Exploratory Analysis of NYC School's Math Results.

In [873…
```
import pandas as pd
import numpy as np
from scipy.stats import zscore
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
%matplotlib inline
```

Uploading all the required files that need to be explored:

- it is the important and first step to clean the data exhaustively in order to get the meaningful information & insights from it.
- Dataset is about the NYC School's Math Test Scores.

Objectives of EDA is following below:

- Uncover the structure and content of the dataset.
- Finding key variables from it.
- Detecting outliers and anomalies.
- Getting maximum insight from it.
- discovering pattern and trends.

First Step: Uploading the datasets.

In [105…
```
df = pd.read_excel('D:\\Data\\Profile Project\\NYC Math Test Results.xlsx', sheet_name='All_district_student')
df1 = pd.read_excel('D:\\Data\\Profile Project\\NYC Math Test Results.xlsx', sheet_name='2006_-_2012_ethnicity-dist.')
df2 = pd.read_excel('D:\\Data\\Profile Project\\NYC Math Test Results.xlsx', sheet_name='Ethnicity_Disttict')
df3 = pd.read_excel('D:\\Data\\Profile Project\\NYC Math Test Results.xlsx', sheet_name='2006-2012_Dist_allStud_math_res'
```

Second Step: Preparing and Cleaning the datasets for analysis:

- Handling missing data: df0.isnull().sum(), df0.dropna().
- Fixing Structural errors.
- Removing duplicate and irrelevant observations: df0.duplicated(), df0.drop_duplicates().
- Transforming the data.

These datasets are pre-cleaned, so some of the processes of data cleaning will not be performed.

Dataset Number One

In [105…
```
cols = ['District', 'Grade', 'Year', 'Dempgraphic', 'Number_Tested', 'Mean_Scale_Score', 'Proficient_Level_1', 'Level_1_%
df.columns=cols
df3.columns=cols
df0 = pd.concat([df,df3], axis=0, ignore_index=True)
df0 = df0.round(decimals=2)
```

In [105…
```
df0 = df0.drop(df0.index[df0['Grade']=='All Grades'])
df0 = df0.reset_index().drop(['index'], axis=1)
df0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2688 entries, 0 to 2687
Data columns (total 16 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   District                    2688 non-null   int64
 1   Grade                       2688 non-null   object
 2   Year                        2688 non-null   int64
 3   Dempgraphic                 2688 non-null   object
 4   Number_Tested               2688 non-null   int64
 5   Mean_Scale_Score            2688 non-null   float64
 6   Proficient_Level_1          2688 non-null   int64
 7   Level_1_%                   2688 non-null   float64
 8   Proficient_Level_2          2688 non-null   int64
 9   Level_2_%                   2688 non-null   float64
 10  Proficient_Level_3          2688 non-null   int64
 11  Level_3_%                   2688 non-null   float64
 12  Proficient_Level_4          2688 non-null   int64
 13  Level_4_%                   2688 non-null   float64
 14  Proficient_Level_3+level_4  2688 non-null   int64
 15  Level-3+4%                  2688 non-null   float64
dtypes: float64(6), int64(8), object(2)
memory usage: 336.1+ KB
```

In [105…
```
df0
```

Out[105…

	District	Grade	Year	Dempgraphic	Number_Tested	Mean_Scale_Score	Proficient_Level_1	Level_1_%	Proficient_Level_2	Level_2_%	Prof
0	1	3	2013	All Students	887	306.69	249	28.07	266	29.99	
1	1	3	2014	All Students	845	307.95	225	26.63	223	26.39	

	District	Grade	Year	Dempgraphic	Number_Tested	Mean_Scale_Score	Proficient_Level_1	Level_1_%	Proficient_Level_2	Level_2_%	Prof
2	1	3	2015	All Students	765	309.46	221	28.89	175	22.88	
3	1	3	2016	All Students	743	313.55	184	24.76	178	23.96	
4	1	3	2017	All Students	726	311.88	185	25.48	166	22.87	
...	...	...	...	...	...	...	...	...	...	...	
2683	32	8	2008	All Students	1517	650.00	202	13.30	528	34.80	
2684	32	8	2009	All Students	1590	662.00	106	6.70	406	25.50	
2685	32	8	2010	All Students	1600	662.00	314	19.60	698	43.60	
2686	32	8	2011	All Students	1541	664.00	215	14.00	708	45.90	
2687	32	8	2012	All Students	1295	666.00	184	14.20	564	43.60	

2688 rows × 16 columns

Third Step: Filtering and removing outliers.

There are several techniques for detecting outliers such as:

1. Sorting the data points.
2. Data Vizualization.
3. Statistical methods.

Interquartile Range method will be used in these datasets.

The Interquartile range method is used in this dataset.

In [106…

```
df_outlier = df0.astype({'District':'str', 'Year':'int', 'Grade':'str', 'Dempgraphic':'str'})
category = df_outlier.iloc[:, 0:4]
numeric=df_outlier.iloc[:,4:17]
Q1 = numeric.quantile(0.25)
Q3 = numeric.quantile(0.75)
IQR = Q3-Q1
print(IQR)
```

```
Number_Tested                1520.0000
Mean_Scale_Score              366.3300
Proficient_Level_1            462.0000
Level_1_%                      28.8950
Proficient_Level_2            485.2500
Level_2_%                      12.1400
Proficient_Level_3            645.5000
Level_3_%                      22.9725
Proficient_Level_4            522.2500
Level_4_%                      18.2825
Proficient_Level_3+level_4    1195.2500
Level-3+4%                     36.2000
dtype: float64
```

In [106…

```
# All the outliers in the dataset:
outliers = numeric[((numeric<(Q1-1.5*IQR)) | (numeric>(Q3+1.5*IQR)))]
outliers.count()
```

Out[106…

```
Number_Tested                  0
Mean_Scale_Score               0
Proficient_Level_1           107
Level_1_%                      0
Proficient_Level_2            39
Level_2_%                     23
Proficient_Level_3            73
Level_3_%                      0
Proficient_Level_4            33
Level_4_%                     33
Proficient_Level_3+level_4    18
Level-3+4%                     0
dtype: int64
```

In [106…

```
print(outliers.max())
print(outliers.min())
```

```
Number_Tested                  NaN
Mean_Scale_Score               NaN
Proficient_Level_1          2298.0
Level_1_%                      NaN
Proficient_Level_2          1885.0
Level_2_%                     53.5
Proficient_Level_3          2913.0
Level_3_%                      NaN
Proficient_Level_4          1842.0
Level_4_%                     72.0
Proficient_Level_3+level_4  4207.0
Level-3+4%                     NaN
dtype: float64
Number_Tested                  NaN
Mean_Scale_Score               NaN
```

```
Proficient_Level_1            1318.00
Level_1_%                         NaN
Proficient_Level_2            1549.00
Level_2_%                        0.60
Proficient_Level_3            1911.00
Level_3_%                         NaN
Proficient_Level_4            1425.00
Level_4_%                       54.04
Proficient_Level_3+level_4    3441.00
Level-3+4%                        NaN
dtype: float64
```

In [106…

```
# Removing outliers from dataset
outlier = numeric[~((numeric<(Q1-1.5*IQR)) | (numeric>(Q3+1.5*IQR)))]
outlier.count()
```

Out[106…

```
Number_Tested                 2688
Mean_Scale_Score              2688
Proficient_Level_1            2581
Level_1_%                     2688
Proficient_Level_2            2649
Level_2_%                     2665
Proficient_Level_3            2615
Level_3_%                     2688
Proficient_Level_4            2655
Level_4_%                     2655
Proficient_Level_3+level_4    2670
Level-3+4%                    2688
dtype: int64
```

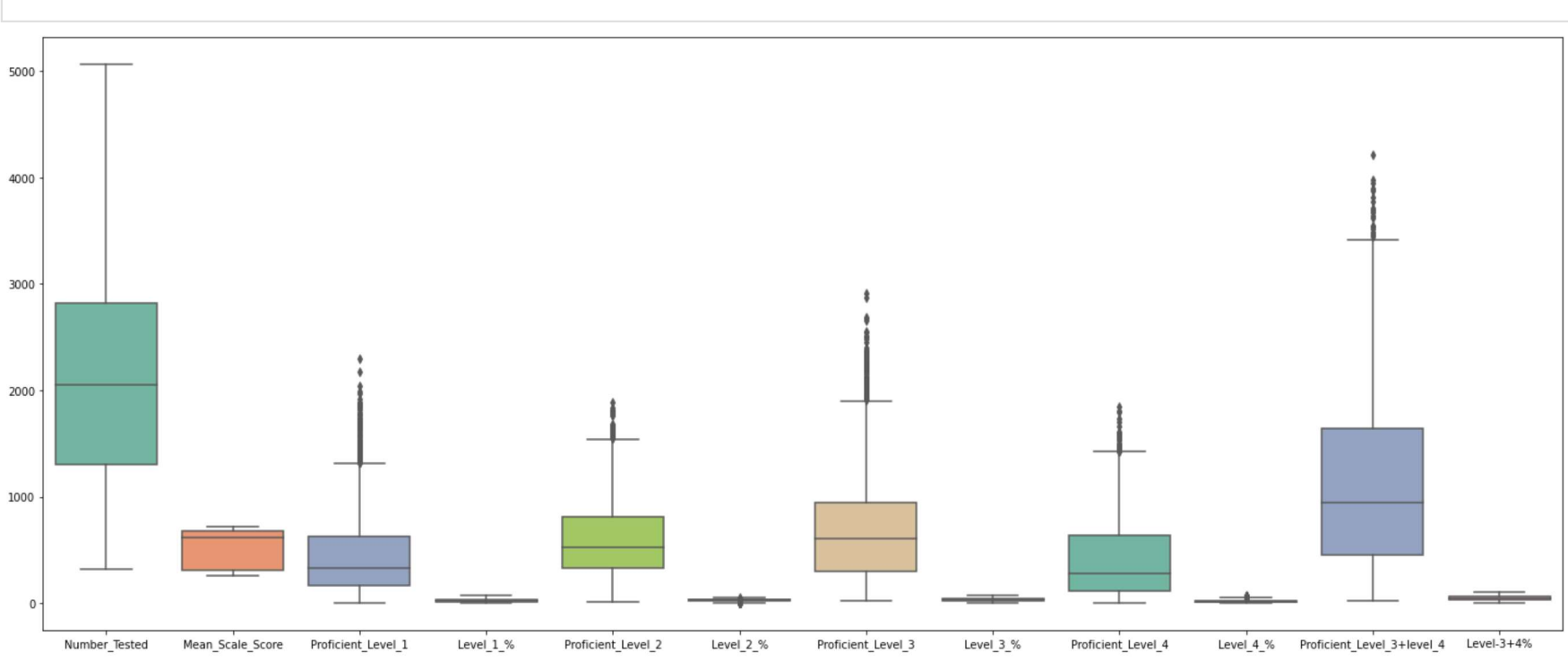
In [106…

```
print(outlier.max())
print(outlier.min())
```

```
Number_Tested                 5061.00
Mean_Scale_Score               723.00
Proficient_Level_1            1317.00
Level_1_%                       71.67
Proficient_Level_2            1538.00
Level_2_%                       53.10
Proficient_Level_3            1900.00
Level_3_%                       72.70
Proficient_Level_4            1422.00
Level_4_%                       53.53
Proficient_Level_3+level_4    3413.00
Level-3+4%                      99.30
dtype: float64
Number_Tested                 322.00
Mean_Scale_Score              262.20
Proficient_Level_1              1.00
Level_1_%                       0.10
Proficient_Level_2             11.00
Level_2_%                       4.60
Proficient_Level_3             19.00
Level_3_%                       3.46
Proficient_Level_4              1.00
Level_4_%                       0.16
Proficient_Level_3+level_4     24.00
Level-3+4%                      3.76
dtype: float64
```

In [106…

```
plt.figure(figsize=(25,10))
sns.boxplot(data=numeric, palette="Set2");
```

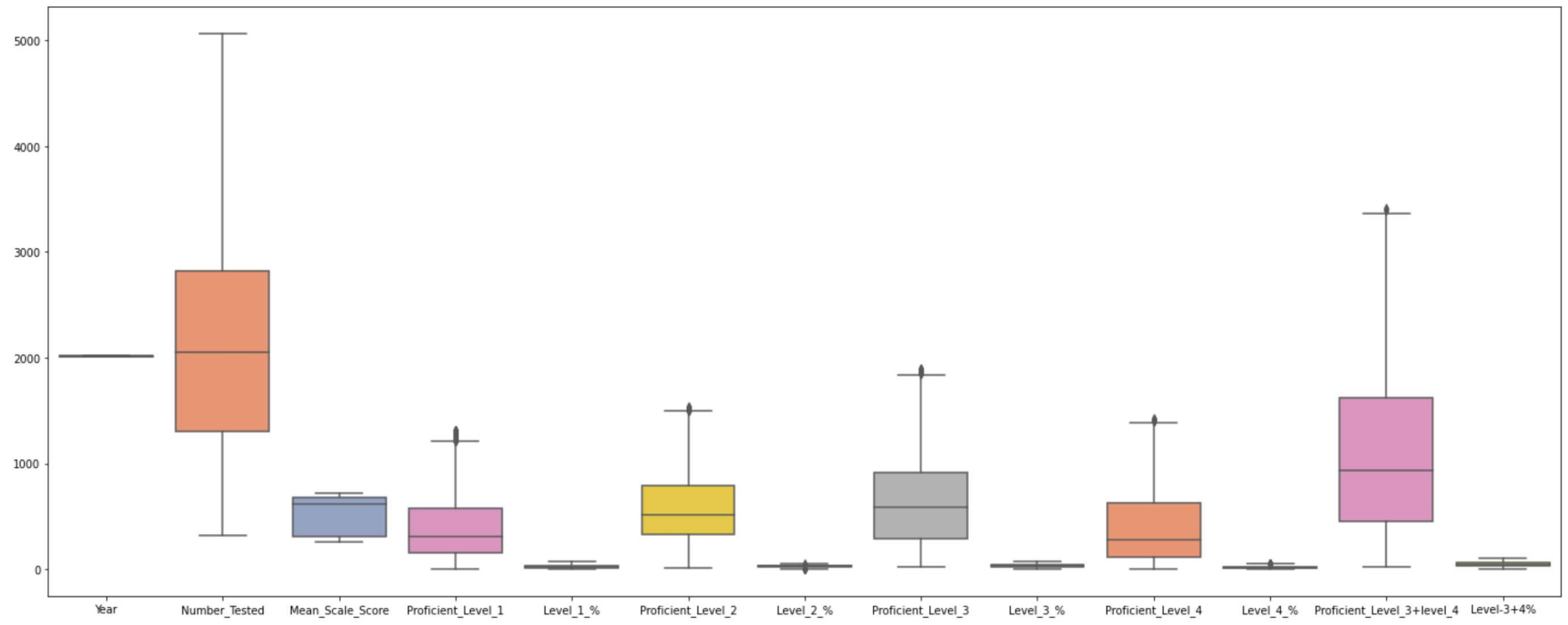


In [106…

```
outlier_removed_data = pd.concat([category, outlier], axis=1)
```

In [106…

```
plt.figure(figsize=(25,10))
sns.boxplot(data=outlier_removed_data, palette="Set2");
```



Dataset Number Two

Similar procedures have been performed on this dataset as in the previous dataset.

