Exploring Relationships Between Country-Wide Health Markers and World Cup Performance

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PROBLEM STATEMENT / MOTIVATION

The Féderation Internationale de Football Association (FIFA) has held 21 World Cup tournaments since its inception in 1930. Seventy-nine different countries have qualified to participate in the World Cup in this same timeframe, with eight different countries becoming champions. The purpose of this project is to explore relationships between country-wide markers of physical and emotional health (e.g. life expectancy, positive affect) with performance at the FIFA World Cup (e.g. goals scored, wins, qualifications).

LITERATURE SURVEY (PREVIOUS WORK)

Since 1966, FIFA has conducted a technical study after each world cup. These reports focus on physical skills, psychological attitude, team performance, and on site conditions. Included are descriptive statistics of each athlete and the official results[1].

Goldman Sachs Global Investment Research, as one example of the big investment banks, constructs and trains predictive models for the 2018 World Cup to predict the tournament's outcome. They mined data on team characteristics, individual players, and recent team performances to analyse the number of goals scored in each match[2]. Statista, a market analysis portal, provides statistical analysis for the 2018 world cup with diverse focuses such as average player age, compensation, stadium capacities, and media and fan interest to name only a few[3]. However, neither of those resources considers country-wide markers of physical and emotional health.

Houston and Wilson found positive correlations between country-level income and World Cup appearances, hypothesizing that increased income allows for increased leisure time to increase proficiency in sport[4]. Population was also found to determine World Cup appearances, possibly due to its increasing the likelihood that a star player is born[4].

Hoffman et al. found differences in the economic factors that influence men's vs. women's international soccer performance. In particular, gender inequality as measured by the ratio of women's to men's earnings explained soccer performance[5].

PROPOSED WORK

We plan to approach finding answers to our questions using classic data mining techniques.

These include an important first step of preprocessing our data.

We will account for missing values by replacing them with a measure of central tendency. This step will involve finding consistently the mean or mode depending on the subject, and using this as the replacement value. Using columns of country data, we split up our sets. To determine findings on World Cup qualifiers we will include all countries who play soccer at the international level. To analyze world cup performance we will create a set which includes only countries participating in the World Cup.

To address the topic of noisy data we will use data visualization including scatterplots, bar graphs, and boxplots. Those visualization techniques will also be helpful to identify outliers as stray items among other outlier detection methods such as proximity-based and density-based approaches. We will trim down our data sets to include only attributes that pertain to questions we will be answering through data analysis.

Merging data sets will be completed by using the country attribute, and the year attribute as items to match on; Allowing us to organize our rows with limitless categories which each uniquely include one country and one year. Since countries may be referenced with slight differences we will create a mapping which includes all referenced names for each country by country, and use that for cases where matching on a country name isn't a direct match. This model sits between multiple data sets and is an interface belonging to the resultant merged dataset.

Dimensionality reduction will be achieved by aggregating wins, goals, and qualificational data when necessary due to an overwhelmingly large dataset. Or to create new rows with which to test trends. We will also use forward stepwise selection as an association rule generating technique to select for sets meeting specifications for strong rules which qualify as interesting based on support and confidence levels and a determined threshold.

To determine correlation we will look carefully at this process of mining single dimensional and multidimensional association rules between data attributes including country related factors and world cup results. We will take this a step beyond finding interesting sets to calculate the Chi-squared (x^2) to determine the statistical significance of our findings, thereby concluding their relevance and quality in finding correlation in data. We will use the Apriori Algorithm to approach finding these sets using a complementary technique to help us mine our the most important sets using the threshold level for pruning out uninteresting correlations. We will keep in mind that correlation doesn't imply causation and work to understand our findings from as centered a source of truth as possible.

To look at some options and exciting possibilities from which to predict results, keeping in mind the stochastic nature of large sporting events, we will look for general trends using regression methods, Decision Trees, KNNs and Bayesian Classifiers. These will allow us to group indicators that serve as predictive attributes for successful and qualifying World Cup teams. If time allows, we will look at how these compare between men and women's soccer, and at what sorts of attribute value pairs create an optimal set, and to which countries these capabilities may belong.

Previous research has examined economic and political factors that are related to performance in the World Cup. While related, this project is unique in that it will specifically look at how measures of country-level emotional health and well-being are related to performance.

DATASETS

Five datasets out of two different domains are used to answer the question if relationships exist between country-wide markers of physical and emotional health and performance at the FIFA World Cup. The following three datasets provide information about the sport. For now, they are restricted to men's soccer.

Measures of World Cup performance will include home goals, away goals, wins, and qualifications, among others. This dataset includes 855 data objects with 12 attributes each. Results from all of the World Cup matches by country and year for all years 1930-2014 will be accessed from Sports Viz Sunday: https://data.world/sportsvizsunday/sports-viz-sundays-2018/workspace/file?filename=World%20Cup%20Results.xlsx.

Data scraped from sofifa.com on 18,000 individual FIFA players with 66 attributes including player rating, club rating, sprint speed, and shot power will be accessed from:
https://data.world/raghav333/fifa-players
And:
https://data.world/sawya/football-world-cup-2018-dataset

The next two datasets provide country-wide markers of physical and emotional health as well as information about populations and GDPs per country..

Country level health statistics from 258 countries from 1960-2015 with 34 attributes including life expectancy, malnutrition, and health expenditure will be accessed from the World Bank: https://www.kaggle.com/theworldbank/health-nutrition-and-population-statistics

Measures of emotional health in 130 countries from 2005 - 2016 by country and year with 27 attributes including positive affect, negative affect, and social support will be accessed from the World Happiness Report: https://data.world/laurel/world-happiness-report-data. Many variables are subjective such as well-being or 'freedom to make life choices'. Survey participants were asked to rate their assessment on a scale from 0 to 10 or to answer binary yes/no questions. The answers were mostly averaged per country and year. Data from other studies are included such as the World Bank's Global Economic Prospects from 2016, and healthy life expectancy statistics from the World Health Organization (WHO) and the World Development Index (WDI).

EVALUATION METHODS

The analytic quality of our discovered correlations and predictions will be determined by different evaluation methods depending on the used mining method. Metrics, such as accuracy, error rate, and precision, will be computed and used to analyze the quality of our Bayesian Classifiers, KNNs, and Decision Trees. ROC curves will be helpful to compare the error rates of different classifiers and choose the most accurate ones.

Statistical significance needs to be established for our found correlations, important sets and chi-squared test results. Confidence intervals will be calculated and provided. Our evaluation results will be visualized in the form of confusion matrices among other techniques. Comparing our correlation results with the results from predictive modeling will provide further insight into our data.

Our regression models will be evaluated using R^2 and adjusted R^2 as well as p-values and eventually f-statistics. In the case of dependencies we will include interaction terms and decide which attributes to include further in order to keep the models efficient.

Along the way, findings in our analysis and evaluation may lead to identification of future change and further interest in exploration.

TOOLS

The data will be preprocessed and analyzed using the Python programming language and relevant statistical libraries in a Jupyter environment. The pandas library will largely be used for preprocessing including cleaning and integrating datasets. Analysis libraries including scikit learn and numpy will be used to conduct statistical tests related to correlation and classification, including Chi-Squared Test, Decision Trees (DT), and Naive Bayes. Matplotlib and Seaborn will be used for data visualization.

MILESTONES

Preprocessing (by 11/03):

- Missing values
- Noise
- Integration
- Dimensionality Reduction

Find correlations in data (by 11/17):

- Determine Correlation between national markers and success of players and teams in world cup:
  - Find: (a => b)(s, c)
  - Support and Confidence.
- Determine if association is strong.
  - Single dimensional associations, Multi-dimensional association rules.
  - Lift
  - Chi-squared (x^2) and determine statistical significance of findings
  - Apriori Algorithm, find consistent attribute sets that determine success in teams.

Build predictive models (by 12/01):

- Decision Trees
- KNN
- Bayesian Classifier
- Regression
- Metrics
- Confusion Matrix

Visualization (by 12/01):

- Bar and line graphs
- Histograms
- Scatterplots
- Boxplots

MILESTONES COMPLETED

The data preprocessing milestone so far included filling in missing values, integrating some datasets, reducing the dimensionality, and plotting single dimensional values in bar graphs.

Missing values in the individual FIFA players dataset have been filled in different ways. Missing values for a team's nationality is filled in with the player's nationality which seems to be a reasonable estimate even though player's are not required to play for their country of origin. The attribute means are used for the player's attributes overall rating, value and wage in Euros and his international reputation. The attributes modes for the categorical attributes are filled in when values for preferred foot and body type are missing. The dimensionality is reduced from 66 attributes to 22 in preparation for future prediction mining tasks. These 22 attributes include the player's skills such as stamina, agility, and ball control, as well as their name, nationality and overall rating.

The world cups results dataset is reduced in multiple ways. One version reduced the original 12 attributes to 4 since the final teams in a tournament can be seen as most successful. Attributes such as the date, time, and stadium seem to be less useful currently. Another table generated from this dataset provides the 4 previous attributes plus 4 frequency attributes for overall goals scored during a world cup, the number of qualified teams, played matches and the average attendance in the stadium.

The world happiness dataset is reduced from 27 attributes down to 13. The original dataset included GINI Index values and descriptive statistics that will be self calculated when needed. Missing values are replaced by the countries mean for that given attribute over the years.

Results from the world cup results dataset for 2018 have been extracted and merged with the preprocessed world happiness data, so that only the countries that have participated in the world cup and have won at least one match are included. This merged dataset will be analysed for potential relationships and expanded over all world cup years.

First visualizations are created that plot top player ratings, life happiness, and the number of times a country has won the World Cup in single dimensional bar graphs for the 8 countries that have won a world cup. At this point correlations analysis haven't been completed, so that the bar graphs are not yet included in this report.

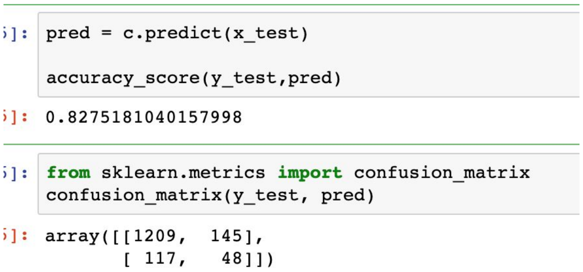
Much of the World Bank data has been pre-processed. This data has been pivoted to allow for efficient merging with the World Cup results. The data has also been pared down by dropping redundant columns and only including years where a World Cup has taken place. Missing values have been filled in with the mean for that attribute across all countries and years. We will explore changing this fill process so that missing values will be filled with the mean for that country if available, as it may be closer to the actual value. Min/max normalization has been conducted on all attributes to prevent differences in the scale of the values of different attributes to influence analysis.

In order to build a decision tree and a KNN classifier to predict whether a country will qualify for the World Cup in a given year, the World Cup data was pared down to only include years present in the World Bank data. Differences in the spelling of country names had to be accounted for with a function. Further work may need to be done to account for countries like Yugoslavia, which split up into multiple countries, but the split up is not reflected in both of the data sets in the same way. Using the World Cup data, a dictionary was made to hold the qualifying countries with the year as the key in order to create a boolean variable to describe whether a country qualified for the World Cup on a given year. Attributes of interest in the World Bank data were hand selected to predict whether a country qualified for the World Cup in a given year.

For the regression analysis with the World Bank Data, the total number of goals was calculated for each country per year from the World Cup data so than an OLS regression may be performed.

RESULTS SO FAR

Early results from the World Bank qualification classifier show some promise, with both Decision Tree and KNN classifiers resulting in accuracies above 80%. Early results from the World Bank regression analysis have produced low R^2 values, which may suggest that these data may be effective in predicting qualification for, but not performance at the World Cup.



```
]: pred = c.predict(x_test)

   accuracy_score(y_test,pred)

]: 0.8275181040157998
```

```
]: from sklearn.metrics import confusion_matrix
   confusion_matrix(y_test, pred)

]: array([[1209,  145],
          [ 117,   48]])
```

MILESTONES ToDo

Preprocessing (by 11/03):

- Noise and Outlier Detection

Find correlations in data (by 11/17):

- Determine Correlation between national markers and success of players and teams in world cup:
    - Find: (a => b)(s, c)
    - Support and Confidence.
- Determine if association is strong.
    - Single dimensional associations, Multi-dimensional association rules.
    - Lift
    - Chi-squared (x^2) and determine statistical significance of findings
    - Apriori Algorithm, find consistent attribute sets that determine success in teams.

Build predictive models (by 12/01):

- Bayesian Classifier
- Metrics
- Confusion Matrix

Visualization (by 12/01)

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