Recall (0)	0.977	0.988	0.996
Test Recall (0)	0.889	0.869	0.376
Training Recall (1)	0.983	0.995	0.997
Test Recall (1)	0.845	0.874	0.959
Training F1 score (0)	0.986	0.993	0.997
Test F1 score (0)	0.919	0.912	0.542
Training F1 score (1)	0.954	0.978	0.991
Test F1 score (1)	0.76	0.753	0.469
Count - Training (0)	19185		
Count - Training (1)	5595		
Count - Test (0)	6391		
Count - Test (1)	1870		

Conclusion

```
Row 123 has been classified as  1 and should be  0
Row 126 has been classified as  1 and should be  0
Row 130 has been classified as  1 and should be  0
Row 131 has been classified as  1 and should be  0
Row 132 has been classified as  1 and should be  0
Row 134 has been classified as  0 and should be  1
Row 136 has been classified as  1 and should be  0
Row 137 has been classified as  1 and should be  0
```

This false positive could be ignored

```
xtest.iloc[132]
```

```
"cardinal hired terry mcdonough eastern brother ryan new gm, making arizo
na's first family."
```

```
xtest.iloc[134]
```

```
'sammy watkins officially active.'
```

This false negative can't be missed

Future Work

- Ensemble methods
- Recognizing when newsworthy Tweets relate to high-profile players
- Pushing notifications to mobile devices in real time
- Creating classification model for other reporters

Recommendations for the Clients

- Starting point or addition to a mobile application
  - Versus email or text
- At minimum, could be used as a highly-curated Twitter feed to be observed