In [106…
```
df1.columns = cols
df2.columns=cols
df7 = pd.concat([df1, df2], axis=0, ignore_index=True)
```

In [106…
```
df7 = df7.drop(df7.index[df7['Grade']=='All Grades'])
df7 = df7.reset_index().drop(['index'], axis=1)
df7 = df7.replace('s',0)
df7 = df7.round(decimals=2)
```

In [107…
```
df7 = df7.drop(df7.index[df7['Mean_Scale_Score']==0])
df7.reset_index()
df7.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10608 entries, 0 to 10751
Data columns (total 16 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   District                    10608 non-null  int64
 1   Grade                       10608 non-null  int64
 2   Year                        10608 non-null  int64
 3   Dempgraphic                 10608 non-null  object
 4   Number_Tested               10608 non-null  int64
 5   Mean_Scale_Score            10608 non-null  float64
 6   Proficient_Level_1          10608 non-null  int64
 7   Level_1_%                   10608 non-null  float64
 8   Proficient_Level_2          10608 non-null  int64
 9   Level_2_%                   10608 non-null  float64
 10  Proficient_Level_3          10608 non-null  int64
 11  Level_3_%                   10608 non-null  float64
 12  Proficient_Level_4          10608 non-null  int64
 13  Level_4_%                   10608 non-null  float64
 14  Proficient_Level_3+level_4  10608 non-null  int64
 15  Level-3+4%                  10608 non-null  float64
dtypes: float64(6), int64(9), object(1)
memory usage: 1.4+ MB
```

In [107…
```
df7
```

Out[107…

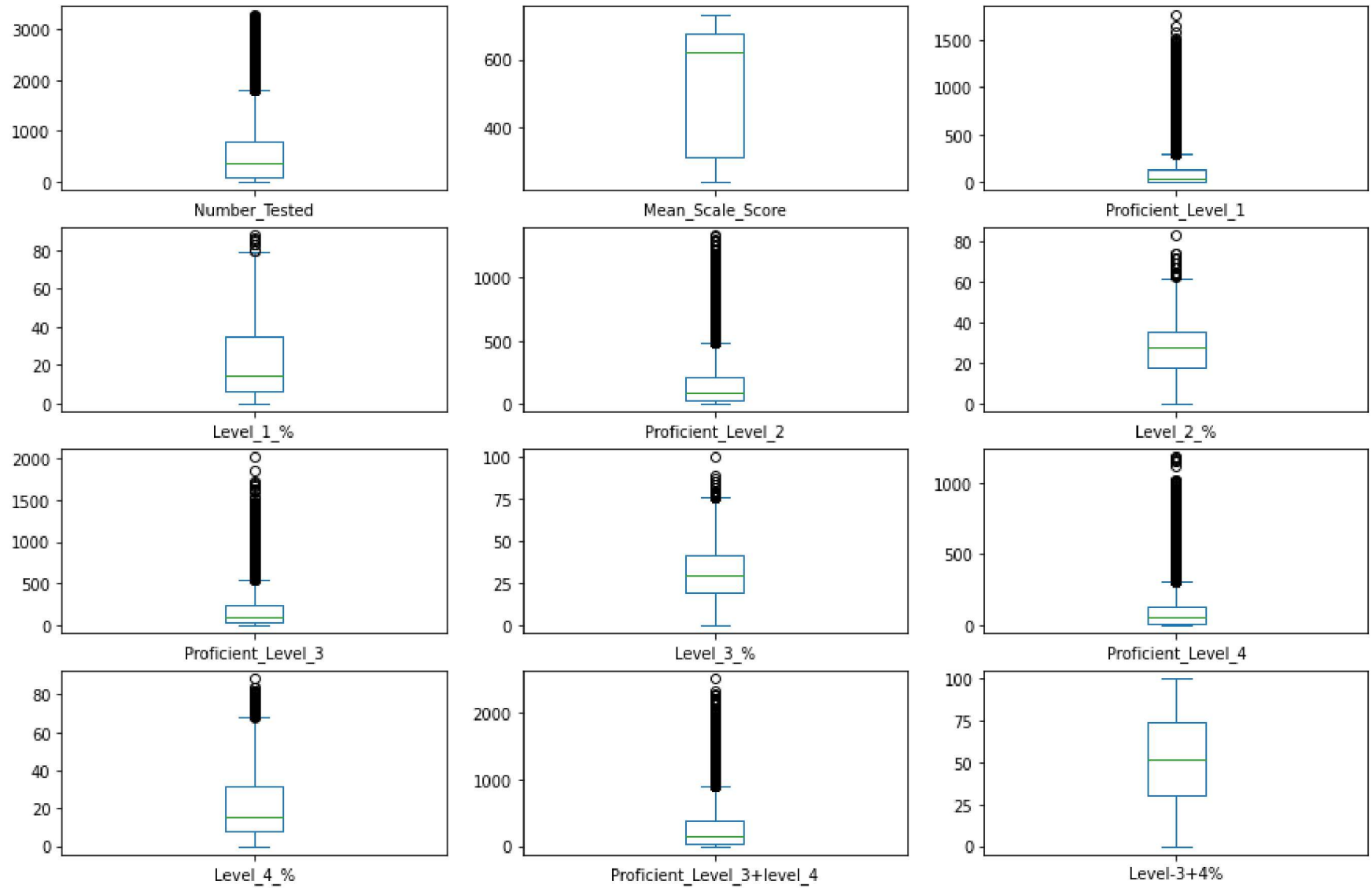
	District	Grade	Year	Dempgraphic	Number_Tested	Mean_Scale_Score	Proficient_Level_1	Level_1_%	Proficient_Level_2	Level_2_%	Pro
0	1	3	2006	Asian	155	704.00	4	2.60	4	2.60	
1	1	3	2006	Black	185	659.00	21	11.40	47	25.40	
2	1	3	2006	Hispanic	494	664.00	46	9.30	111	22.50	
3	1	3	2006	White	94	702.00	1	1.10	5	5.30	
4	1	3	2007	Asian	131	703.00	2	1.50	4	3.10	
...	...	...	...	...	...	...	...	...	...	...	
10747	32	8	2015	White	30	285.57	14	46.67	13	43.33	
10748	32	8	2016	White	12	286.75	6	50.00	4	33.33	
10749	32	8	2017	White	13	279.15	7	53.85	4	30.77	
10750	32	8	2018	White	17	603.35	5	29.41	5	29.41	
10751	32	8	2019	White	13	591.92	5	38.46	5	38.46	

10608 rows × 16 columns

In [107…
```
categorical = df7.iloc[:, 0:4]
numerical = df7.iloc[:, 4:17]
```

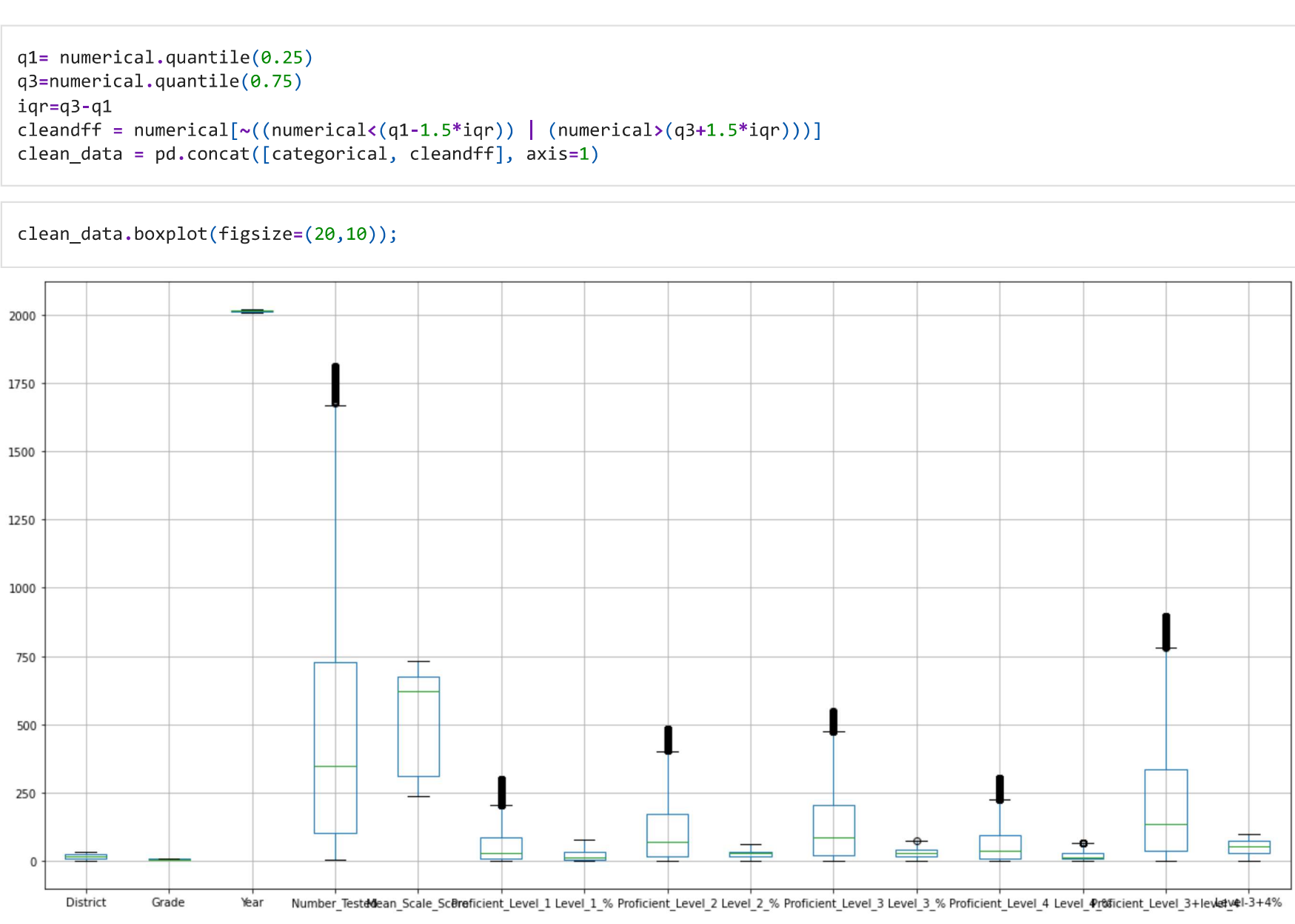
In [107…
```
numerical.plot(kind="box", subplots=True, layout=(4,3), figsize=(15,10))
```

Out[107…
```
Number_Tested                    AxesSubplot(0.125,0.71587;0.227941x0.16413)
Mean_Scale_Score                AxesSubplot(0.398529,0.71587;0.227941x0.16413)
Proficient_Level_1              AxesSubplot(0.672059,0.71587;0.227941x0.16413)
Level_1_%                         AxesSubplot(0.125,0.518913;0.227941x0.16413)
Proficient_Level_2              AxesSubplot(0.398529,0.518913;0.227941x0.16413)
Level_2_%                       AxesSubplot(0.672059,0.518913;0.227941x0.16413)
Proficient_Level_3                AxesSubplot(0.125,0.321957;0.227941x0.16413)
Level_3_%                       AxesSubplot(0.398529,0.321957;0.227941x0.16413)
Proficient_Level_4              AxesSubplot(0.672059,0.321957;0.227941x0.16413)
Level_4_%                           AxesSubplot(0.125,0.125;0.227941x0.16413)
Proficient_Level_3+level_4        AxesSubplot(0.398529,0.125;0.227941x0.16413)
Level-3+4%                        AxesSubplot(0.672059,0.125;0.227941x0.16413)
dtype: object
```



In [107…
```
q1= numerical.quantile(0.25)
q3=numerical.quantile(0.75)
iqr=q3-q1
cleandff = numerical[~((numerical<(q1-1.5*iqr)) | (numerical>(q3+1.5*iqr)))]
clean_data = pd.concat([categorical, cleandff], axis=1)
```

In [107…
```
clean_data.boxplot(figsize=(20,10));
```



NOTE - Some data poins are still reflecting as a outlier in the plots in both datasets. But these data points are valid observations and these are validating other variables in the datasets. That's why, these haven't been discarded.

Now both the datasets are cleaned.

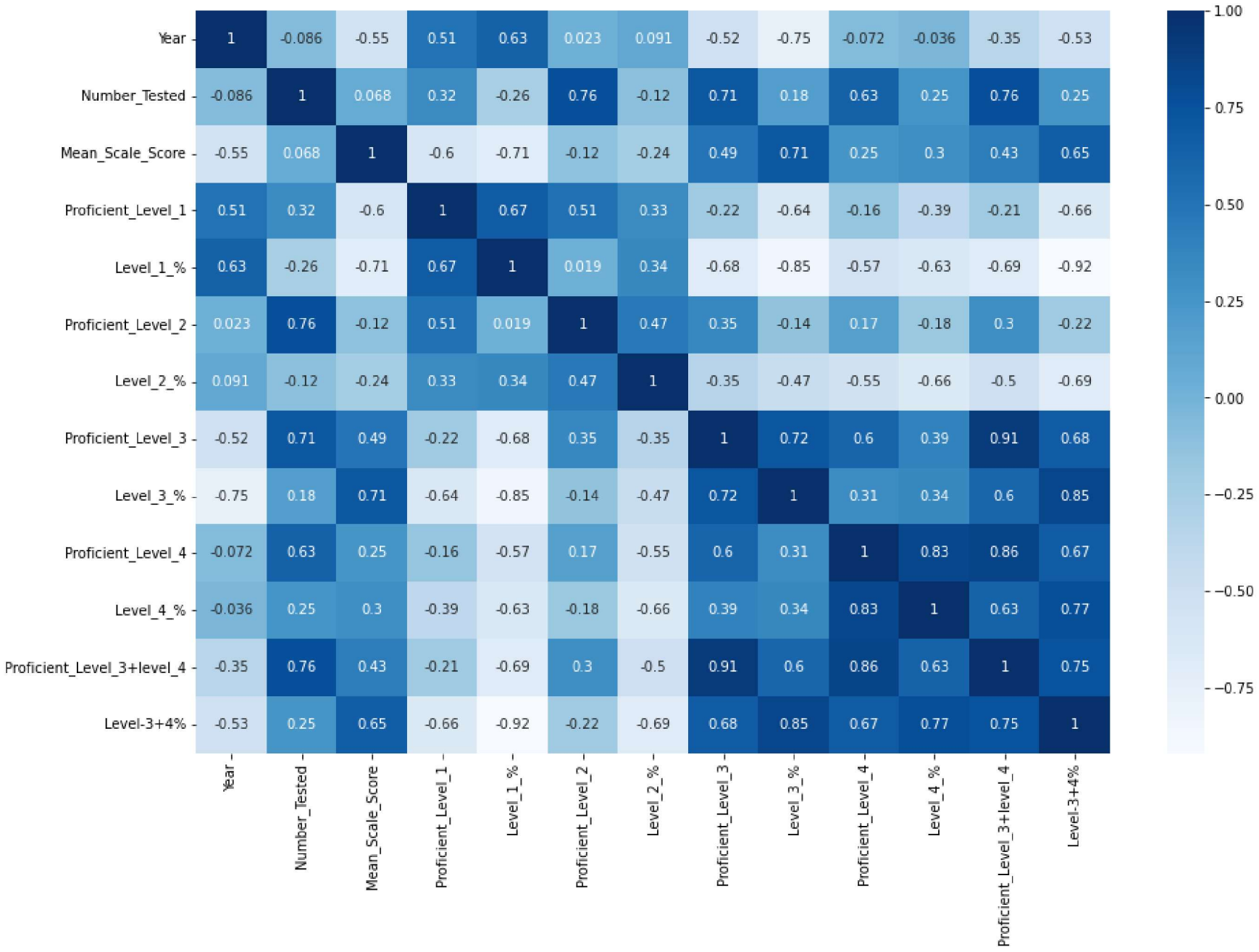
Next step is QA and validate the datasets.

1. Does the data make sense?
2. Does it prove or disprove your theory and expected outcomes.
3. Can you find the trends and patterns in the data that can help you unleash the insights or develop a new theory upon it.
4. if not, what is the issue?
5. is it because of data quality or in other respects.

This can be achieved by asking analytical queries and data visualization.

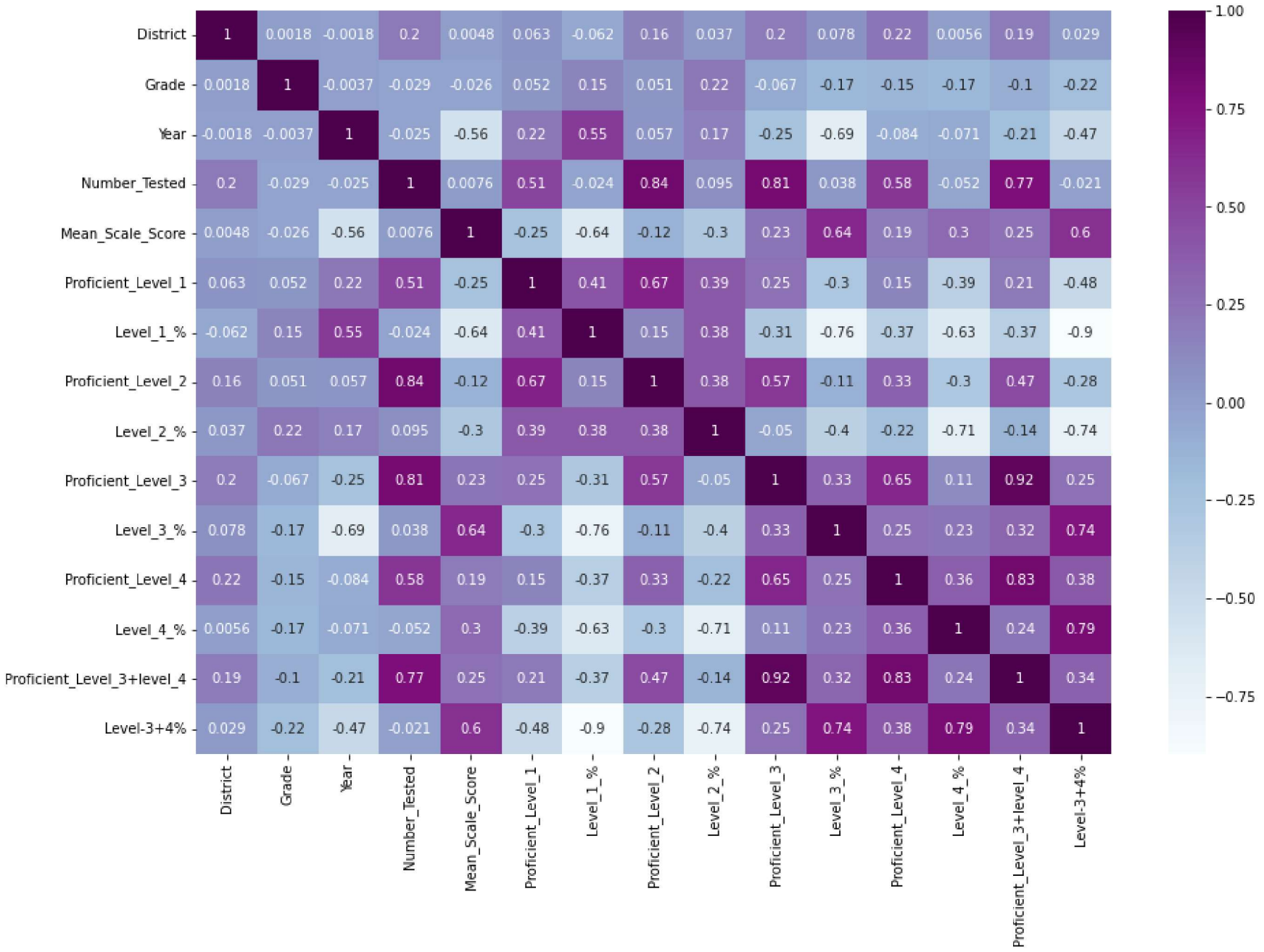
In [107…

```
# Correlation tool can find the positive and negative relation between the variables.
plt.figure(figsize=(15,10))
sns.heatmap(outlier_removed_data.corr(),cbar=True,annot=True,cmap='Blues');
```



In [107…

```
plt.figure(figsize=(15,10))
sns.heatmap(clean_data.corr(),cbar=True,annot=True,cmap='BuPu');
```



In [107…

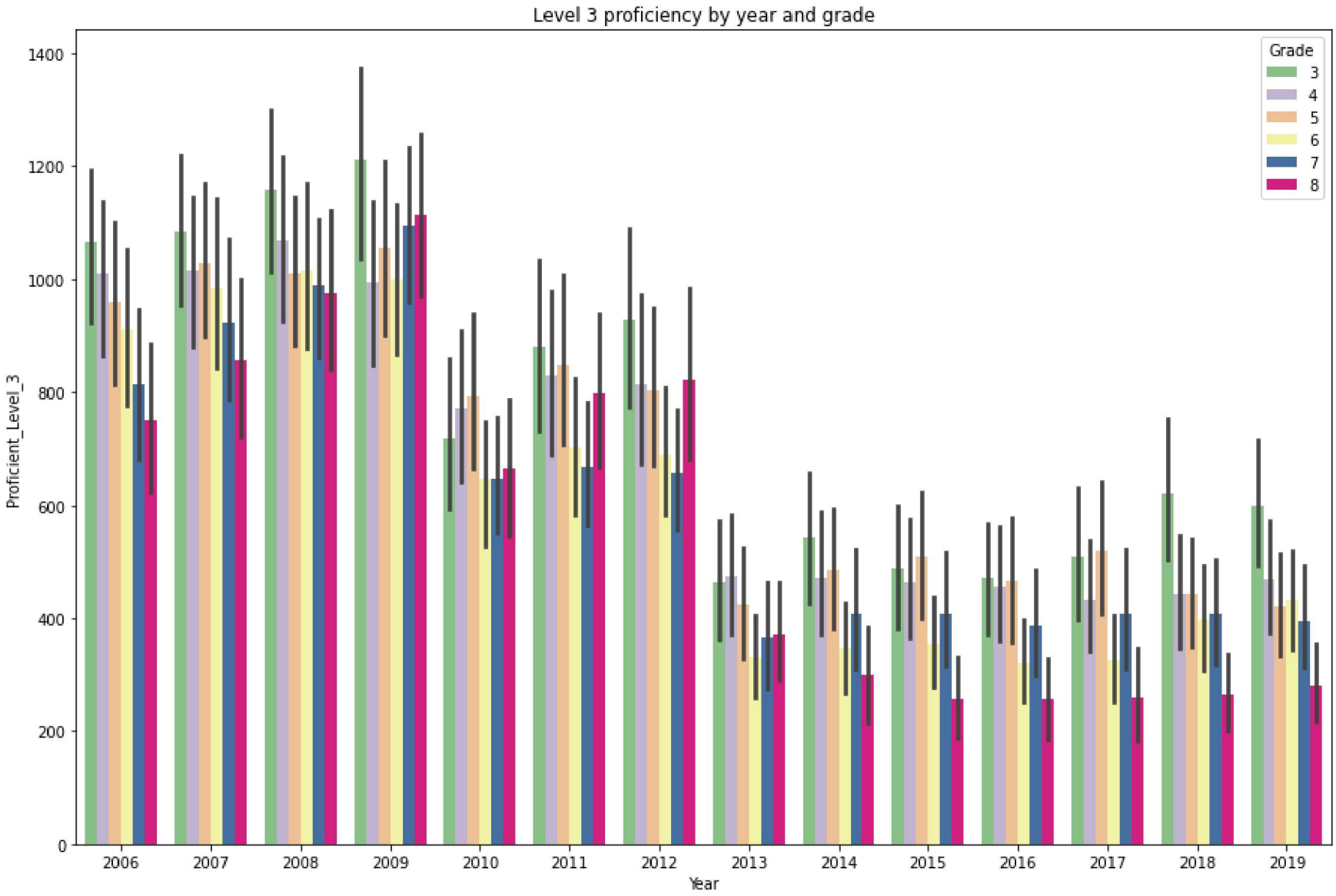
```
# Can create comparison, relationship and correlation charts to extract the insight from the data.
outlier_removed_data.head(2)
```

Out[107…

	District	Grade	Year	Dempgraphic	Number_Tested	Mean_Scale_Score	Proficient_Level_1	Level_1_%	Proficient_Level_2	Level_2_%	Proficie
0	1	3	2013	All Students	887	306.69	249.0	28.07	266.0	29.99	
1	1	3	2014	All Students	845	307.95	225.0	26.63	223.0	26.39	

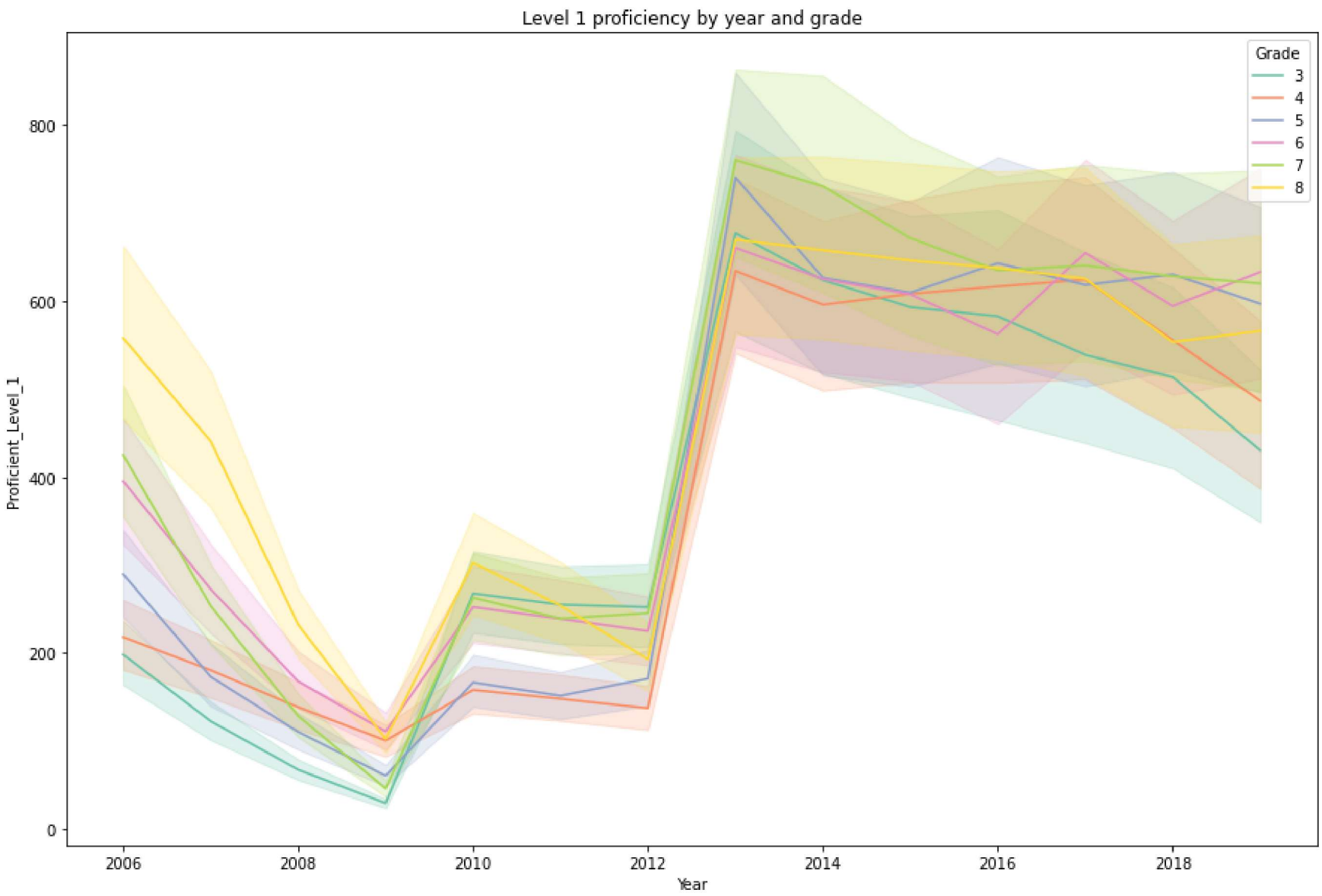
In [110…

```
plt.figure(figsize=(15,10))
sns.barplot(data=outlier_removed_data, x='Year', y='Proficient_Level_3', hue='Grade', palette="Accent")
plt.title('Level 3 proficiency by year and grade')
plt.show()
```



In [108…

```
plt.figure(figsize=(15,10))
sns.lineplot(data=outlier_removed_data, x='Year', y='Proficient_Level_1', hue='Grade', palette="Set2")
plt.title('Level 1 proficiency by year and grade')
plt.show()
```

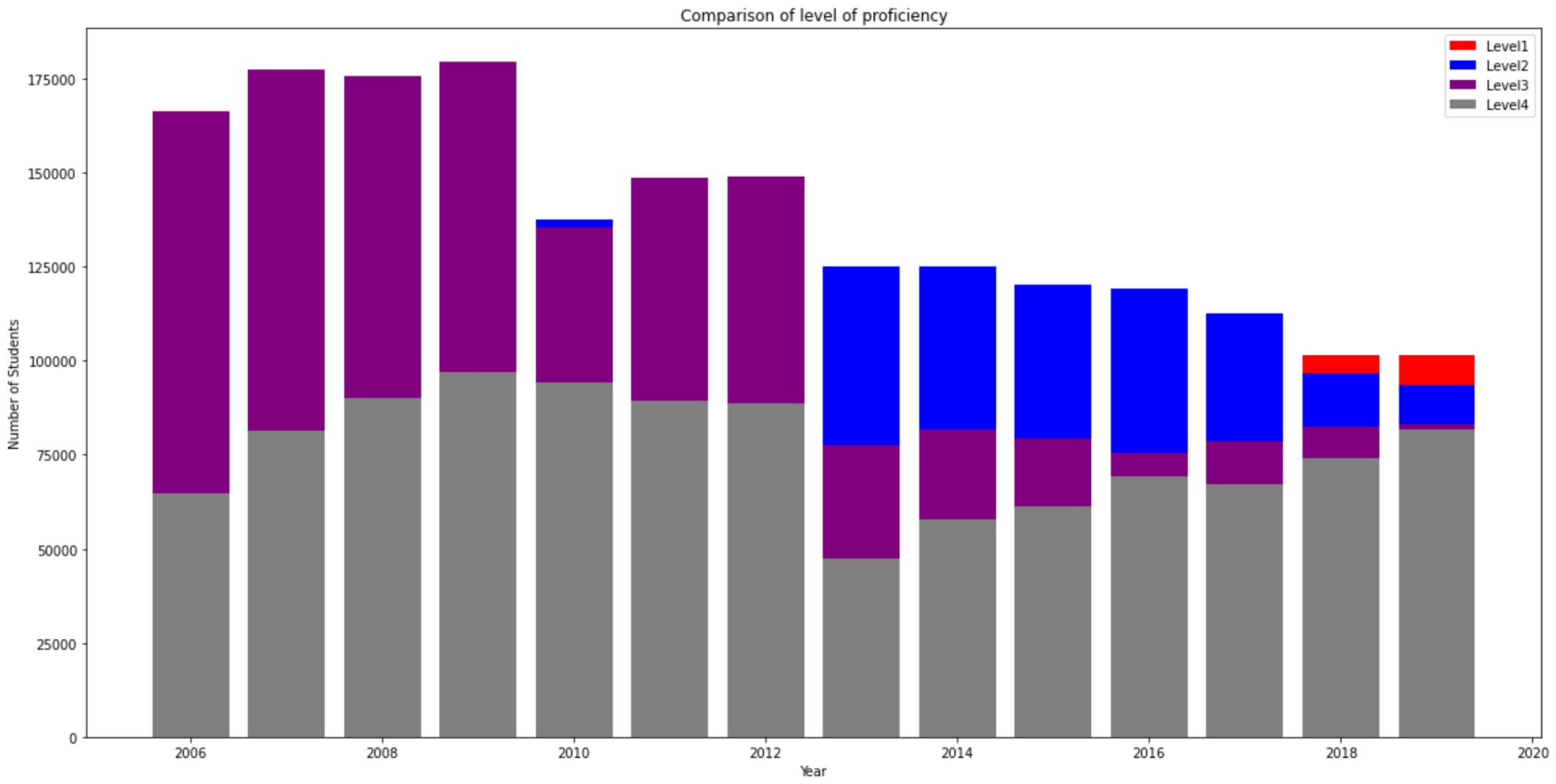


In [108…

```
grouped=outlier_removed_data.groupby('Year').sum()
```

In [110…

```
plt.figure(figsize=(20,10))
plt.bar(grouped.index, grouped.Proficient_Level_1, label='Level1', color='red')
plt.bar(grouped.index, grouped.Proficient_Level_2, label='Level2', color='blue')
plt.bar(grouped.index, grouped.Proficient_Level_3, label='Level3', color='purple')
plt.bar(grouped.index, grouped.Proficient_Level_4, label='Level4', color='grey')
plt.xlabel('Year')
plt.ylabel('Number of Students')
plt.title('Comparison of level of proficiency')
plt.legend()
plt.show()
```



In [108…

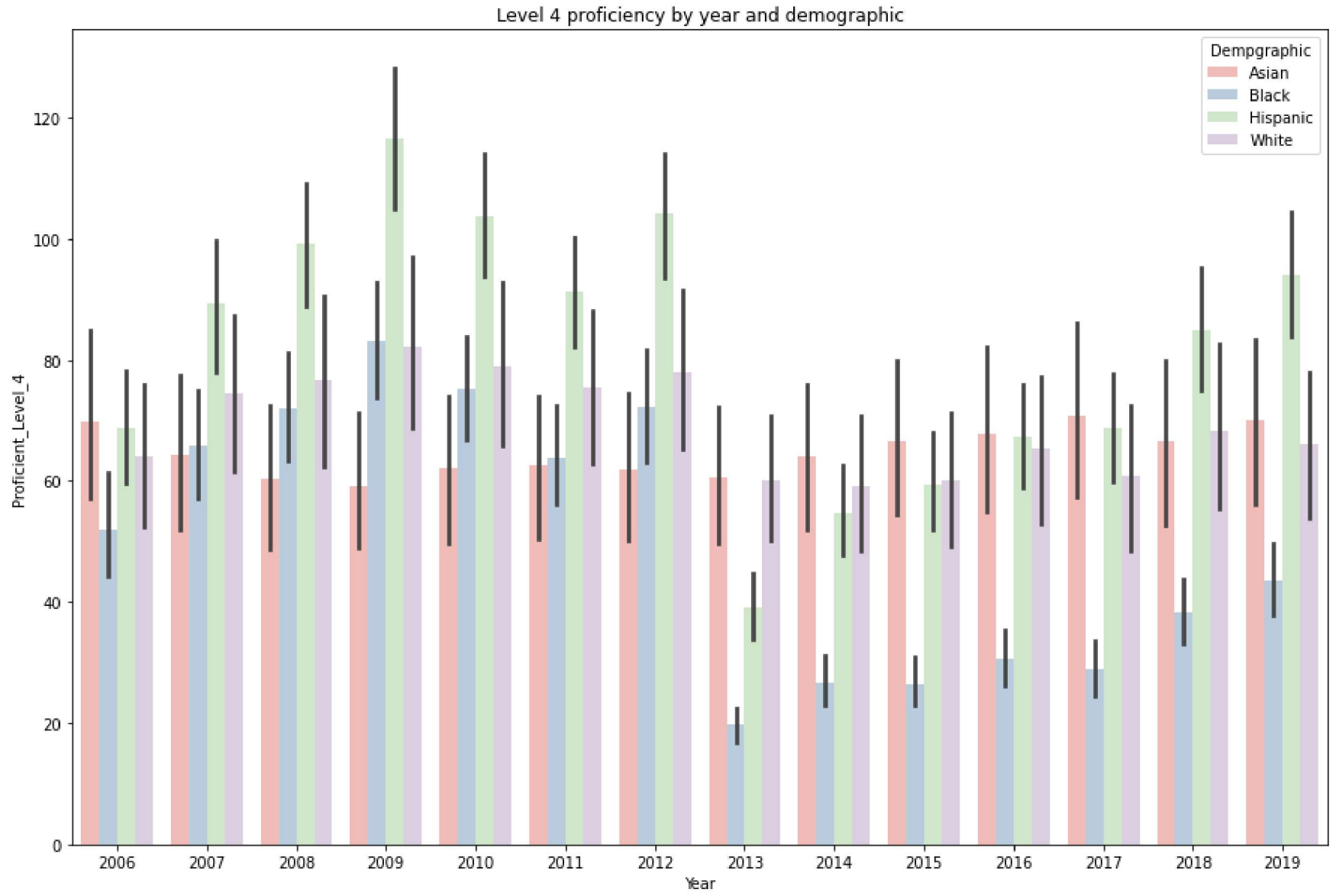
```
clean_data['Grade'].astype('str')
clean_data.head(2)
```

Out[108…

	District	Grade	Year	Dempgraphic	Number_Tested	Mean_Scale_Score	Proficient_Level_1	Level_1_%	Proficient_Level_2	Level_2_%	Proficie
0	1	3	2006	Asian	155.0	704.0	4.0	2.6	4.0	2.6	
1	1	3	2006	Black	185.0	659.0	21.0	11.4	47.0	25.4	

