data-vis-report

March 8, 2018

1 White Swan AS Data Analysis Report

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Theme: Data validation and visual analysis

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This report contains an exploratory analysis of the different datasets available to this study.

```
In [22]: import numpy as np
        import pandas as pd
        from matplotlib import pyplot as plt
        import seaborn as sns
        sns.set()
        %matplotlib inline
```

1.0.1 Load all datasets

```
In [23]: basmi_df = pd.read_excel('.../data/clean_basmi.xls', index_col=(0,1))
    basmi_df['Drug'].replace(np.nan,'None', inplace=True)

normed_bs_df = pd.read_excel('.../data/bs_normed_full.xls', index_col=0)
    agg_bs_df = pd.read_excel('.../data/bs_normed_agg.xls', index_col=0, header=[0,1])

# Demographics Data
demo_df = pd.read_excel('.../data/demographics and Biologics data.xlsx')
```

1.1 Preview the datasets

View the first 5 rows for each dataset

1.1.1 BASMI data

```
In [17]: basmi_df.head()
```

```
Out[17]:
                               CRS
                                   TWS LSFS LFS IMS
                                                          BS Drug
        patient_id Date
        40
                   1995-05-09
                                 3
                                                 5
                                                      3 3.6
                                      1
                                            6
                                                             None
                   1995-06-01
                                 3
                                      1
                                            8
                                                 5
                                                      3 4.0
                                                             None
                                 2
                                            5
                                                 3
                                                      2 2.6 None
                   1995-06-12
                                      1
                                                      2 2.2 None
                   1995-11-02
                                 1
                                            3
                                                 4
                                                 3
                                                      2 2.4 None
                   1996-05-02
```

1.1.2 BS Score with Normalized timeline

In [18]: normed_bs_df.head()

Out[18]:		BS	norm_years
	<pre>patient_id</pre>		
	40	2.96	0
	40	3.00	1
	40	3.20	2
	40	3.10	3
	40	3.40	4

1.1.3 Normalized timeline - Aggregated per year in study (norm_years)

In [19]: agg_bs_df.head()

Out [19]:		BS		count
		mean	std	len
	norm_years			
	0	3.40	1.98	910
	1	3.32	1.99	766
	2	3.39	1.99	738
	3	3.42	2.00	716
	4	3.47	2.02	696

1.1.4 Demographics Data

In [20]: demo_df.head()

Out[20]:	<pre>patient_id</pre>	patient_gende	r_id pa	atient_date_of_diagnosis	Age at di	agnosis	\
0	40	Fe	male	1994-01-01	46	. 255989	
1	41		Male	2003-01-01	46	.644764	
2	43		Male	1978-01-01	20	.410678	
3	44		Male	1994-01-01	22	.047912	
4	45		Male	1998-01-01	37	.048597	
	patient_hla_	bUnknown7_id	EIBP	patient_condition_subtype	Current	biologic	\
0		Positive	False	AS	In	fliximab	
1		Positive	False	AS	Ad	alimumab	
2		Positive	False	AS	Ad	alimumab	
3		Unknown	False	AS	Ad	alimumab	

4 Positive False AS Etanercept Number of biologics used (not including brand/biosimilar switch) \ 0 1 1 2 1 3 1 4 1 year of Birth 0 1947 1956 1 2 1957 3 1971

1.2 Age Distribution

1960

4

Show what the age distribution is for the patients' "Age at diagnosis". This will give us an idea of what age do patients enter the study

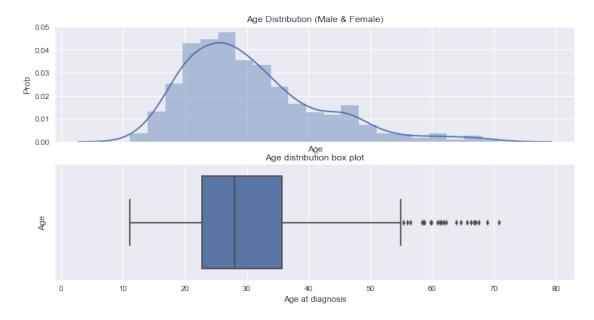
Process:

First, remove patients from demographics data that we do not have BASMI data for and remove patients with any missing data.

Then, plot the age distribution for males and females and afterwards split the process for both genders

```
In [12]: # Patients in BASMI dataset
         basmi_patient_ids = set(basmi_df.index.get_level_values('patient_id').unique().values)
         # Patients in Demographics dataset
         demo_patient_ids = set(demo_df['patient_id'].unique())
         # Patients in BOTH datasets
         overlap_patient_ids = basmi_patient_ids.intersection(demo_patient_ids)
         # Keep only overlapping patient data
         demo_df = demo_df[demo_df['patient_id'].isin(list(overlap_patient_ids))]
         # Remove the rows with missing values
         demo_df.dropna(how='any',inplace=True)
         # Overall distribution Plot
         age_at_entry = demo_df['Age at diagnosis']
         fig, ax_1 = plt.subplots(nrows=2, ncols=1, figsize=(12,6), sharex=True)
         sns.distplot(age_at_entry, ax=ax_1[0])
         ax_1[0].set_title('Age Distribution (Male & Female)')
         ax_1[0].set_xlabel('Age')
```

```
ax_1[0].set_ylabel('Prob')
sns.boxplot(age_at_entry, ax=ax_1[1])
ax_1[1].set_title('Age distribution box plot')
ax_1[1].set_ylabel('Age')
plt.show()
print('Descriptive stats for age at entry:')
print(age_at_entry.describe())
```



Descriptive stats for age at entry:

663.000000 count mean 30.526917 10.833736 std min 11.156742 25% 22.737851 50% 28.106776 75% 35.712526 70.904860 max

Name: Age at diagnosis, dtype: float64

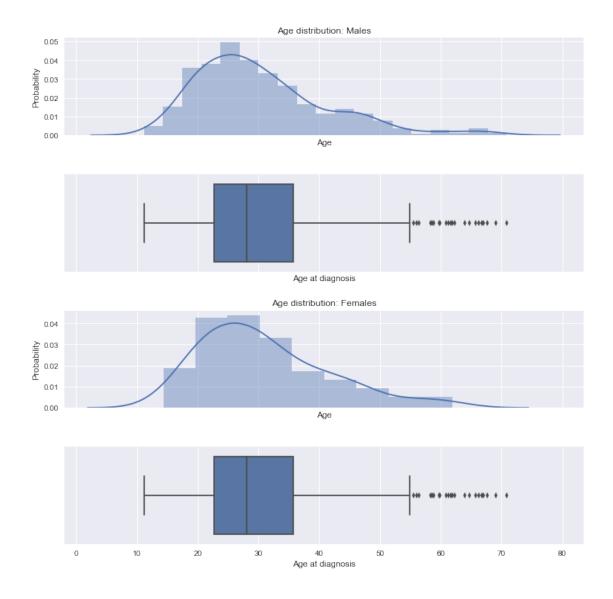
It is observed that the age distribution is slightly positively skewed.

Furthermore, the modal age at entry is approximately 25 years. This is younger than expected (by me at least).

1.2.1 Age distribution by gender

Split the process up for males and females

```
In [21]: genders = demo_df['patient_gender_id']
         # Get male and female index
         male_ids = demo_df[genders == 'Male']['patient_id']
         female_ids = demo_df[genders == 'Female']['patient_id']
         # Get demographics about males and females
         male_demo_df = demo_df[demo_df['patient_id'].isin(male_ids)]
         female_demo_df = demo_df[demo_df['patient_id'].isin(female_ids)]
         # Plot age at entry distribution for males and females
         age_at_entry_male = male_demo_df['Age at diagnosis'].values
         age_at_entry_female = female_demo_df['Age at diagnosis'].values
         fig, ax_2 = plt.subplots(nrows=4,ncols=1,sharex=True, figsize=(12,12))
         plt.subplots_adjust(hspace=0.4)
         sns.distplot(age_at_entry_male, ax = ax_2[0])
         ax_2[0].set_title('Age distribution: Males')
         ax_2[0].set_xlabel('Age')
         ax_2[0].set_ylabel('Probability')
         sns.boxplot(age_at_entry, ax=ax_2[1])
         sns.distplot(age_at_entry_female, ax = ax_2[2] )
         ax_2[2].set_title('Age distribution: Females')
         ax_2[2].set_xlabel('Age')
         ax_2[2].set_ylabel('Probability')
         sns.boxplot(age_at_entry, ax=ax_2[3])
         plt.show()
```



It is seen that the shape of the two histograms are similar. Hence, there is not a massive difference between the age at entry of males and females. Notice that females are diagnosed at an earlier stage than males, although this is only a marginal difference.

2 BS Score Over Time

Now we look at how the BS score progresses over time for the average patient.

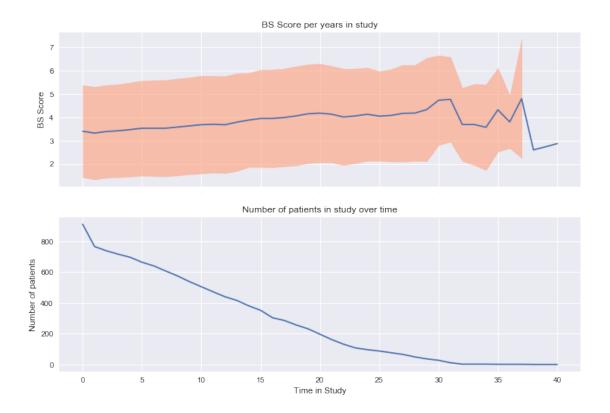
A more complete analysis can be found in the bs-over-time.ipynb notebook.

To do this, we first *normalized* the patient timelines so that the year in which the patient entered the study is set to 0 and the next year is 1 and so forth. Then the *average* BS score is calculated for each year in the study as well as the number of patients that were included in the study for that many years.

For example, if patient A started in May 1998 and patient B started in June 2007 then the BS score of patient A in 1998 will be averaged with the BS score of patient B in 2007 for the year 0 in graph below, as 1998 and 2007 were the respective "0th" year in the study.

If either patient had more than 1 measurement in their first year in the study, these measurements are averaged for that year to attain a single score per year in study, per patient.

```
In [26]: std_bs = agg_bs_df['BS', 'std']
         mean_bs = agg_bs_df['BS', 'mean']
         num_patients = agg_bs_df['count','len']
         def plot_bs_over_time(mean_bs, std_bs, num_patients,title=''):
             fig = plt.figure(figsize=(12,8))
             ax1 = plt.subplot(211)
             plt.plot(mean_bs)
             plt.fill_between(mean_bs.index, y1=mean_bs+std_bs, y2=mean_bs-std_bs, color='lights
             plt.setp(ax1.get_xticklabels(), fontsize=0)
             plt.title(title)
             ax1.set_ylabel('BS Score')
             ax2 = plt.subplot(212, sharex=ax1)
             plt.plot(num_patients)
             plt.title('Number of patients in study over time')
             ax2.set_xlabel('Time in Study')
             ax2.set_ylabel('Number of patients')
             plt.show()
         plot_bs_over_time(mean_bs, std_bs, num_patients, title='BS Score per years in study')
         print(f'Number of patients in study at year 0 vs year 30 = {num_patients.loc[30]} / {num_patients.loc[30]}
```



Number of patients in study at year 0 vs year 30 = 28 / 910

Interpretation Firstly, we can observe a approximately linear increase in BS score as time in study increases, while the number of patients in study also decreases approximately linearly. These observations are in line with what we expected.

Secondly, we can see that at around the 30 year mark there are very few patients in the study (28 vs 910 at start), which shows corresponding erratic measurements

We can see a high variability in the average BS score per year in study. This could be motivated by the fact that we are taking an average over patients that are in different phases of disease progression. For example, patient A might join the study with a BS score of 2 and patient B might join with a BS score of 4.2 - vastly different stages in disease progression, but both will be considered in the calculation of the mean BS score for year-in-study = 0.

Also, at the last few datapoints we only have 1 patient in the study, and thus the standard deviation is not defined.

2.1 Repeat the above analysis for both males and females

The first step is to identify which patients are male and female.

```
In [27]: demo_df = pd.read_excel('../data/demographics and Biologics data.xlsx')
# Get patient ids of males and females
```

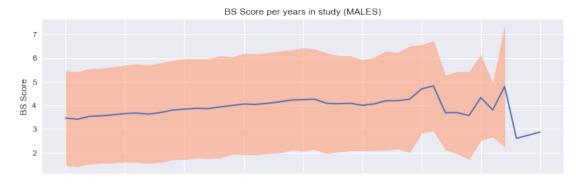
```
genders = demo_df['patient_gender_id'].values

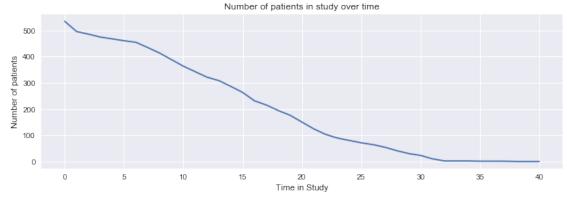
# Get male and female index
male_ids = demo_df[genders == 'Male']['patient_id']
female_ids = demo_df[genders == 'Female']['patient_id']

# # Get BS dataset of males and females
male_bs_df = normed_bs_df.loc[male_ids]
female_bs_df = normed_bs_df.loc[female_ids]
```

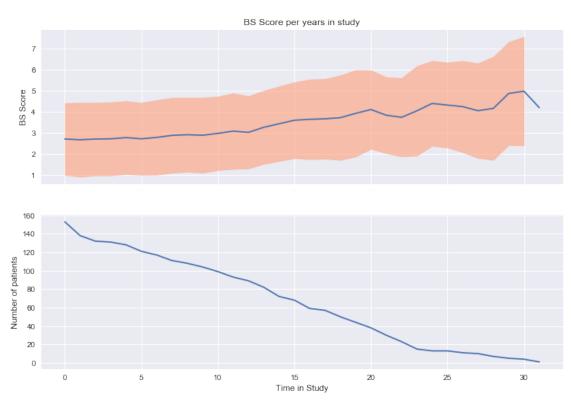
2.2 Plot BS score over time for males

plot_bs_over_time(mean_bs, std_bs, num_patients, title='BS Score per years in study (MA





2.3 Plot BS over time for females



2.4 Average duration of treatment (days)

What is the average duration spent by a patient on a specific drug or no medication at all?

```
for group, group_df in basmi_df.groupby(['Drug','patient_id']):
             start = min(group_df.index.get_level_values('Date'))
             end = max(group_df.index.get_level_values('Date'))
             days = pd.Timedelta(end-start).days
             drugs_days[group[0]].append(days)
         for drug,days in drugs_days.items():
             drugs_duration_df.loc[drug] = [np.mean(days), np.median(days),np.std(days), len(days)
         drugs_duration_df
Out[10]:
                            avg_days median_days std_dev_days count
         None
                             4355.49
                                             4026
                                                       3243.97
                                                                 907
         Infliximab
                                             3256
                                                       890.052
                                                                  12
                             3132.58
         Adalimumab
                                             1843
                                                       1155.04
                                                                  75
                              1763.2
                                           2677.5
                                                       1063.13
                                                                  50
         Etanercept
                             2489.46
         Certolizumab Pegol
                                  11
                                               11
                                                             0
                                                                   1
         Golimumab
                               405.5
                                              361
                                                       381.702
                                                                   8
         Rituximab
                                 1291
                                             1291
                                                           850
                                                                    2
```