cognitive_bias_in_elite_figure_skating

May 6, 2019

1 Introduction

The purpose of this report is to show that **bias originating in the judgement of the technical elements portion of professional figure skating affects the component portion of the competition.** As a quick summary, the judged aspects of all professional figure skating performances are split into 2 categories:

1) **Technical elements**

2) **Components**

Together the two categories make up the total segment score for the performance. Technical elements are calculated from a metric developed by the ISU Judging System meant to eliminate bias in this portion of the judging, while the component scores are designed to be more subjective. More information on each judged aspect will be discussed later in this report.

The long program of ladies figure skating will be analyzed in order to standardize the scores, number of elements, as well as to study competitors that are relatively similar to one another. The first section of this report will explore the differences in the components and elements, provide visualizations on their importance to the overall segment score, and further discuss the hypothesis. The second section will test this hypothesis through machine learning models. The third section identifies possible forms of bias and summarizes the results.

2 1) Exploration of the Judged Aspects of Professional Figure Skating

There are four types of competition in professional figure skating: - **Mens** - **Ladies** - **Pairs** - **Ice Dancing**

The scoring for each type of competition differs according to the new ISU Judging System. Each type of competition has a long program, or free skate, and a short program.

The data used in this report contains information on figure skating competitions, judges and skaters from 2016-2017. The data shows both element and component scores, aspects of each judged category, and information on the judges themselves. The performances.csv and judged-aspects.csv datasets are used in this report, showing 23932 datapoints from 17 competitions.

The data for the performances and judged aspects were combined into the performances_judges.csv dataset using SQL. This provides a dataframe that shows the elements and components of each skater during each competition they participated in. The SQL code is as follows:

select

*

from

`performances`

left join

`judged_aspects`

on

`performances.performance_id=judged_aspects.performance_id`

2.1 Summary of the ladies' long program

The ladies' long program has more technical elements and components to analyze, so this section will be the focus of this report. Here is a quick summary of the typical performance in the ladies long program:

Maximum of seven jump elements: - One must be an axel type jump - Maximum of three jump combinations/sequences; one jump combination may contain three jumps - Double jumps cannot be included more than twice - Of all the triple and quadruple jumps only two can be executed twice; of the two, only one can be a quadruple jump

Maximum of three spins: - One combination spin; minimum of 10 revolutions - One flying spin or spin with a flying entrance; minimum of six revolutions - One spin with only one position; minimum of six revolutions - A change of foot optional in all spins

Maximum of one step sequence

Maximum of one choreographic sequence

Skaters can choose the order of the above elements, but all elements must be in one performance. Jumps from the second half of a performance also recieve a 10% bonus to the overall element score.

2.2 Data inspection/cleaning

In [1]:
```
# load and inspect data
%matplotlib inline
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
from scipy import stats
path=r"/Users/kyleknoebel/Desktop/ThinkfulNotebooks/Unit 3 Capstone/performances_judged
pj=pd.read_csv(path)
# replace all null values with 0
pj=pj.fillna(0)
pj.describe()
```

Out[1]:
```
                rank  starting_number  total_segment_score  \
count  23932.000000     23932.000000         23932.000000
mean       7.883169         7.929550            99.361830
std        6.525922         6.548071            37.110716
min        1.000000         1.000000            24.550000
25%        3.000000         3.000000            68.250000
50%        6.000000         6.000000            93.480000
75%       10.000000        10.000000           126.510000
max       37.000000        37.000000           223.200000

       total_element_score  total_component_score  total_deductions  \
count         23932.000000           23932.000000      23932.000000
mean             50.394217              49.395199          0.427586
std              18.879934              18.907632          0.751289
min               8.750000              15.800000          0.000000
25%              35.570000              32.650000          0.000000
50%              46.970000              46.420000          0.000000
75%              62.600000              64.410000          1.000000
max             126.120000              97.080000          9.000000

         aspect_num    base_value        factor           goe      ref  \
count  23932.000000  23932.000000  23932.000000  23932.000000  23932.0
mean       3.431765      3.143990      0.438743      0.278006      0.0
std        3.641213      3.167566      0.639486      0.834628      0.0
min        0.000000      0.000000      0.000000     -4.000000      0.0
25%        0.000000      0.000000      0.000000      0.000000      0.0
50%        2.000000      3.000000      0.000000      0.000000      0.0
75%        6.000000      5.000000      0.800000      0.710000      0.0
max       14.000000     17.900000      2.000000      3.300000      0.0

       scores_of_panel
count     23932.000000
mean          6.147335
std           2.536225
min           0.000000
25%           4.070000
50%           6.300000
75%           7.860000
max          20.330000
```

In [2]:
```
# show the listing of columns with proper indexing
for index, value in enumerate(pj, 1):
    print("{}. {}".format((index-1), value))
```

```
0. performance_id
1. competition
2. competition1
3. name
```

4. nation
5. rank
6. starting_number
7. total_segment_score
8. total_element_score
9. total_component_score
10. total_deductions
11. aspect_id
12. performance_id-2
13. section
14. aspect_num
15. aspect_desc
16. info_flag
17. credit_flag
18. base_value
19. factor
20. goe
21. ref
22. scores_of_panel

2.2.1 Clean the data and create data frames for elements and components

First, the dataset will be cleaned for better formatting/slicing.

```
In [3]: # lower the capilization of the program and competition1 columns to standardize format
        pj.iloc[:, 2] = pj.iloc[:, 2].str.lower()
        pj.iloc[:, 1] = pj.iloc[:, 1].str.lower()
        # clean the text for interpretations
        pj.iloc[:, 15]=pj.iloc[:, 15].str.replace('Interpretation of the Music / Timing',
                                                                  'Interpretation of the Music')
        pj.iloc[:, 15]=pj.iloc[:, 15].str.replace('Interpretation of the Music/Timing',
                                                                  'Interpretation of the Music')
        # remove ice dancing from the dataset
        pj=pj[~pj['competition1'].str.contains('ice dance')]
        #remove short program from the dataset
        pj=pj[~pj['competition1'].str.contains('short')]
```

Then a column for the type of element will be added called 'elem_type.' Types of elements will be discussed later in the report, and a list of abbreviations can be found in Appendix A.

```
In [4]: # add element type for each technical element
        pj.loc[pj['aspect_desc'].str.contains('Sp'), 'elem_type']='spin'
        pj.loc[pj['aspect_desc'].str.contains('Sq'), 'elem_type']='step'
        pj.loc[pj['aspect_desc'].str.contains('Th'), 'elem_type']='throw jump'
        pj.loc[pj['aspect_desc'].str.contains('Tw'), 'elem_type']='twist lift'
        pj.loc[pj['aspect_desc'].str.contains('Li'), 'elem_type']='lift'
        pj.loc[pj['aspect_desc'].str.contains('Ds' or 'Pi'), 'elem_type']='death spirals'
        pj.loc[pj['aspect_desc'].str.contains('PsP' or 'PCoSp'), 'elem_type']='pair spins'
```

```
# the remaining rows with NaN in the elem_type column are either jumps or components
## since all jumps have a number in the aspect_desc and components do not, the jumps w
pj.loc[pj['aspect_desc'].str.contains('(\d+)') & (pj['elem_type'].isnull()), 'elem_type
```

```
/Users/kyleknoebel/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:11: UserWarning
  # This is added back by InteractiveShellApp.init_path()
```

Next, create separate dataframes for components and elements, and also create a separate dataste for the pairs competition since the elements in pairs skating differ from the singles categories.

```
In [5]: # create separate dataframe for ladies competition
        # find the rows that contain 'ladies' in the name of each program category in the data
        ladies=pj[pj.iloc[:, 2].str.contains('ladies' , regex=False, case=False, na=False)]

        # create separate dataframes for components and elements
        elems=ladies[ladies['section']=='elements']
        compos=ladies[ladies['section']=='components']

        # create a data frame for the components of the ladies
        ladies_compo=ladies[ladies.iloc[:, 13].str.contains('components', regex=False, case=Fal
        # create a data frame for the elements of the ladies
        ladies_elem=ladies[ladies.iloc[:, 13].str.contains('elements', regex=False, case=False
```

The aspect_desc for the components will be converted to a categorical variable for modelling.

```
In [6]: # recategorize the object columns as category
        compos_model=ladies_compo.copy()
        compos_model = pd.concat([
                compos.select_dtypes([], ['object']),
               compos.select_dtypes(['object']).apply(pd.Series.astype, dtype='category')
                ], axis=1).reindex(compos.columns, axis=1)
        # create categorical values
        objs=compos_model[['aspect_desc']]
        objs= objs.apply(lambda x: x.cat.codes)
        objs=objs.rename(columns={"aspect_desc": "aspect_cat"})
        # drop string values and add categorical values
        compos_model=pd.concat([compos_model, objs], 1)
```

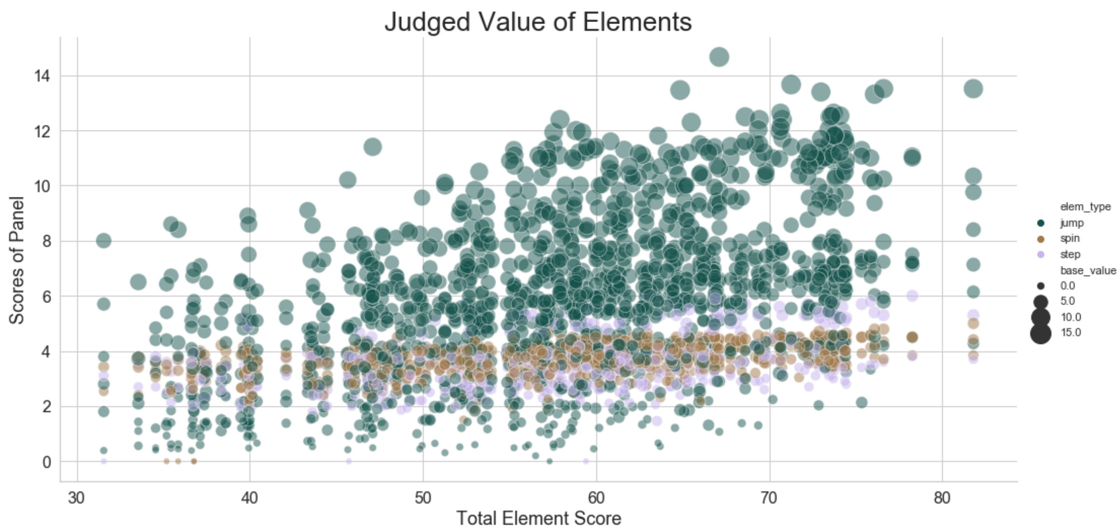
2.3 Exploring elements

The technical elements of ladies competitions are organized into the following categories: - jumps - spins - steps

More information for the codes for the different categories can be found in Appendix A at the end of the document. The element scores are calculated by awarding a grade of execution (GOE) factor for each element, which is then translated into a value using a scale of value (SOV), shown in Appendix B. The GOE values are then averaged using a trimmed mean process, and finally the averaged value is added to the base value for the element.

Since the scoring for the element category is somewhat complicated, the following visualizations will aim to show how the element types and scores are distributed in the data.

```
In [7]: # create a relplot showing the type of elements in the dataset
        sns.set(style='whitegrid')
        sns.relplot(x="total_element_score", y="scores_of_panel", hue="elem_type", size="base_v
                    sizes=(40, 400), alpha=.5, palette="cubehelix", height=7, aspect=2,
                    data=ladies_elem)
        plt.title('Judged Value of Elements', fontsize=26)
        plt.ylabel('Scores of Panel', fontsize=18)
        plt.xlabel('Total Element Score', fontsize=18)
        plt.tick_params(axis='both', which='major', labelsize=16)
```

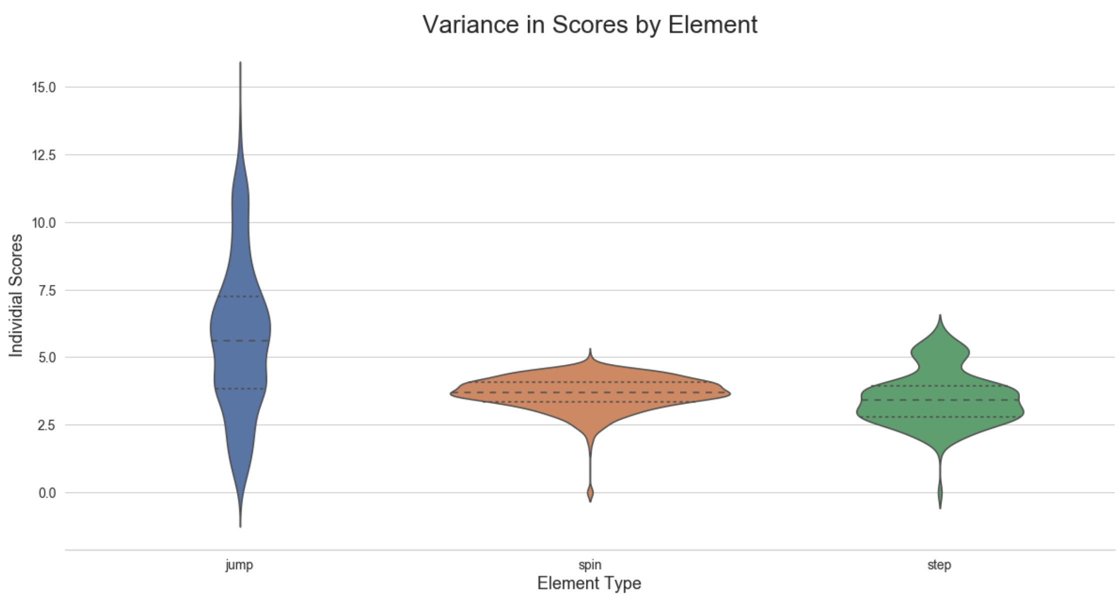



```
In [8]: ladies_elem['elem_type'].value_counts()

Out[8]: jump    1600
        spin     686
        step     447
        Name: elem_type, dtype: int64
```

Jumps tend to make up a larger majority of the total element score, and jumps are the most attempted element in the data.

```
In [9]: # plot the variance in scores by type of comoponent
        plt.figure(figsize=(20, 10))
        sns.violinplot(x="elem_type", y="scores_of_panel",
                       split=True, inner="quart",
                       data=ladies_elem)
        plt.xlabel('Element Type', fontsize=18)
        plt.ylabel('Individial Scores', fontsize=18)
```

```
plt.title('Variance in Scores by Element', fontsize=26)
plt.tick_params(axis='both', which='both', labelsize=14)
sns.despine(left=True)
```



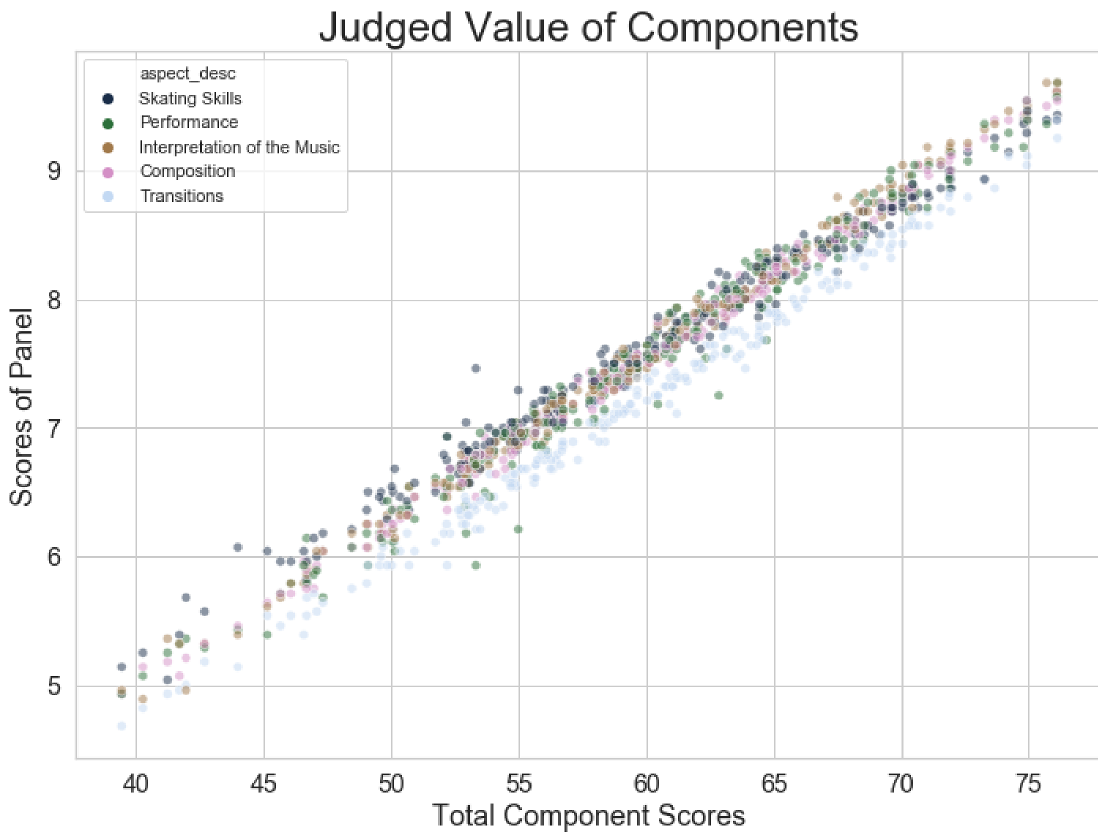
Jumps are the technical element most attempted, that recieve the highest score, and also have the most varaince among the scores.

2.4 Exploring components

Program Component Scores (PCS) fall into five categories: - Skating Skills - Transitions - Performance - Composition - Interpretation of the Music/Timing

Component scores are based on a 1-10 scale, are not averaged nor dependent on a GOE, but components can be marked for deductions and are based on a factor depending on type category of competition (mens, ladies, pairs). The components are largely considered the more artistic, or subjective, of the two judged aspects, and therefore considered the most open to interpretation. How do the component scores compare to the scores of the panel?

```
In [10]: # create a scatter of total component scores vs. the scores of the panel by program t
         sns.set(style='whitegrid')
         fig, ax = plt.subplots()
         fig.set_size_inches(11.7, 8.27)
         sns.scatterplot(x="total_component_score", y="scores_of_panel", hue="aspect_desc", al
                         data=ladies_compo)
         plt.title('Judged Value of Components', fontsize=26)
         plt.ylabel('Scores of Panel', fontsize=18)
         plt.xlabel('Total Component Scores', fontsize=18)
         plt.tick_params(axis='both', which='major', labelsize=16)
```



This chart shows that component scores are much less varied than the technical elements. This is likely due to the scale components are judged on, which also means they could make a good indicator population when exploring the relationship between technical elements and components.

In addition, the chart shows that transitions are nearly always the component with the lowest score amongst all ladies performances in the data.

2.5 Relationship between elements and components

The analysis above shows that despite components being considered the most subjective of the two judged aspects, elements tend to have the largest variance among individual scores, and have a larger range of total scores (as shown by the the x-axes of both 'Judged Value' plots above). Since components are judged on a scale as oppose to a GOE factor, the component scores are naturally more uniform than their counterparts. How does each cateogry compare to the other?

```
In [11]: sns.set(style='whitegrid')
         # get coeffs of linear fit
         slope, intercept, r_value, p_value, std_err = stats.linregress(ladies['total_element_s
                                                                         ladies['total_componen
         # create plot
         fig, ax = plt.subplots()
         fig.set_size_inches(10, 8)
         ax=sns.regplot(x='total_element_score', y='total_component_score', data=ladies,
```

```
                line_kws={'label':"y={0:.1f}x+{1:.1f}".format(slope,intercept)})
plt.title('Relationship Between Component and Elements Score', fontsize=18)
plt.ylabel('Element Score', fontsize=18)
plt.xlabel('Component Score', fontsize=18)
plt.tick_params(axis='both', which='major', labelsize=16)
# plot legend
ax.legend()
plt.show()
```

There is a clear linear relationship between the component and element scores. This relationship further supports the hypothesis that technical elements affect the score of components in ladies professional figure skating.

While this chart by no means proves the hypothesis one way or another, it does show that a trend exists which deserves further analysis.

3 2) Predicting the relationship between elements and components

A gradient boosting machine will be used to test the hypothesis that component scores can be predicted from the attributes of an element score. The H2O Flow gradient boosting estimator will be used as it gives a better opportunity to explore the statisical significance of the results.

3.1 Data engineering

3.1.1 Create data table

In order to properly train the model, the data will be organized to show the selected data for each performance. Since the hypothesis posits that the attributes of an element score affect the component score, the base values, GOE's, and deductions of the element portion will be selected.

Since the GOE shown in the data is the averaged value, a new GOE will be calculated by dividing the GOE by the base value to show the true GOE value awarded when the element is performed. Total deductions will also be removed now and added to the final model dataframe as the deduction in each line is the total number of deductions for the performance.

```
In [12]: # create a dataframe with only variables of interest and show format
         df_model = ladies_elem.drop(['competition', 'competition1', 'name', 'nation', 'rank',
                                  'total_segment_score', 'total_element_score', 'total_componen
                                 'performance_id-2', 'section', 'factor', 'aspect_num', 'aspec
                                      'credit_flag', 'ref', 'scores_of_panel', 'elem_type'], 1)
         # create actual GOE value and remove old value
         df_model['goe_actual']=df_model['goe']/df_model['base_value']
         df_model.head()
```

```
Out[12]:    performance_id  total_deductions  base_value   goe  goe_actual
         10     e37083608d               0.0        3.63  0.14    0.038567
         21     1b967c18c5               0.0        3.50  0.07    0.020000
         26     2adfc0ee61               0.0        3.63  0.71    0.195592
         32     64a3a7349a               0.0        2.70  1.00    0.370370
         39     3c12ecb0ee               0.0        7.26  0.50    0.068871
```

In order to organize the data for each performance, a rank column will be added to the elements for each performance id. This rank will then be used to sort the elements from highest to lowest base value, while keeping the element attributes (base value, goe, element category) in the same corresponding pattern. This means the highest base value score will be first, while it's corresponding GOE will be first among that category. This will add logic to the table that will ensure the GBM model is accurate.

In addition, the total deductions shown in each row of the data is the total number of deductions in the performance. As such, the total deductions will be removed from the data and appended at the end of the engineering process.

```
In [13]: # add a rank column to rank the base values by performance id
         df_model["rank"] = df_model.groupby("performance_id")["base_value"].rank("dense", asc
         df_model=df_model.reset_index()
         # sort the values by this ranking
         df_model=df_model.sort_values('rank')
         df_model.head()
```

```
Out[13]:      index performance_id  total_deductions  base_value  goe  goe_actual  \
         2416  21048     059039bcf6               0.0       11.22  0.6    0.053476
```

```
1063   9525     c351343d7d               0.0        8.30 -0.4   -0.048193
747    6647     7d9640cf7e               1.0        9.60  1.3    0.135417
296    2667     8712edfbc0               0.0        8.20  0.8    0.097561
294    2658     265a603120               0.0       11.33 -0.5   -0.044131

      rank
2416   1.0
1063   1.0
747    1.0
296    1.0
294    1.0
```

In [14]:
```
# create separate data frame for deductions
df_deduc=df_model.copy()
df_deduc=df_deduc.drop(['base_value', 'goe', 'goe_actual', 'rank'], 1)
# drop duplicate performances
df_deduc['performance_id']=df_deduc['performance_id'].drop_duplicates()
df_deduc=df_deduc.dropna()
df_deduc.head()
```

Out[14]:

	index	performance_id	total_deductions
2416	21048	059039bcf6	0.0
1063	9525	c351343d7d	0.0
747	6647	7d9640cf7e	1.0
296	2667	8712edfbc0	0.0
294	2658	265a603120	0.0

In [15]:
```
# create a pivot table showing the base value, goe, and deductions for each performan
df_model=pd.pivot_table(df_model, index=['performance_id'], columns=df_model.groupby(
                  values=['base_value','goe_actual', 'rank'], aggfunc='sum')
# relabel columns with proper titles
df_model.columns=df_model.columns.map('{0[0]}{0[1]}'.format)
# reset index for modeling
df_model=df_model.reset_index()
# drop the ranks columns, they are not needed for model
df_model=df_model.drop(['rank1', 'rank2', 'rank3', 'rank4', 'rank5', 'rank6', 'rank7'
                       'rank11', 'rank12'], 1)
# add the deduction column
df_model=df_model.merge(df_deduc, how='left', on=['performance_id'])
df_model.head()
```

Out[15]:

	performance_id	base_value1	base_value2	base_value3	base_value4	\
0	010e399739	9.46	8.60	6.00	5.61	
1	018b293978	10.30	8.36	5.61	5.30	
2	01b0b01f6f	8.25	6.60	6.00	5.54	
3	01e5ba3b8e	8.60	8.20	6.00	5.83	
4	0375e990b4	11.99	9.60	6.00	5.61	

```
   base_value5  base_value6  base_value7  base_value8  base_value9  ...  \
```

```
0          4.84          3.70          3.63           3.5          3.30  ...
1          4.84          3.90          3.50           3.3          3.00  ...
2          5.10          3.63          3.30           3.2          3.00  ...
3          5.61          5.06          4.62           3.2          3.00  ...
4          3.63          3.63          3.50           3.0          2.77  ...

   goe_actual5  goe_actual6  goe_actual7  goe_actual8  goe_actual9  \
0    -0.330579    -0.486486     0.195592     0.225714     0.193939
1     0.144628     0.282051     0.182857     0.151515     0.190000
2     0.000000     0.000000     0.151515     0.134375     0.070000
3     0.089127     0.057312    -0.454545     0.246875     0.010000
4     0.019284     0.079890     0.162857     0.166667    -0.758123

   goe_actual10  goe_actual11  goe_actual12  index  total_deductions
0      0.156250      0.190000      0.650000  14650               0.0
1      0.166667      0.400000     -0.318182  18582               0.0
2      0.208333      0.100000     -0.181818    340               0.0
3      0.165385      0.029167      0.450000  18815               2.0
4      0.022222      0.384615      0.500000  16178               1.0

[5 rows x 27 columns]
```

3.1.2 Create target table

The target table will be the total component score of each performance. The process below will show the scores of each component per performance, but this data is only shown in case it is necessary for future analysis. The individual scores will not be used in the model.

In [16]:
```
# only keep variables of interest for modeling
df_target=compos_model.drop(['competition', 'competition1', 'name', 'nation', 'rank',
                             'total_segment_score', 'total_element_score', 'total_dedu
                             'performance_id-2', 'section', 'aspect_num', 'info_flag'
                             'credit_flag', 'base_value', 'factor', 'goe', 'ref', 'ele
                            'total_component_score'],
                            1)
# create pivot table of values
df_target=pd.pivot_table(df_target, index=["performance_id"], columns=['aspect_cat'],
                         values=(['scores_of_panel']), aggfunc='sum')
# add total column to target table
df_target['total_score']=df_target.sum(axis=1)
# multiply by 2 to account for the factor
df_target['total_score']=df_target['total_score']*2
# reset index
df_target=df_target.reindex()
df_target.head()
```

Out[16]:
```
               scores_of_panel                          total_score
aspect_cat                   0     1     2     3     4
```

```
performance_id
010e399739                  8.21  8.14  8.18  8.29  7.89        81.42
018b293978                  7.82  7.82  7.82  8.11  7.54        78.22
01b0b01f6f                  6.07  6.18  6.07  6.21  5.75        60.56
01e5ba3b8e                  7.68  7.75  7.68  7.82  7.39        76.64
0375e990b4                  8.36  8.43  8.25  8.46  8.21        83.42
```

Then the total score is added to the end of the model dataframe to create one model dataframe.

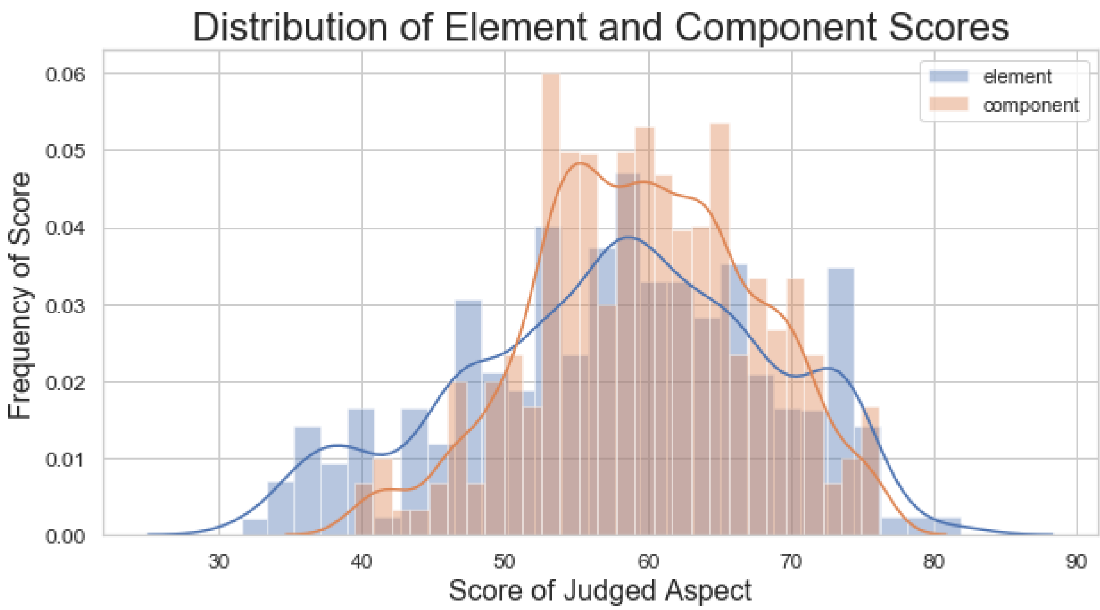
In [17]:
```
# add the total score column from the target table to the model table
df_model=df_model.merge(df_target['total_score'], how='left', on=['performance_id'])
df_model.head()
```

Out[17]:
```
  performance_id  base_value1  base_value2  base_value3  base_value4  \
0     010e399739         9.46         8.60         6.00         5.61
1     018b293978        10.30         8.36         5.61         5.30
2     01b0b01f6f         8.25         6.60         6.00         5.54
3     01e5ba3b8e         8.60         8.20         6.00         5.83
4     0375e990b4        11.99         9.60         6.00         5.61

   base_value5  base_value6  base_value7  base_value8  base_value9  ...  \
0         4.84         3.70         3.63          3.5         3.30  ...
1         4.84         3.90         3.50          3.3         3.00  ...
2         5.10         3.63         3.30          3.2         3.00  ...
3         5.61         5.06         4.62          3.2         3.00  ...
4         3.63         3.63         3.50          3.0         2.77  ...

   goe_actual6  goe_actual7  goe_actual8  goe_actual9  goe_actual10  \
0    -0.486486     0.195592     0.225714     0.193939      0.156250
1     0.282051     0.182857     0.151515     0.190000      0.166667
2     0.000000     0.151515     0.134375     0.070000      0.208333
3     0.057312    -0.454545     0.246875     0.010000      0.165385
4     0.079890     0.162857     0.166667    -0.758123      0.022222

   goe_actual11  goe_actual12  index  total_deductions  total_score
0      0.190000      0.650000  14650               0.0        81.42
1      0.400000     -0.318182  18582               0.0        78.22
2      0.100000     -0.181818    340               0.0        60.56
3      0.029167      0.450000  18815               2.0        76.64
4      0.384615      0.500000  16178               1.0        83.42

[5 rows x 28 columns]
```

The only remaining questions is what distribution to use in the model?

In [18]:
```
# show the distribution of component and element scores
plt.figure(figsize=(10, 5))
ax=sns.distplot(ladies['total_element_score'], label='element')
ax=sns.distplot(ladies['total_component_score'], label='component')
```

```
plt.title('Distribution of Element and Component Scores', fontsize=22)
plt.xlabel('Score of Judged Aspect', fontsize=16)
plt.ylabel('Frequency of Score', fontsize=16)
ax.legend()
plt.tick_params(axis='both', which='major', labelsize=12)
```



The distributions of the element and component scores are normal. The distribution of the GBM model should match the dsitribution of the response variable, so a gaussian distribution will be used.

3.1.3 Run model

```
In [19]: import h2o
         h2o.init()
         from h2o.estimators.gbm import H2OGradientBoostingEstimator
         # convert pandas dataframe to h2o dataframe
         df_run_model=h2o.H2OFrame(df_model)
         # Split the data into Train/Test/Validation with Train having 70% and test and valida
         train,test,valid = df_run_model.split_frame(ratios=[0.7, 0.15])
         gbm = H2OGradientBoostingEstimator(distribution = "gaussian", ntrees=100, learn_rate=
                                            max_depth=4, nfolds=5, keep_cross_validation_predi
                                            stopping_metric='deviance', seed=1234)
         gbm.train(y='total_score', x=['base_value1', 'base_value2', 'base_value3', 'base_valu
                                       'base_value6', 'base_value7', 'base_value8', 'base_value
                                       'base_value11', 'base_value12', 'goe_actual1', 'goe_actu
                                       'goe_actual4', 'goe_actual5', 'goe_actual6', 'goe_actual
                                       'goe_actual9', 'goe_actual10', 'goe_actual11', 'goe_actu
                   training_frame=train, validation_frame=train)
```

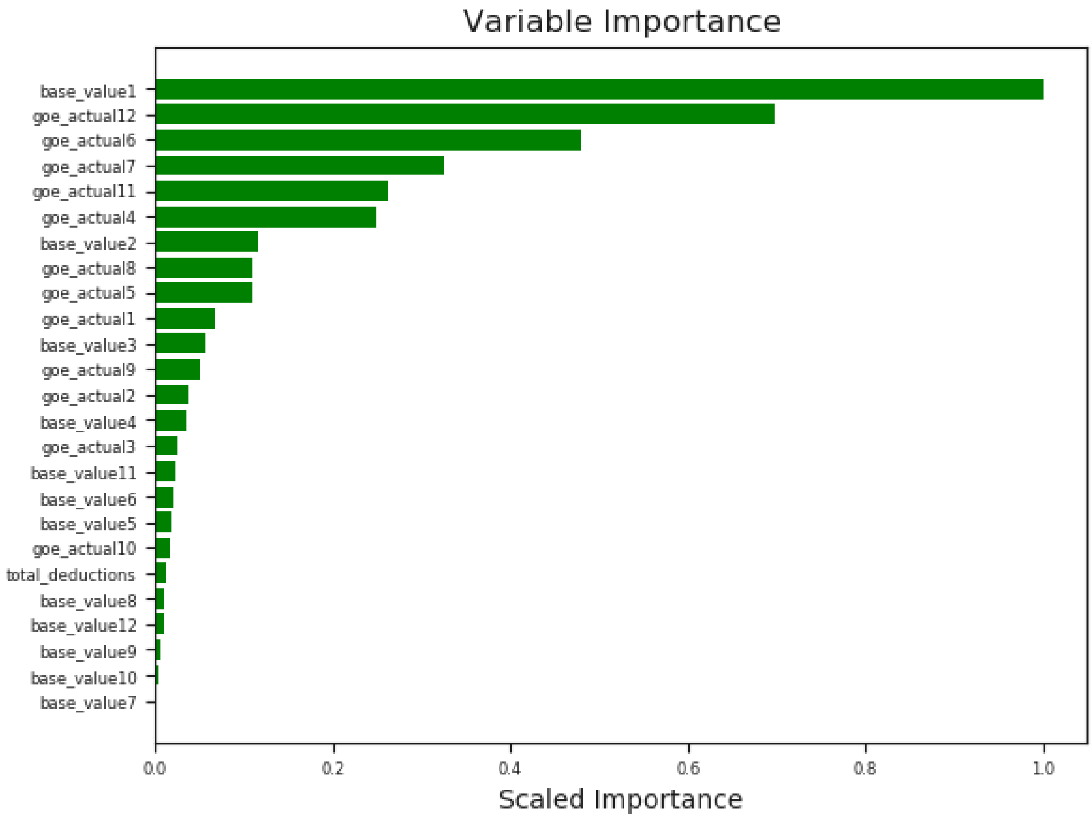
```python
# show cross validation scores
cv_summary = gbm.cross_validation_metrics_summary().as_data_frame()
print(cv_summary)
# run validation testing
print(gbm.model_performance(valid=True))
```

```
/Users/kyleknoebel/anaconda3/lib/python3.6/site-packages/requests/__init__.py:80: RequestsDeper
  RequestsDependencyWarning)


Checking whether there is an H2O instance running at http://localhost:54321... not found.
Attempting to start a local H2O server...
  Java Version: openjdk version "1.8.0_152-release"; OpenJDK Runtime Environment (build 1.8.0_
  Starting server from /Users/kyleknoebel/anaconda3/h2o_jar/h2o.jar
  Ice root: /var/folders/9j/nmg9nt1n0hv2wyylxv2f4_xh0000gn/T/tmpioyk35wf
  JVM stdout: /var/folders/9j/nmg9nt1n0hv2wyylxv2f4_xh0000gn/T/tmpioyk35wf/h2o_kyleknoebel_sta
  JVM stderr: /var/folders/9j/nmg9nt1n0hv2wyylxv2f4_xh0000gn/T/tmpioyk35wf/h2o_kyleknoebel_sta
  Server is running at http://127.0.0.1:54321
Connecting to H2O server at http://127.0.0.1:54321... successful.
Warning: Your H2O cluster version is too old (11 months and 2 days)! Please download and insta


--------------------------  ----------------------------------------
H2O cluster uptime:         02 secs
H2O cluster timezone:       America/Los_Angeles
H2O data parsing timezone:  UTC
H2O cluster version:        3.18.0.2
H2O cluster version age:    11 months and 2 days !!!
H2O cluster name:           H2O_from_python_kyleknoebel_8ee316
H2O cluster total nodes:    1
H2O cluster free memory:    1.778 Gb
H2O cluster total cores:    4
H2O cluster allowed cores:  4
H2O cluster status:         accepting new members, healthy
H2O connection url:         http://127.0.0.1:54321
H2O connection proxy:
H2O internal security:      False
H2O API Extensions:         XGBoost, Algos, AutoML, Core V3, Core V4
Python version:             3.6.5 final
--------------------------  ----------------------------------------


/Users/kyleknoebel/anaconda3/lib/python3.6/site-packages/h2o/utils/shared_utils.py:170: Future
  data = _handle_python_lists(python_obj.as_matrix().tolist(), -1)[1]


Parse progress: || 100%
gbm Model Build progress: || 100%
                                 mean           sd   cv_1_valid  cv_2_valid  \
```

```
0                    mae   3.5870585    0.24666834    3.2672966   4.1972613
1  mean_residual_deviance   21.115566     2.8642073     18.88758   27.626787
2                    mse   21.115566     2.8642073     18.88758   27.626787
3                     r2   0.7798661   0.032428175    0.8451646  0.70439506
4      residual_deviance   21.115566     2.8642073     18.88758   27.626787
5                   rmse   4.5747895    0.30566937    4.3459845   5.2561193
6                  rmsle  0.06422262  0.0032810639  0.064116165  0.07092826

    cv_3_valid cv_4_valid  cv_5_valid
0    3.4181762  3.7475803   3.3049786
1    18.315437   23.96124   16.786789
2    18.315437   23.96124   16.786789
3   0.79315186  0.7919977  0.76462126
4    18.315437   23.96124   16.786789
5     4.279654   4.895022   4.0971684
6  0.060625426  0.0674772  0.05796604

ModelMetricsRegression: gbm
** Reported on validation data. **

MSE: 0.7621066386291948
RMSE: 0.8729871927062818
MAE: 0.6631422464150271
RMSLE: 0.012663841975791273
Mean Residual Deviance: 0.7621066386291948
```

In [20]:
```
plt.rcdefaults()
plt.figure(figsize=(25, 10))
fig, ax = plt.subplots()
variables = gbm._model_json['output']['variable_importances']['variable']
y_pos = np.arange(len(variables))
scaled_importance = gbm._model_json['output']['variable_importances']['scaled_importa
ax.barh(y_pos, scaled_importance, align='center', color='green', ecolor='black')
ax.set_yticks(y_pos)
ax.set_yticklabels(variables)
ax.invert_yaxis()
ax.set_xlabel('Scaled Importance')
ax.set_title('Variable Importance')
plt.tick_params(axis='both', which='major', labelsize=6)
plt.show()
```

```
<Figure size 2500x1000 with 0 Axes>
```



The fact that the goe_actual12 has the most importance among the GOE features shows that the goe of the lowest scoring element has the most effect on the component score. Interestingly the base value of the highest scoring element has the most weight on the model. This could show that the judges are swayed by the highest and lowest scoring elements in the performance.

There is some imbalance in the data, likely arising from multicollinearity amongst the features. What happens when the model is run on just GOE and base value features?

3.1.4 GOE model

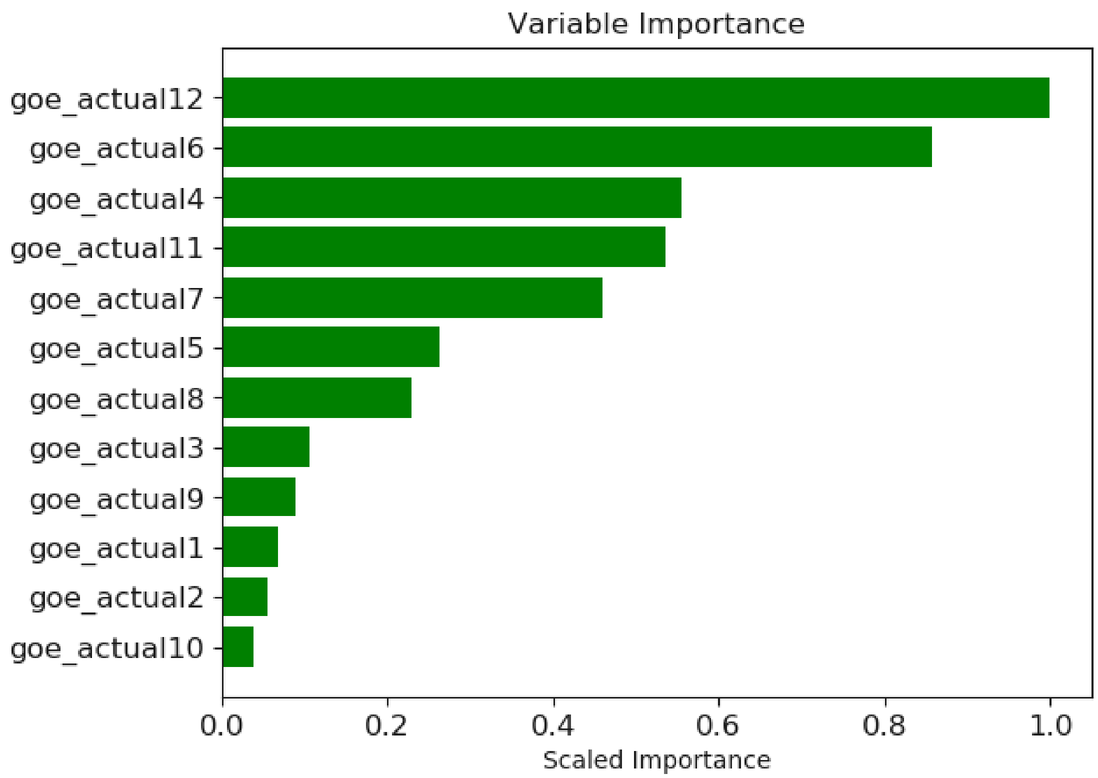
```
In [22]: gbm_goe = H2OGradientBoostingEstimator(distribution = "gaussian", ntrees=100, learn_ra
                                                max_depth=4, nfolds=5, keep_cross_validation_predic
                                                stopping_metric='deviance', seed=1234)
         gbm_goe.train(y='total_score', x=['goe_actual1', 'goe_actual2', 'goe_actual3',
                                           'goe_actual4', 'goe_actual5', 'goe_actual6', 'goe_actual7
                                           'goe_actual9', 'goe_actual10', 'goe_actual11', 'goe_actua
                     training_frame=train, validation_frame=train)
         # show cross validation scores
         cv_summary_goe = gbm_goe.cross_validation_metrics_summary().as_data_frame()
         print(cv_summary_goe)
         # run validation testing
         print(gbm_goe.model_performance(valid=True))
```

```
gbm Model Build progress: || 100%
                              mean           sd   cv_1_valid  cv_2_valid  \
0                    mae   3.9435306   0.29755127    3.2450097   4.5707865
1  mean_residual_deviance   26.196426    4.5400333     17.16726    36.86748
2                    mse   26.196426    4.5400333     17.16726    36.86748
3                     r2  0.72093034  0.060327284   0.85926735   0.6055202
4      residual_deviance   26.196426    4.5400333     17.16726    36.86748
5                   rmse   5.0798383   0.44253308     4.143339     6.07186
6                  rmsle  0.07151337  0.006012601  0.058337018  0.08378718

   cv_3_valid  cv_4_valid   cv_5_valid
0   3.9783285   3.9942448    3.9292839
1   25.738323   27.819397    23.389673
2   25.738323   27.819397    23.389673
3   0.7093204   0.7585058    0.6720378
4   25.738323   27.819397    23.389673
5    5.073295     5.27441     4.836287
6  0.07140502  0.07630416  0.067733474

ModelMetricsRegression: gbm
** Reported on validation data. **

MSE: 1.8332705826843947
RMSE: 1.353983228361561
MAE: 1.0337883397420988
RMSLE: 0.01948904985534613
Mean Residual Deviance: 1.8332705826843947
```

In [23]:

```
plt.rcdefaults()
plt.figure(figsize=(25, 10))
fig, ax = plt.subplots()
variables = gbm_goe._model_json['output']['variable_importances']['variable']
y_pos = np.arange(len(variables))
scaled_importance = gbm_goe._model_json['output']['variable_importances']['scaled_impo
ax.barh(y_pos, scaled_importance, align='center', color='green', ecolor='black')
ax.set_yticks(y_pos)
ax.set_yticklabels(variables)
ax.invert_yaxis()
ax.set_xlabel('Scaled Importance')
ax.set_title('Variable Importance')
plt.tick_params(axis='both', which='major', labelsize=12)
plt.show()
```

```
<Figure size 2500x1000 with 0 Axes>
```



3.1.5 Base value model

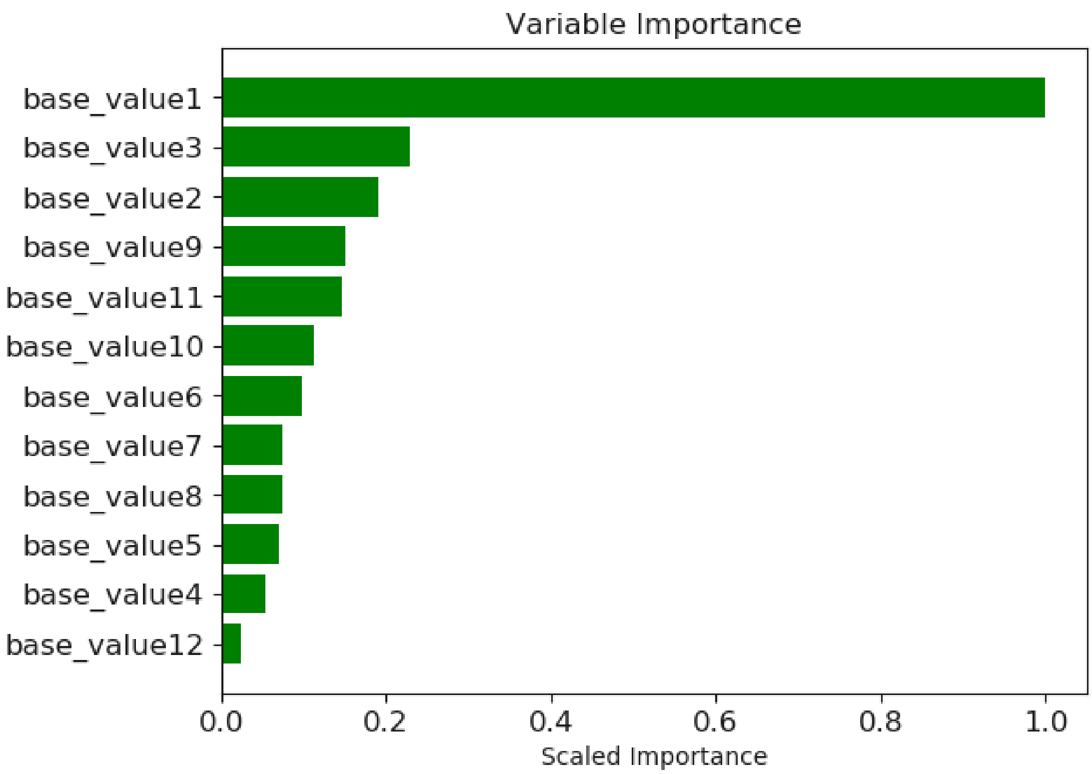
```
In [24]: gbm_bv = H2OGradientBoostingEstimator(distribution = "gaussian", ntrees=100, learn_ra
                                               max_depth=4, nfolds=5, keep_cross_validation_predi
                                               stopping_metric='deviance', seed=1234)
         gbm_bv.train(y='total_score', x=['base_value1', 'base_value2', 'base_value3', 'base_va
                                         'base_value6', 'base_value7', 'base_value8', 'base_value9
                                         'base_value11', 'base_value12'],
                     training_frame=train, validation_frame=train)
         # show cross validation scores
         cv_summary_bv = gbm_bv.cross_validation_metrics_summary().as_data_frame()
         print(cv_summary_bv)
         # run validation testing
         print(gbm_bv.model_performance(valid=True))
```

```
gbm Model Build progress: || 100%
                                mean          sd   cv_1_valid   cv_2_valid  \
0                    mae    5.312034  0.60576713     4.869537      5.24109
1 mean_residual_deviance   48.042717   10.377319    44.031254     45.38475
2                    mse   48.042717   10.377319    44.031254     45.38475
3                     r2  0.51292783  0.06952737    0.6390434   0.51438594
4      residual_deviance   48.042717   10.377319    44.031254     45.38475
```

```
5                 rmse    6.855235   0.7240407    6.635605   6.7368207
6                rmsle  0.09310809  0.00927429  0.09528442  0.08832154

   cv_3_valid  cv_4_valid   cv_5_valid
0   5.4067373   6.8198757    4.2229304
1    46.22816    74.80636    29.763058
2    46.22816    74.80636    29.763058
3  0.47791535   0.3506222   0.58267236
4    46.22816    74.80636    29.763058
5   6.7991295    8.649067     5.455553
6  0.09372069  0.11447975  0.073734045

ModelMetricsRegression: gbm
** Reported on validation data. **

MSE: 8.375414746525411
RMSE: 2.8940308820960103
MAE: 2.2138912109496403
RMSLE: 0.040872120607234455
Mean Residual Deviance: 8.375414746525411
```

In [25]:
```python
plt.rcdefaults()
plt.figure(figsize=(25, 10))
fig, ax = plt.subplots()
variables = gbm_bv._model_json['output']['variable_importances']['variable']
y_pos = np.arange(len(variables))
scaled_importance = gbm_bv._model_json['output']['variable_importances']['scaled_impo
ax.barh(y_pos, scaled_importance, align='center', color='green', ecolor='black')
ax.set_yticks(y_pos)
ax.set_yticklabels(variables)
ax.invert_yaxis()
ax.set_xlabel('Scaled Importance')
ax.set_title('Variable Importance')
plt.tick_params(axis='both', which='major', labelsize=12)
plt.show()
```

```
<Figure size 2500x1000 with 0 Axes>
```



The cross validation scores and validation testing improve when the model is run on just GOE scores, and the opposite is true for base value scores. This shows that the GOE is the most important feature for predicting component scores.

3.1.6 Chronological model

In order to test whether the model is improved by organizing the data by value rather than chrnologically, the same model will be run on chronologucal data.

```
In [26]: # create a dataframe
         df_chrono = ladies_elem.drop(['competition', 'competition1', 'name', 'nation', 'rank'
                                       'total_segment_score', 'total_element_score', 'total_compone
                                      'performance_id-2', 'section', 'factor', 'aspect_num', 'aspec
                                           'credit_flag', 'ref', 'scores_of_panel'], 1)
         # create actual GOE value and remove old value
         df_chrono['goe_actual']=df_chrono['goe']/df_chrono['base_value']
         # create separate data frame for deductions
         df_deduc=ladies_elem.copy()
         df_deduc=df_deduc.drop(['base_value', 'goe', 'elem_type'], 1)
         # drop duplicate performances
         df_deduc['performance_id']=df_deduc['performance_id'].drop_duplicates()
         df_deduc=df_deduc.dropna()
         # create a pivot table showing the base value, goe, and deductions for each performan
```

```
df_chrono=pd.pivot_table(df_chrono, index=['performance_id'], columns=df_chrono.groupb
                    values=['base_value','goe_actual'], aggfunc='sum')
# relabel columns with proper titles
df_chrono.columns=df_chrono.columns.map('{0[0]}{0[1]}'.format)
# reset index for modeling
df_chrono=df_chrono.reset_index()
# add the deduction column
df_chrono=df_chrono.merge(df_deduc, how='left', on=['performance_id'])
# add the mean score column from the target table to the model table
# add the mean score column from the target table to the model table
df_chrono=df_chrono.merge(df_target['total_score'], how='left', on=['performance_id']
df_chrono.head()
```

Out[26]:

```
  performance_id  base_value1  base_value2  base_value3  base_value4  \
0     010e399739         4.84         3.20         3.63          3.7
1     018b293978         3.50         4.84         3.30          3.0
2     01b0b01f6f         8.25         3.00         6.00          2.4
3     01e5ba3b8e         5.83         2.40         2.00          8.2
4     0375e990b4         5.61         6.00         2.77          3.0

   base_value5  base_value6  base_value7  base_value8  base_value9  ...  \
0         2.00         3.50         5.61         8.60         9.46  ...
1         5.61         8.36         3.00         5.30         3.90  ...
2         3.20         2.00         5.54         5.10         0.55  ...
3         5.61         3.00         3.20         4.62         2.60  ...
4         3.50         2.70         3.63        11.99         3.63  ...

   performance_id-2   section  aspect_num  aspect_desc  info_flag  \
0        010e399739  elements        10.0           3S          0
1        018b293978  elements        12.0      FCCoSp4          0
2        01b0b01f6f  elements         7.0    3S+2T+2Lo          0
3        01e5ba3b8e  elements         7.0           3F          0
4        0375e990b4  elements         7.0          3Lo          0

   credit_flag  factor  ref  scores_of_panel  total_score
0            x     0.0  0.0             3.24        81.42
1            0     0.0  0.0             4.14        78.22
2            x     0.0  0.0             8.25        60.56
3            x     0.0  0.0             3.73        76.64
4            x     0.0  0.0             4.71        83.42

[5 rows x 46 columns]
```

In [27]:

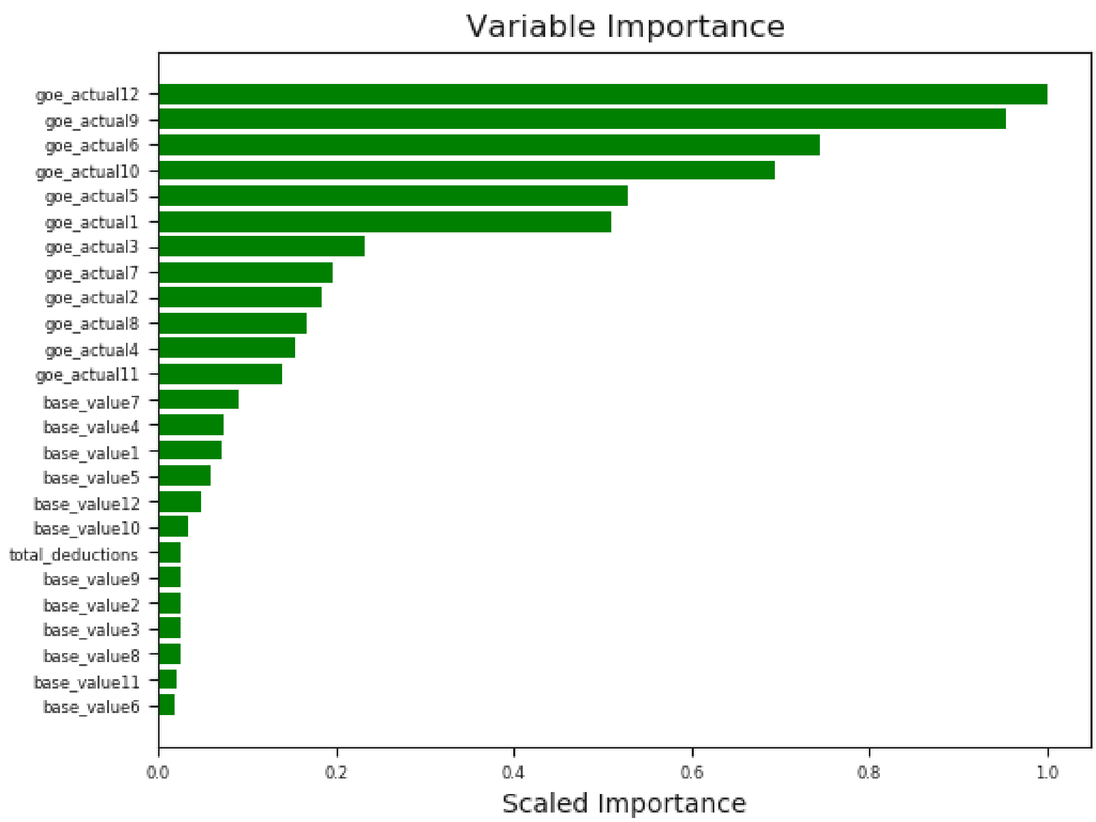
```
# convert pandas dataframe to h2o dataframe
df_run_chrono=h2o.H2OFrame(df_chrono)
# Split the data into Train/Test/Validation with Train having 70% and test and valida
train,test,valid = df_run_chrono.split_frame(ratios=[0.7, 0.15])
gbm_chrono = H2OGradientBoostingEstimator(distribution = "gaussian", ntrees=100, lear
```

```python
                                          max_depth=4, nfolds=5, keep_cross_validation_predic
                                          stopping_metric='deviance', seed=1234)
gbm_chrono.train(y='total_score', x=['base_value1', 'base_value2', 'base_value3', 'bas
                             'base_value6', 'base_value7', 'base_value8', 'base_value9
                             'base_value11', 'base_value12', 'goe_actual1', 'goe_actua
                             'goe_actual4', 'goe_actual5', 'goe_actual6', 'goe_actual7
                             'goe_actual9', 'goe_actual10', 'goe_actual11', 'goe_actua
          training_frame=train, validation_frame=train)
# show cross validation scores
cv_summary_chrono = gbm_chrono.cross_validation_metrics_summary().as_data_frame()
print(cv_summary_chrono)
# run validation testing
print(gbm_chrono.model_performance(valid=True))
```

```
/Users/kyleknoebel/anaconda3/lib/python3.6/site-packages/h2o/utils/shared_utils.py:170: FutureW
  data = _handle_python_lists(python_obj.as_matrix().tolist(), -1)[1]


Parse progress: || 100%
gbm Model Build progress: || 100%
                                mean           sd  cv_1_valid  cv_2_valid  \
0                    mae   4.4375978   0.58667064   5.6256943   4.5909743
1  mean_residual_deviance    32.68633     9.974677   57.938244   35.123596
2                    mse    32.68633     9.974677   57.938244   35.123596
3                     r2  0.64457816  0.094924934  0.43322265  0.66512376
4      residual_deviance    32.68633     9.974677   57.938244   35.123596
5                   rmse   5.5938005   0.83538145   7.6117177   5.9265165
6                  rmsle   0.0767415  0.013087956   0.1108671  0.07811327

    cv_3_valid  cv_4_valid   cv_5_valid
0    3.5658426   3.4489312    4.9565463
1    19.440119    19.48235    31.447336
2    19.440119    19.48235    31.447336
3   0.75595665  0.80564934   0.56293833
4    19.440119    19.48235    31.447336
5     4.409095   4.4138813    5.6077924
6  0.059234194  0.06149423  0.073998705

ModelMetricsRegression: gbm
** Reported on validation data. **

MSE: 0.9664172395007532
RMSE: 0.9830652264731742
MAE: 0.7258698944724368
RMSLE: 0.014414792952988104
Mean Residual Deviance: 0.9664172395007532
```

```
In [28]: plt.rcdefaults()
         plt.figure(figsize=(25, 10))
         fig, ax = plt.subplots()
         variables = gbm_chrono._model_json['output']['variable_importances']['variable']
         y_pos = np.arange(len(variables))
         scaled_importance = gbm_chrono._model_json['output']['variable_importances']['scaled_i
         ax.barh(y_pos, scaled_importance, align='center', color='green', ecolor='black')
         ax.set_yticks(y_pos)
         ax.set_yticklabels(variables)
         ax.invert_yaxis()
         ax.set_xlabel('Scaled Importance')
         ax.set_title('Variable Importance')
         plt.tick_params(axis='both', which='major', labelsize=6)
         plt.show()
```

```
<Figure size 2500x1000 with 0 Axes>
```



The model accuracy shows that the value of the elements is more important than their order in the performance when predicting component scores.

3.1.7 Test on other data

The original data also include performances from the 2016 Olympics, data which was not included in this analysis. How does the model perform when predicting the component scores of these performances?

In [30]:
```
# import olympic performance data
path=r"/Users/kyleknoebel/Desktop/ThinkfulNotebooks/Unit 3 Capstone/performances_2018
test_perf=pd.read_csv(path)
path2=r"/Users/kyleknoebel/Desktop/ThinkfulNotebooks/Unit 3 Capstone/judged-aspects_20
test_asp=pd.read_csv(path2)
test_perf['total_deductions']=test_perf['total_deductions'].astype(str)
test_perf['total_deductions']=test_perf['total_deductions'].str.replace('-', ' ')
test_perf['total_deductions']=test_perf['total_deductions'].astype(float)
# merge the dataframes
df_test=test_perf.merge(test_asp, how='left', on=['performance_id'])
# fill null values
df_test=df_test.fillna(0)
df_test.head()
```

Out[30]:
```
  performance_id                competition                  program  \
0     a3f8fac157  Olympic Winter Games 2018  Ice Dance - Free Dance
1     a3f8fac157  Olympic Winter Games 2018  Ice Dance - Free Dance
2     a3f8fac157  Olympic Winter Games 2018  Ice Dance - Free Dance
3     a3f8fac157  Olympic Winter Games 2018  Ice Dance - Free Dance
4     a3f8fac157  Olympic Winter Games 2018  Ice Dance - Free Dance

                                name nation  rank  starting_number  \
0  LAURIAULT Marie-Jade / le GAC Romain    FRA    17                1
1  LAURIAULT Marie-Jade / le GAC Romain    FRA    17                1
2  LAURIAULT Marie-Jade / le GAC Romain    FRA    17                1
3  LAURIAULT Marie-Jade / le GAC Romain    FRA    17                1
4  LAURIAULT Marie-Jade / le GAC Romain    FRA    17                1

   total_segment_score  total_element_score  total_component_score  ...  \
0                89.62                47.04                  42.58  ...
1                89.62                47.04                  42.58  ...
2                89.62                47.04                  42.58  ...
3                89.62                47.04                  42.58  ...
4                89.62                47.04                  42.58  ...

      section aspect_num                       aspect_desc  info_flag  \
0  components        0.0  Interpretation of the Music/Timing          0
1    elements        8.0                             ChLi1          0
2  components        0.0                   Skating Skills          0
3    elements        7.0                            DiSt2          0
4    elements        6.0                            CuLi4          0

  credit_flag base_value factor   goe   ref   scores_of_panel
```

```
0          0        0.0    1.2  0.00  0.0             7.07
1          0        1.0    0.0  0.70  0.0             1.70
2          0        0.0    1.2  0.00  0.0             7.25
3          0        5.6    0.0  0.79  0.0             6.39
4          0        4.5    0.0  0.77  0.0             5.27

[5 rows x 22 columns]
```

In [31]:
```
# clean data
# lower the capilization of the program and competition1 columns to standardize forma
df_test.iloc[:, 2] = df_test.iloc[:, 2].str.lower()
df_test.iloc[:, 1] = df_test.iloc[:, 1].str.lower()
# clean the text for interpretations
df_test.iloc[:, 15]=df_test.iloc[:, 15].str.replace('Interpretation of the Music / Ti
                                                    'Interpretation of the Music')
df_test.iloc[:, 15]=df_test.iloc[:, 15].str.replace('Interpretation of the Music/Timi
                                                    'Interpretation of the Music')
# remove ice dancing from the dataset
df_test=df_test[~df_test['program'].str.contains('ice dance')]
#remove short program from the dataset
df_test=df_test[~df_test['program'].str.contains('short')]
# create separate dataframe for ladies competition
# find the rows that contain 'ladies' in the name of each program category in the dat
ladies_test=df_test[df_test.iloc[:, 2].str.contains('ladies' , regex=False, case=Fals

# create separate dataframes for components and elements
elems_test=ladies_test[ladies_test['section']=='elements']
compos_test=ladies_test[ladies_test['section']=='components']

# recategorize the object columns as category
compos_model_test=compos_test.copy()
compos_model_test = pd.concat([
        compos_test.select_dtypes([], ['object']),
        compos_test.select_dtypes(['object']).apply(pd.Series.astype, dtype='category
        ], axis=1).reindex(compos_test.columns, axis=1)
# create categorical values
objs_test=compos_model_test[['aspect_desc']]
compos_model_test=compos_model_test.drop(['aspect_desc'], 1)
objs_test= objs_test.apply(lambda x: x.cat.codes)
objs_test=objs_test.rename(columns={"aspect_desc": "aspect_cat"})
# drop string values and add categorical values
compos_model_test=pd.concat([compos_model_test, objs_test], 1)

# create a dataframe with only variables of interest and show format
df_model_test = elems_test.drop(['competition', 'program', 'name', 'nation', 'rank',
                        'total_segment_score', 'total_element_score', 'total_compone
                       'section', 'factor', 'aspect_num', 'aspect_desc', 'info_flag'
                            'credit_flag', 'ref', 'scores_of_panel'], 1)
```

```python
# create actual GOE value and remove old value
df_model_test['goe_actual']=df_model_test['goe']/df_model_test['base_value']
# add a rank column to rank the base values by performance id
df_model_test["rank"] = df_model_test.groupby("performance_id")["base_value"].rank("de
df_model_test=df_model_test.reset_index()
# sort the values by this ranking
df_model_test=df_model_test.sort_values('rank')
# create separate data frame for deductions
df_deduc_test=df_model_test.copy()
df_deduc_test=df_deduc_test.drop(['base_value', 'goe', 'goe_actual', 'rank'], 1)
# drop duplicate performances
df_deduc_test['performance_id']=df_deduc_test['performance_id'].drop_duplicates()
df_deduc_test=df_deduc_test.dropna()
# create a pivot table showing the base value, goe, and deductions for each performan
df_model_test=pd.pivot_table(df_model_test, index=['performance_id'],
                             columns=df_model_test.groupby(['performance_id']).cumcou
                  values=['base_value','goe_actual', 'rank'], aggfunc='sum')
# relabel columns with proper titles
df_model_test.columns=df_model_test.columns.map('{0[0]}{0[1]}'.format)
# reset index for modeling
df_model_test=df_model_test.reset_index()
# drop the ranks columns, they are not needed for model
df_model_test=df_model_test.drop(['rank1', 'rank2', 'rank3', 'rank4', 'rank5', 'rank6
                       'rank11', 'rank12'], 1)
# add the deduction column
df_model_test=df_model_test.merge(df_deduc_test, how='left', on=['performance_id'])
# create target table
# only keep variables of interest for modeling
df_target_test=compos_model_test.drop(['competition', 'program', 'name', 'nation', 'ra
                             'total_segment_score', 'total_element_score', 'total_dedu
                             'section', 'aspect_num', 'info_flag', 'credit_flag', 'bas
                                 'ref', 'total_component_score'],
                            1)
# create pivot table of values
df_target_test=pd.pivot_table(df_target_test, index=["performance_id"], columns=['aspe
                        values=(['scores_of_panel']), aggfunc='sum')
# add mean column to target table
df_target_test['total_score']=df_target_test.sum(axis=1)
# add the factor into component score
df_target_test['total_score']=df_target_test['total_score']*2
# reset index
df_target_test=df_target_test.reindex()
# add the mean score column from the target table to the model table
df_model_test=df_model_test.merge(df_target_test['total_score'], how='left', on=['per
df_model_test.head()
```

```
Out[31]:   performance_id  base_value1  base_value2  base_value3  base_value4  \
        0      187be2a42e         9.60         9.57         6.49          6.0
```

```
1     18d403622f         8.60         6.90          6.40           6.0
2     1ba3d7fa7d        10.30         9.02          6.93           5.3
3     2178d0174d         7.48         6.60          6.27           6.0
4     2f7f38af84        10.30        10.01          8.36           5.3

   base_value5  base_value6  base_value7  base_value8  base_value9  ...  \
0         5.83         5.61          3.9         3.63          3.5  ...
1         3.63         3.50          3.3         2.30          2.0  ...
2         4.84         4.62          3.9         3.50          3.5  ...
3         5.10         4.73          3.9         3.50          3.2  ...
4         5.10         4.84          3.9         3.63          3.5  ...

   goe_actual6  goe_actual7  goe_actual8  goe_actual9  goe_actual10  \
0     0.303030     0.512821     0.195592     0.325714      0.305714
1     0.142857     0.281818    -0.091304     0.450000      0.226316
2    -0.432900     0.282051     0.285714     0.285714      0.260606
3     0.042283     0.512821     0.142857     0.221875      0.333333
4     0.165289     0.384615     0.157025     0.245714      0.290625

   goe_actual11  goe_actual12  index  total_deductions  total_score
0      0.422222      0.900000    911               0.0        96.84
1      0.000000     -0.054545    649               1.0        70.58
2      0.370370      0.450000    758               0.0        78.66
3     -0.197628      0.900000   2839               0.0        92.84
4      0.555556      0.850000    836               0.0        89.06

[5 rows x 28 columns]
```

Note: In Olympic judging deductions are give a negative value, but are changed to positive here for modeling.

```
In [32]: # create test H2O frame and get prediction scores
         # convert pandas dataframe to h2o dataframe
         df_run_test=h2o.H2OFrame(df_model_test)
         # get prediction score
         preds=gbm.predict(test_data=df_run_test)
         preds=preds.as_data_frame()
         df_pred = pd.DataFrame({'Component Scores':df_model_test['total_score'],'Predicted':p
         # run validation testing
         print(df_pred)

         print('The correlation between the score sets is {}%.'.format(df_pred['Component Score
```

```
/Users/kyleknoebel/anaconda3/lib/python3.6/site-packages/h2o/utils/shared_utils.py:170: FutureW
  data = _handle_python_lists(python_obj.as_matrix().tolist(), -1)[1]


Parse progress: || 100%
gbm prediction progress: || 100%
```

```
    Component Scores  Predicted
0              96.84  93.805343
1              70.58  69.795704
2              78.66  79.039260
3              92.84  76.064862
4              89.06  87.150092
5              67.92  72.419833
6              62.58  70.911117
7              94.56  90.538968
8              83.00  73.582030
9              93.78  88.457166
10             77.20  69.434511
11             85.14  81.344987
12             69.98  75.178098
13             63.80  57.447962
14             84.14  75.164228
15             93.78  89.145040
16             80.20  74.985662
17             73.50  69.587161
18             63.00  63.710294
19             85.34  80.932442
20             67.44  70.257192
21             77.56  73.293745
22             64.26  68.713547
23             94.56  81.158198
24             65.16  62.464346
25             78.44  74.794764
26             80.12  76.653299
27             71.00  71.834602
28             70.74  77.180499
The correlation between the score sets is 0.860830329501855%.
```

4 3) Summary

Any competition which relies on human judgement to score individuals is susceptible to cognitive bias. Figure skating is no exception, even with a reformed judging system there is the opportunity for bias to affect the outcome. This report illustrates that there is **statistical evidence that the attributes of technical elements have an effect on the components scores of professional figure skating.**

One possible source of bias is the focusing effect. The focusing effect is the tendency to place too much emphasis on one aspect of an event. When the model is tested on just the GOE and base value scores, we can see the focusing effect in more detail. It seems the judges are focused on the highest valued element in a performance, and the degree of difficulty of the lowest valued element, no matter what type of element is performed. This focus on the greatest and least valued elements of the performance has a direct correlation to the final component score.

Since the componenet score is considered the most subjective of the judged categories, it is surprising to find the technical elements have such a large effect on this portion of the performance. Judges have to score numerous competitors throughout a competition. For example, there are 30 skaters in the Olympic ladies long program, each with at least 12 elements. It seems natural that judges would take mental 'shortcuts' to process this information, and using the element score as a basis for the component score could be one of these shortcuts.

5 Appendices

5.1 Appendix A

```
In [ ]: from IPython.display import IFrame
        IFrame("http://www.isuresults.com/seminars/AbbreviationsElements_2014_15.pdf", width=90
```

5.2 Appendix B - Scale of Values (SOV)

```
In [ ]: from IPython.display import IFrame
        IFrame("http://www.usfsa.org/content/2018-19%20SP%20Scale%20of%20Values.pdf", width=900
```