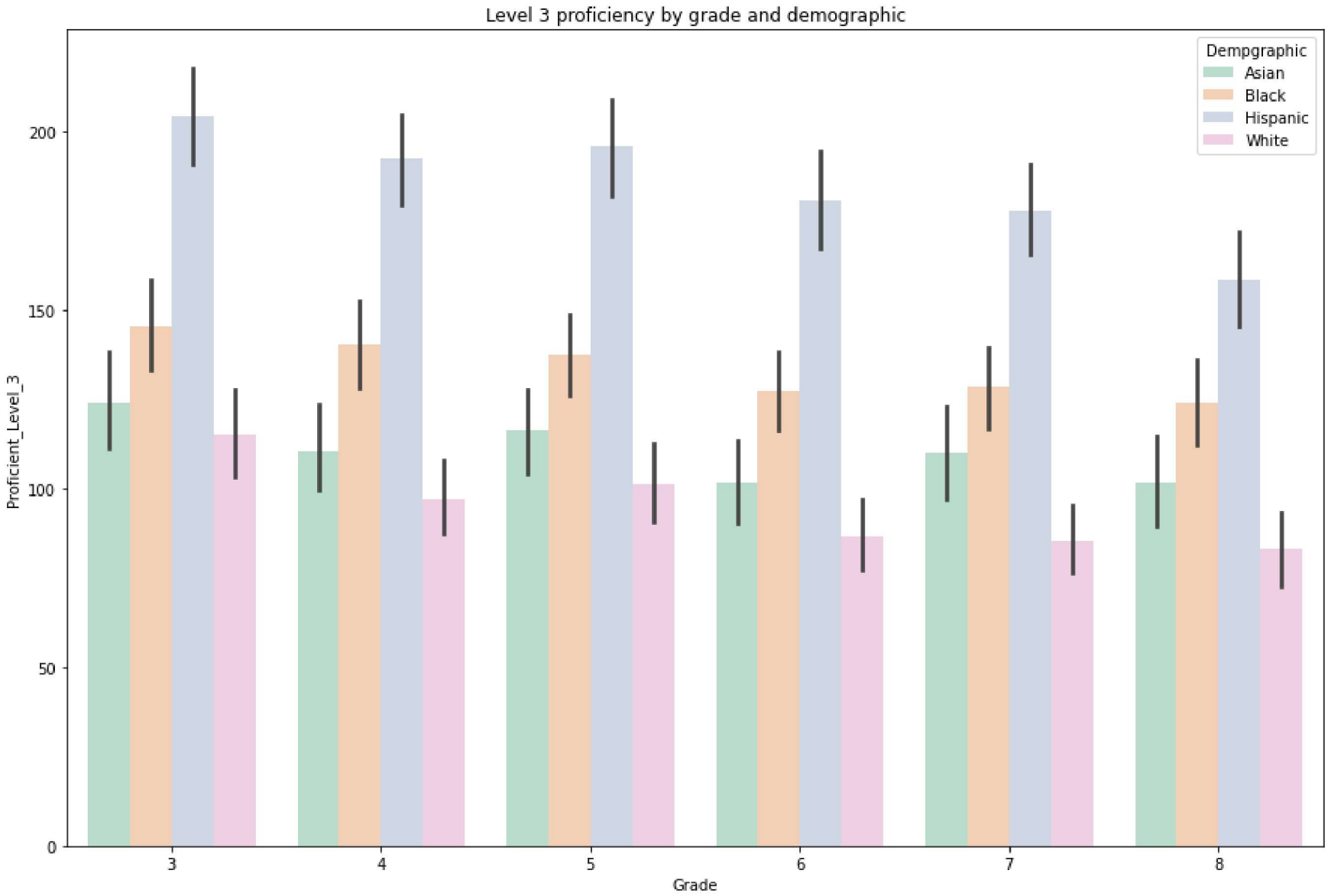
In [110…

```
plt.figure(figsize=(15,10))
sns.barplot(data=clean_data, x='Year', y='Proficient_Level_4', hue='Dempgraphic', palette="Pastel1")
plt.title('Level 4 proficiency by year and demographic')
plt.show()
```



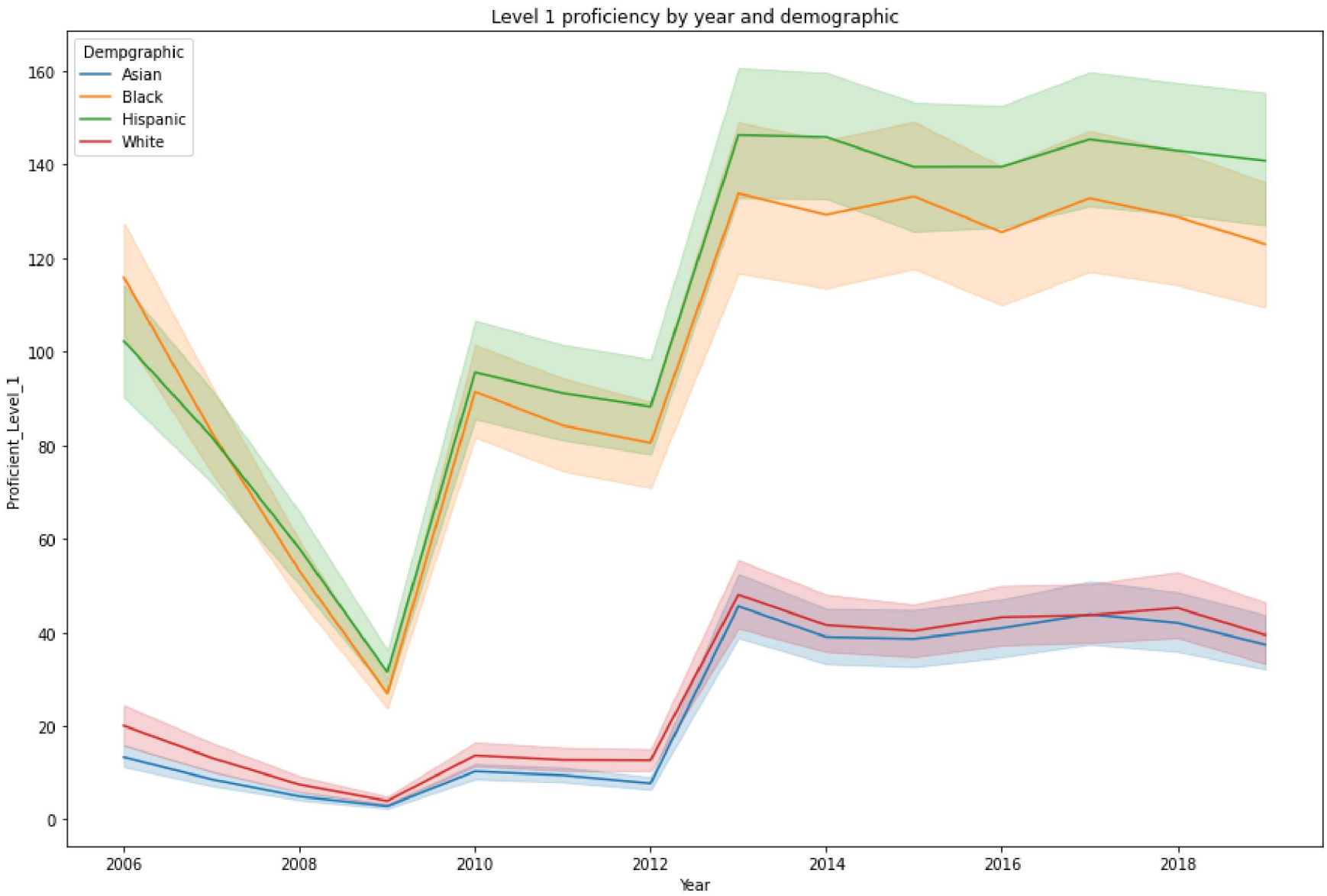
In [111…

```
plt.figure(figsize=(15,10))
sns.barplot(data=clean_data, x='Grade', y='Proficient_Level_3', hue='Dempgraphic', palette="Pastel2")
plt.title('Level 3 proficiency by grade and demographic')
plt.show()
```



In [108…

```
plt.figure(figsize=(15,10))
sns.lineplot(data=clean_data, x='Year', y='Proficient_Level_1', hue='Dempgraphic')
plt.title('Level 1 proficiency by year and demographic')
plt.show()
```



These datasets are ready for further analysis.

In [ ]: