Basic EDA

Get score level analytics on Numerical Variables available

In [40]:
```
import matplotlib.pyplot as plt
import seaborn as sns
# Sometimes we want to see more than a single output in the cell below command enables
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity="all"
```

In [41]:
```
from lightgbm import LGBMRegressor
```

In [42]:
```
import warnings
warnings.filterwarnings("ignore")
```

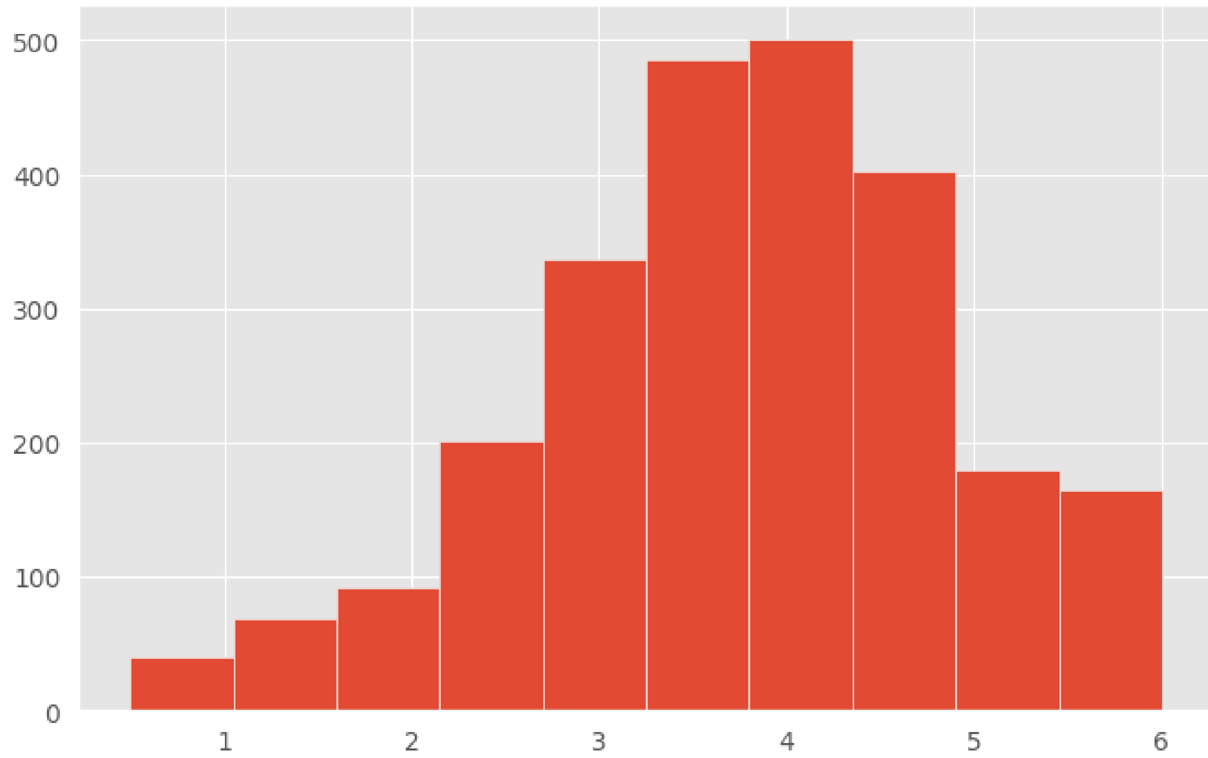
In [43]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/cat-dict/cat_dict
/kaggle/input/linking-writing-processes-to-writing-quality/sample_submission.csv
/kaggle/input/linking-writing-processes-to-writing-quality/test_logs.csv
/kaggle/input/linking-writing-processes-to-writing-quality/train_scores.csv
/kaggle/input/linking-writing-processes-to-writing-quality/train_logs.csv
```

In [44]:
```
train = pd.read_csv("/kaggle/input/linking-writing-processes-to-writing-quality/train_
test = pd.read_csv("/kaggle/input/linking-writing-processes-to-writing-quality/test_lo
train_scores = pd.read_csv("/kaggle/input/linking-writing-processes-to-writing-quality
sample_submission = pd.read_csv("/kaggle/input/linking-writing-processes-to-writing-qu
```

In [45]:
```
train_scores.score.hist()
plt.show();
```



In [46]:
```
train['id'] = train['id'].astype(str)
train_scores['id'] = train_scores['id'].astype(str)
```

In [47]:
```
# Add the score
train=train.merge(train_scores,left_on ="id",right_on="id",how="left")
```

Averages on Action time

In [48]:
```
# See average word count and action time corresponding to scores
train.groupby("score").agg({"action_time":"mean",
                                  "word_count":(max,min,"mean"),
                                   "event_id":"mean"
                           })
```

Out[48]:

	action_time			word_count	event_id
	mean	max	min	mean	mean
score					
0.5	108.179308	313	0	114.293968	802.570756
1.0	105.574167	451	0	136.023399	1206.570358
1.5	95.382315	568	0	143.304741	1259.687360
2.0	98.456583	855	0	131.562149	1161.031217
2.5	99.696969	847	0	150.510128	1380.885537
3.0	101.614095	887	0	160.319410	1519.664800
3.5	99.468483	1071	0	194.954310	1741.764347
4.0	99.711023	1247	0	223.114869	2032.933342
4.5	95.665620	1141	0	258.940124	2308.972109
5.0	94.237049	1186	0	292.785950	2600.685248
5.5	96.717079	1326	0	341.192093	2940.417711
6.0	95.085620	1233	0	370.985322	3027.016845

- Average word count is higher in higher scores but the above metric is actually the average of "word count after every event"
- Average number of events also increase with score...
- Action time average above is the mean of the action time after every event
- So low action time accompanied by higher word count/ number of events corresponds to a good score
- But these are not exact metrics at ID level, we will need to create a dataframe at ID level taking mean, min, max of event_id , action_time , word_count

In [49]:

```
# to build the legend as it is not appearing with the normal command
import matplotlib.patches as mpatches
from matplotlib.lines import Line2D
import matplotlib.ticker
```

Average Word Count& Events

In [50]:

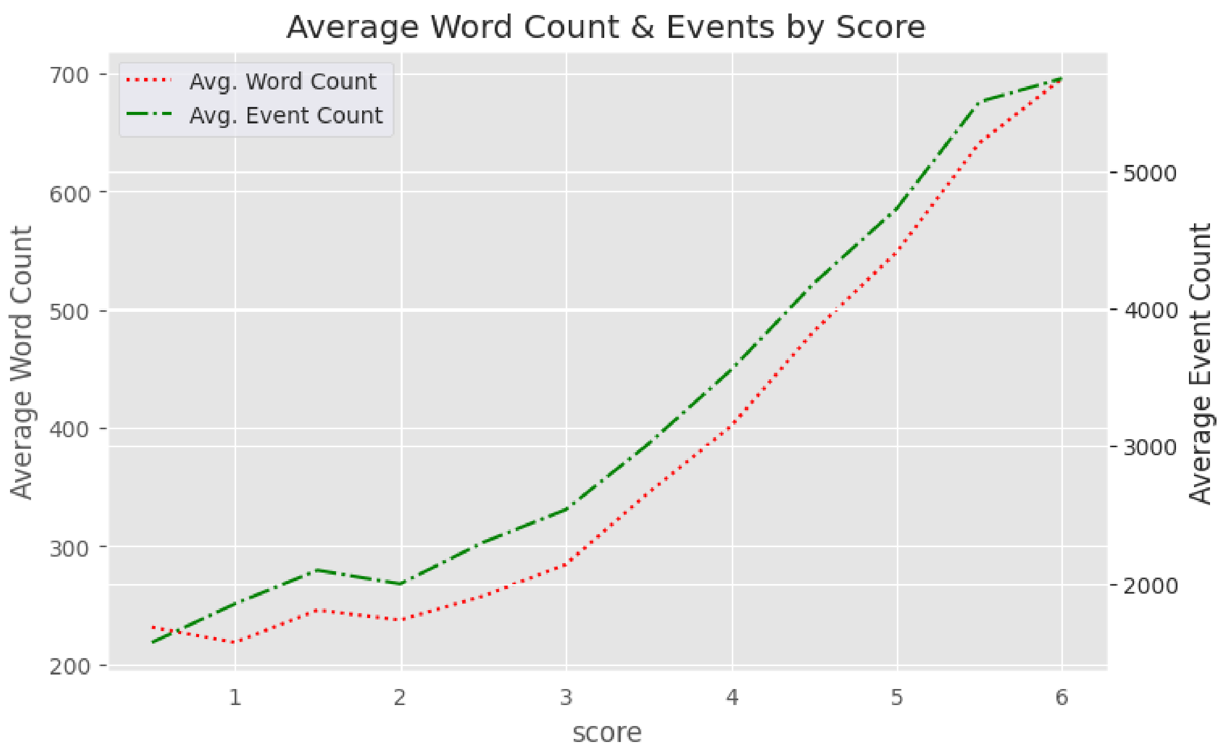
```
# let's get avg of word count in the essays corresponding to each score
# and the max events that an essay has
# We are taking max for event and word count because we want to see the total events t
# and average word count of writers in each score level
essay=train.groupby("id").agg({"action_time":"mean",
                                 "word_count":max,
                                  "event_id":max,
                                   "score":max})

# Display the score wise word counts from each ID
```

```
# this enables us to view what was the word count level at a use
lineplot =essay.groupby("score").agg({"action_time":"mean",
                                  "word_count":("mean"),
                                   "event_id":("mean")
                            })

lineplot

fig,ax= plt.subplots()
sns.set_style('darkgrid')
plt.rcParams["figure.figsize"]=(8,5)
#sns.lineplot(data=lineplot,x="score",y="action_time",ax=ax)
sns.lineplot(data=lineplot,x="score",y="word_count",ax=ax,color="red",linestyle="dotte
plt.ylabel("Average Word Count")
ax2=ax.twinx()
sns.lineplot(data=lineplot,x="score",y="event_id",ax=ax2,color="green",linestyle="-.")
plt.ylabel("Average Event Count")
plt.title("Average Word Count & Events by Score")
red_patch=Line2D([0],[0],color="red",label="Avg. Word Count",linestyle="dotted")
green_patch=Line2D([0],[0],color="green",label="Avg. Event Count",linestyle="-.")
plt.legend(handles=[red_patch,green_patch],loc="upper left")
plt.show();
```



In [51]:

```
lineplot
```

Out[51]:

	action_time	word_count	event_id
score			
0.5	105.367020	231.400000	1571.600000
1.0	101.907062	218.457143	1852.371429
1.5	97.733989	245.855072	2097.289855
2.0	100.038292	237.510870	1997.923913
2.5	100.669885	257.701493	2298.995025
3.0	101.860359	284.449405	2537.883929
3.5	101.193658	345.119342	3015.973251
4.0	101.707980	401.532934	3554.778443
4.5	96.978518	481.843284	4184.850746
5.0	96.116819	548.698324	4727.731844
5.5	98.462551	641.101562	5504.703125
6.0	95.934151	695.702703	5675.000000

Takeaway

So we can confirm that people who write longer worded essays score higher They have more events as a reason but the action time between their events is low

In [52]:

```
# Add most common actions in eachs core band, % of events that happen for a
train.head()
```

Out[52]:

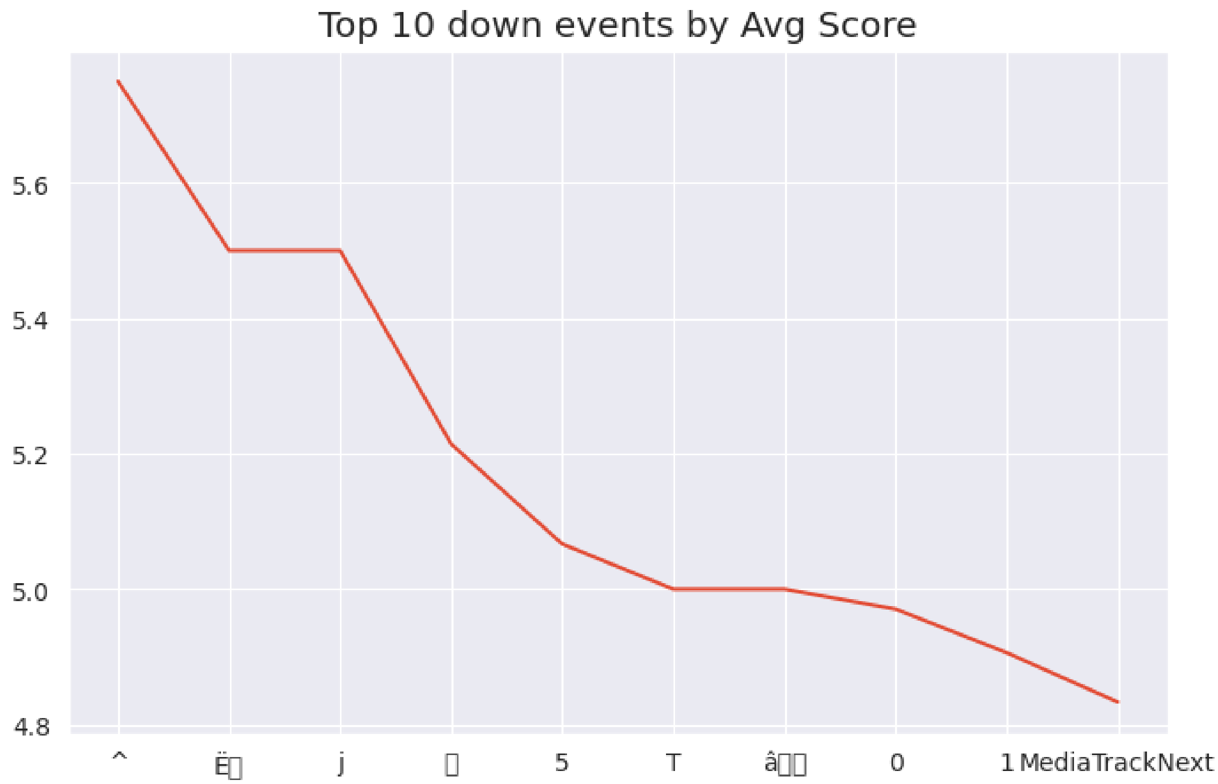
	id	event_id	down_time	up_time	action_time	activity	down_event	up_event	text_
0	001519c8	1	4526	4557	31	Nonproduction	Leftclick	Leftclick	No
1	001519c8	2	4558	4962	404	Nonproduction	Leftclick	Leftclick	No
2	001519c8	3	106571	106571	0	Nonproduction	Shift	Shift	No
3	001519c8	4	106686	106777	91	Input	q	q	
4	001519c8	5	107196	107323	127	Input	q	q	

In [53]:

```
# What events correspond to high scores
# lets compute
# Avg Score per down event and up event
# In each score bin what are 10 most occuring upevents and down events
# In each score band what is the ditribtuin of activities Non production , input , rep
```

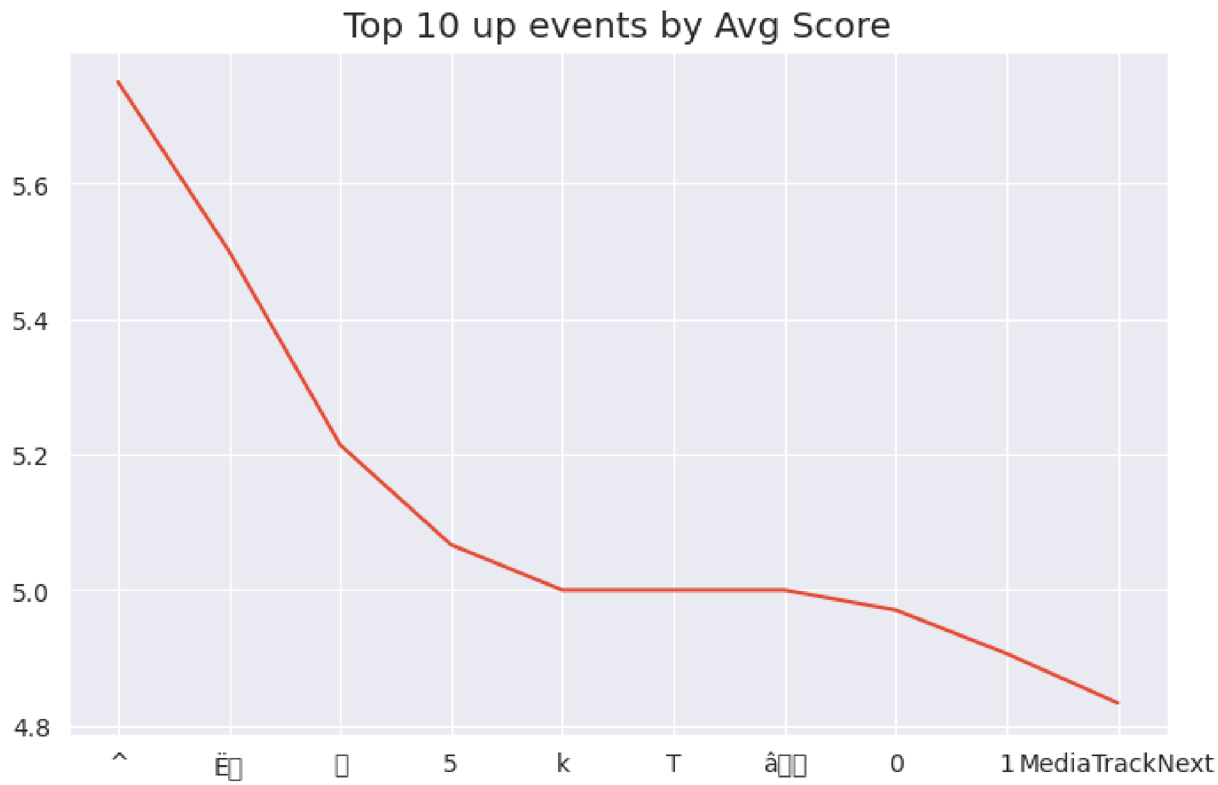
Avg Score vs Down Event

In [54]:
```
plt.plot(train.groupby("down_event").agg({'score':"mean"}).sort_values("score",ascendi
plt.title("Top 10 down events by Avg Score")
plt.show();
```



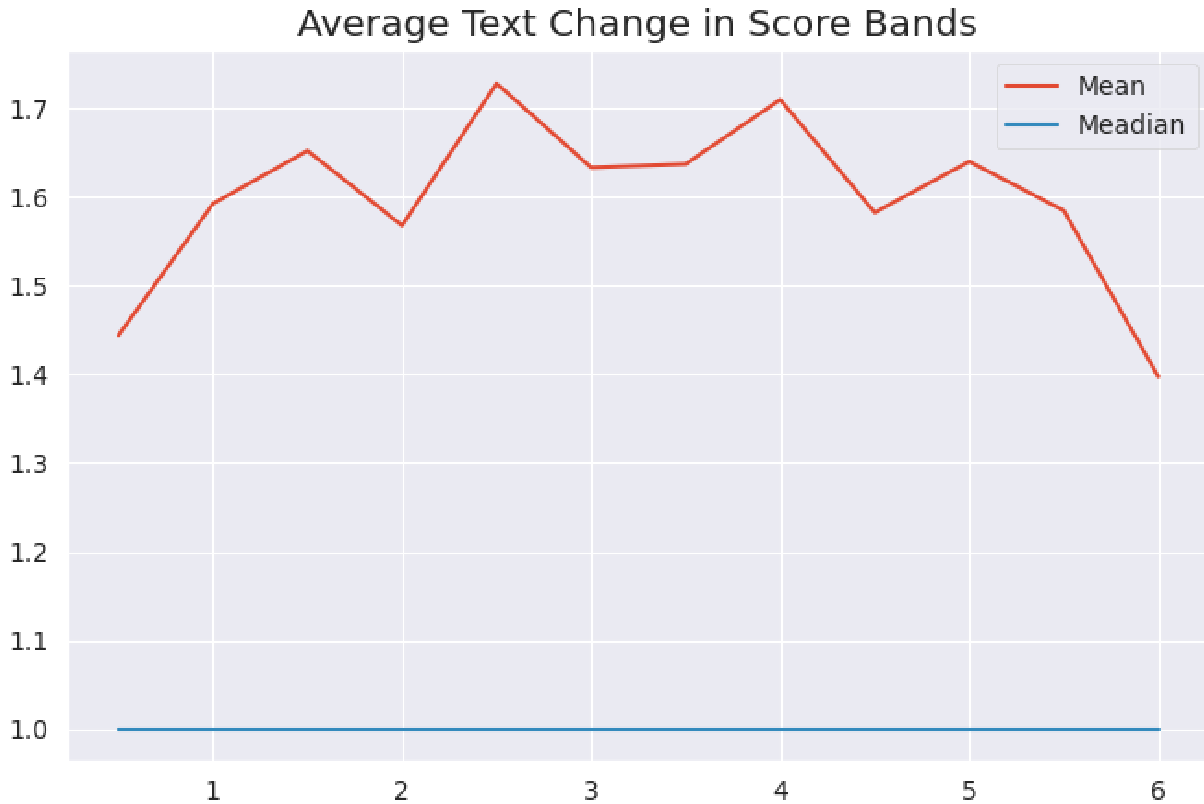
Avg Score by Upevent

In [55]:
```
plt.plot(train.groupby("up_event").agg({'score':"mean"}).sort_values("score",ascending
plt.title("Top 10 up events by Avg Score")
plt.show();
```



Avg Text by Score

In [56]:
```
#  Text change how much did the person actually write or change his previous version c
train.loc[:,'text_change_length'] = train['text_change'].apply(lambda x:len(x))
plt.plot(train.groupby("score").agg({'text_change_length':"mean"}),label="Mean")
plt.plot(train.groupby("score").agg({'text_change_length':"median"}),label="Meadian")
plt.legend()
plt.title("Average Text Change in Score Bands")
plt.show();
```



hmmm. so avg low lenght of text changes can be indicative of low or high score. Fishy. Variable is proabably segmented with effect of another variable or this means that the lenght of text changes are consistent and then there are large deviations which shit the mean but they do not happen in either of high scores or low scores..... so some events could consistently point to a low score and some likely to hhigh score.

Lightgbm

In [57]:

```
# Lets build a baseline light gbm and then use shap to generate feature importance cha
```

In [58]:

```
import re
import math
def extract_nums(s):
    # Use regular expression to extract numbers inside square brackets
    numbers = re.findall(r'\d+', s)
    #print(s)
    #print(numbers)
    if numbers:
        x1=int(numbers[0])
        y1=int(numbers[1])
        x2=int(numbers[2])
        y2=int(numbers[3])
        return str(math.sqrt((x1-x2)**2+(y1-y2)**2))
    else:
        return "no_movement"
```

In [59]:

```
from random import sample
# We want to make sure there is peeking into the test set
```

```
# In the first pass let's just simplify these variables
train.loc[:,'text_change_length'] = train['text_change'].apply(lambda x:len(x))
train.loc[:,'activity_c']=train['activity'].apply(lambda x:extract_nums(x) if "Move" i

test_id=sample(list(train.id.unique()),300)
# Get train and test based on test id
train_m= train[~train.id.isin(test_id)]
test_m= train[train.id.isin(test_id)]
```

In [60]:
```
# Let's create a dictionary to store the factorisers for categorical variables
cats=['activity_c','down_event','up_event']
# This is basically code to create dictionary
# cat_dict={}
# for i in cats:
#     cat_dict[i]={}
#     for j in range(0,len(list(train_m[i].unique()))):
#         cat_dict[i][list(train_m[i].unique())[j]]=j
```

In [61]:
```
import joblib
# lets load the saved data dictionary
cat_dict=joblib.load("/kaggle/input/cat-dict/cat_dict")
```

In [62]:
```
model_vars=['event_id', 'down_time', 'up_time', 'action_time',
       'down_event', 'up_event', 'cursor_position',
       'word_count','text_change_length', 'activity_c']

X_train=train_m.copy()
X_test=test_m.copy()
# Convert categorical to mapping
for i in cats:
    X_train[i]=X_train[i].map(cat_dict[i])
    X_test[i]=X_test[i].map(cat_dict[i])
    #X_train.loc[:,i]=X_train[i].astype("int")
    #X_test.loc[:,i]=X_test[i].astype("int")
```

In [63]:
```
lgb=LGBMRegressor()
lgb.fit(X_train[model_vars], X_train['score'],
        eval_set=[(X_test[model_vars], X_test['score'])],
        categorical_feature=cats,
        verbose=0,
        early_stopping_rounds=8)
```

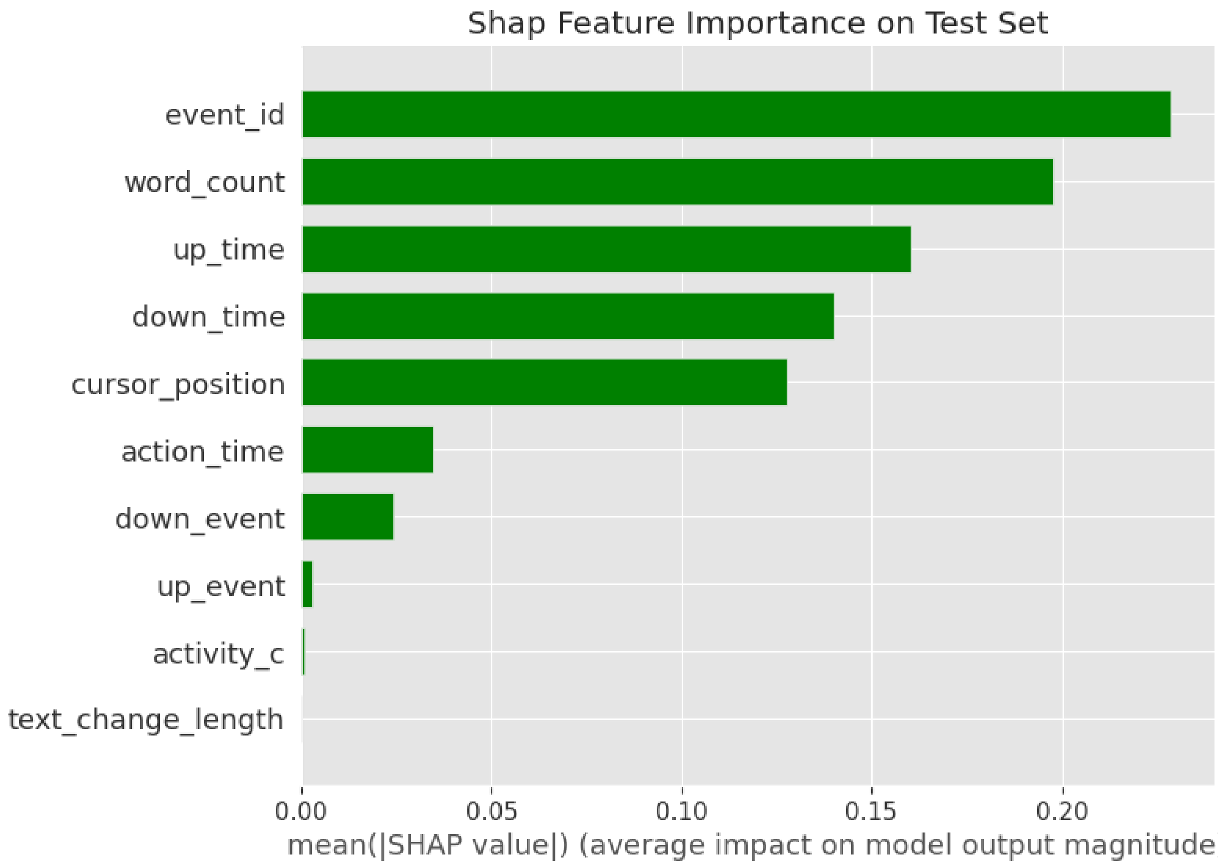
Out[63]:
```
▾ LGBMRegressor
LGBMRegressor()
```

Feature Importance

In [64]:
```
import shap
```

In [65]:
```
# Explain model predictions using shap library:
explainer = shap.TreeExplainer(lgb)
shap_values = explainer.shap_values(X_test[model_vars])
```

In [66]:
```
# Plot summary_plot as barplot:
plt.style.use('ggplot')
shap.summary_plot(shap_values, X_test[model_vars], plot_type='bar',color ='green',show
plt.title("Shap Feature Importance on Test Set")
plt.show();
```



So basically activity and text change are useless the way used above. We need to extract the cordinate change from activity and identify some way of modelling text change as it has too high cardinality to model even for light gbm

In [72]:
```
!jupyter nbconvert --to html /kaggle/input/file-read/edabasiclightgbm.ipynb --output /
```

```
[NbConvertApp] WARNING | Config option `kernel_spec_manager_class` not recognized by `NbConvertApp`.
[NbConvertApp] Converting notebook /kaggle/input/file-read/edabasiclightgbm.ipynb to html
[NbConvertApp] Writing 892919 bytes to /kaggle/working/output.html
```

In [ ]: