eda

April 10, 2023

[1]:
```
!pip3 install -q langdetect
```

```
WARNING: Running pip as the 'root' user can result in broken permissions
and conflicting behaviour with the system package manager. It is recommended to
use a virtual environment instead: https://pip.pypa.io/warnings/venv
```

#

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**

Introduction

**

The goal of this competition is to understand the relationship between code and comments in Python notebooks. You are challenged to reconstruct the order of markdown cells in a given notebook based on the order of the code cells, demonstrating comprehension of which natural language references which code.

Predictions are evaluated by the Kendall tau correlation between predicted cell orders and ground truth cell orders accumulated across the entire collection of test set notebooks.

Check more about Kendall tau correlation - https://en.wikipedia.org/wiki/Kendall_rank_correlation_coefficient

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**

Imports

**

[2]:
```
import os, re, gc
import nltk, string
import json
```

```python
import wordcloud
import numpy as np
import pandas as pd
import plotly.express as px
import matplotlib.pyplot as plt
import plotly.graph_objects as go
from tqdm.notebook import tqdm, trange
from langdetect import detect_langs
import seaborn as sns
```

0.1 Loading Data :

Pandas Dataframe used is created by Darien Schettler. Link to dataset - https://www.kaggle.com/datasets/dschettler8845/ai4code-train-dataframe

[3]:
```python
## train dataframes
df = pd.read_csv("../input/ai4code-train-dataframe/train.csv", index_col= [0,1])
df.dropna(inplace = True)

df_ancestors = pd.read_csv('../input/AI4Code/train_ancestors.csv',␣
 ↪index_col='id')
df_orders = pd.read_csv("../input/AI4Code/train_orders.
 ↪csv",index_col='id',squeeze=True,) .str.split()
```

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EDA

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 <u>Observations :</u>

- A total of 139256 notebooks are provided train set.
- A total of 4 notebooks are provided test set. This will be replaced with a hidden test set for scoring
- There are total of 146300 cells in train the train dataframe constructed which include two types of cell_type.
- Two types of cell_type - code and markdown.
- Almost 2/3rd of the training data consist of Code Cells and remaining 1/3rd consist of Markdown Cells.

[4]:
```python
print(f"\033[94mNumber of notebooks present in train set  = ",len(os.listdir("..
 ↪/input/AI4Code/train")))
print(f"\033[94mNumber of notebooks present in test set  = ",len(os.listdir("../
 ↪input/AI4Code/test")))
```

```
Number of notebooks present in train set  =  139256

Number of notebooks present in test set  =  4
```

Quick View of train data :

 `df` is a Multi-level indexing Padnas Dataframe with 2 index - id and cell_id. <

Learn more about Multi-level indexing Padnas Dataframe - https://pandas.pydata.org/docs/user_guide/advanced.html

[5]:
```
df.head()
```

[5]:
```
                              cell_type  \
id               cell_id
8a2564b730a575 8395ab7c       code
                 ebc844d6       code
                 49251f17       code
                 3a6623e3       code
                 24e09d1a       code

                                                                     source
id               cell_id
8a2564b730a575 8395ab7c  import numpy as np\nimport matplotlib.pyplot a…
                 ebc844d6  df_train = pd.read_csv('../input/tensorflow-gr…
                 49251f17  def bbox_inv_iou(boxA, boxB):\n    """Copied f…
                 3a6623e3  test_sequence_id = np.unique(df_train.sequence…
                 24e09d1a  seq_df_with_cots_ids, stats = find_unique_cots…
```

[ ]:

Training data consists out of 139256 JSON files, each containing a notebook where markdown cells have been shuffeled. Additional files regarding correct markdown order, as well as, information of "forked notebook" has also been given. Following table is a combination of all given training files, including the correct order and ancestor_id/parent_id.

- **`id` - Unique identification of notebook.**
- **`cell_id` - Unique identification of cell within notebooks.**
- **`cell_type` - Factor specifying cell type, either being a code cell or markdown cell.**
- **`source` - String with content of cell.**
- **`ancestor_id` - Identifies sets of notebooks with common origin.**
- **`parent_id` - Some version of the notebook id was forked from some version of the notebook `parent_id`. It may or may not be present (i.e. `parent_id` may be missing due to someone having forked a private notebook).**

[6]:
```
df_ancestors.head(5)
```

[6]:
```
                 ancestor_id       parent_id
id
00001756c60be8     945aea18             NaN
```

00015c83e2717b	aa2da37e	317b65d12af9df
0001bdd4021779	a7711fde	NaN
0001daf4c2c76d	090152ca	NaN
0002115f48f982	272b483a	NaN

train_ancestors.csv - On Kaggle, a user may "fork" (that is, copy) the notebook of another user to create their own version. This file contains the forking history of notebooks in the training set. Note: There is no corresponding file for the test set. - **Columns** * **ancestor_id** * Identifies sets of notebooks that have a common origin or "ancestor". * As no notebook in the test set has an ancestor in the training set, you may find this field to be of use as a grouping factor when constructing validation splits. * **parent_id** * Indicates that some version of the notebook id was forked from some version of the notebook **parent_id**. * The notebook **parent_id** may or may not be present in the training data. * The parent may be missing because someone had forked a private notebook of their own, for instance.

Train data distribution :

[7]:
```python
code_df = df[df["cell_type"] == "code"]
mkd_df = df[df["cell_type"] == "markdown"]


print(f'\033[94mNumber of Code Cells: {len(code_df)}')
print(f'\033[94mNumber of Markdown Cells: {len(mkd_df)}')

labels=['Code Cells', 'Markdown Cells']
values= [len(code_df), len(mkd_df)]
colors = ['#DE3163', '#58D68D']

fig = go.Figure(data=[go.Pie(
    labels=labels,
    values=values,
    pull=[0.1, 0 ],
    marker=dict(colors=colors,
                line=dict(color='#000000',
                          width=2))
)])
fig.show()
```

```
Number of Code Cells: 4204578
```

```
Number of Markdown Cells: 2166064
```

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Code cells analysis :

```
 <b><u>Observations:</u></b><br>
```

- Mean Length for Code Cells is 25 words
- Max words in a Code Cell is 74589 words
- There are many outliers in Code Cells

0.1.1 Sample Code Cell:

[8]:
```
print(f'\033[94m')
print(code_df.iloc[0]["source"])
```

```
import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

import pandas as pd

import uuid

import os

import scipy

import cv2

from tqdm import tqdm

import math

import ast

sns.set()
```

Code cells Length Distribution :

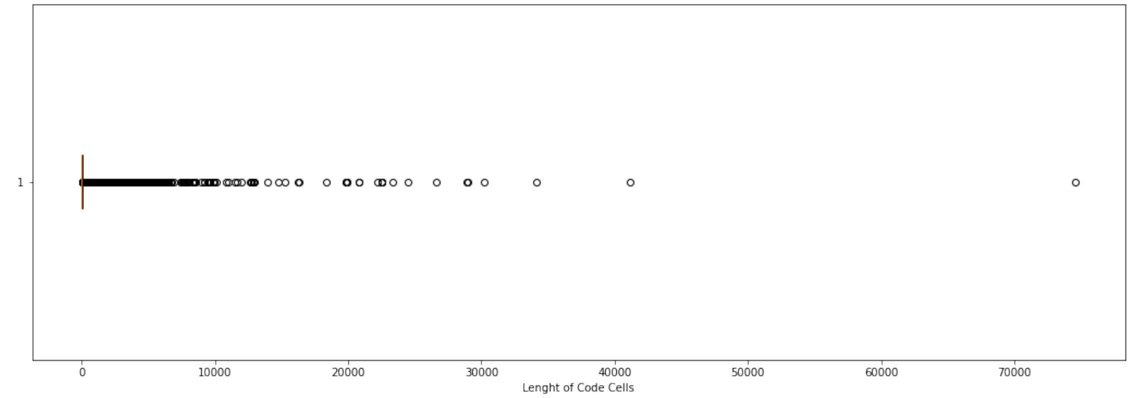
[9]:
```
code_lengths = np.array([len(code_df["source"][i].split()) for i in␣
 ↪range(len(code_df))])
print(f'\033[94m Min Code Cells Length = ', min(code_lengths))
print(f'\033[94m Mean Code cells Length = ', round(np.mean(code_lengths),2))
print(f'\033[94m Max Code Cells Length = ', max(code_lengths))
```

```
Min Code Cells Length =  1

Mean Code cells Length =  25.24

Max Code Cells Length =  74589
```

[10]:
```
fig,ax= plt.subplots(figsize= (18,6))
plt.boxplot(code_lengths, vert = False)
plt.xlabel("Lenght of Code Cells");
```




```
[ ]:
```

Code cells WordCloud :

```
[11]: # # show words cloud
# wordcloud_notes = wordcloud.WordCloud(stopwords=wordcloud.STOPWORDS,␣
 ↪max_font_size=120, max_words=5000,
#                        width = 600, height = 400,
#                        background_color='white').generate("".
 ↪join(code_df["source"][:1000]))
# fig, ax = plt.subplots(figsize=(14,10))
# ax.imshow(wordcloud_notes, interpolation='bilinear')
# ax.set_axis_off()
# plt.imshow(wordcloud_notes);
```

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0.2 Markdown cells analysis :

 <u>Observations:</u>

- Mean Length for Markdown Cells is 29 words
- Max words in a Markdown Cell is 38939 words
- There are many outliers in Markdown Cells as well.

0.2.1 Sample Markdown Cell:

```
[12]: print(f'\033[94m')
print(mkd_df.iloc[59]["source"])
```

Pipeline

At this stage, it is worth introducing pipeline. In machine learning, it is common to run a sequence of algorithms to process and learn from data. In our example, we performed StringIndexer, VectorAssembler, and ML model. In other cases, the intermediate stages can be standardization, vectorization (for text processing), normalization, etc. These operations have to be performed on a specific order. Spark represents such a workflow as a Pipeline, which consists of a sequence of stages to be run in a specific order. Pipeline chains multiple Transformers and Estimators together to specify an ML workflow.

Without the pipeline, we have to execute each stage, store the outcome, and feed into the next stage and evaluate, and so on. We prefer pipeline over this manual approach because of the following reasons:

- The pipeline is less prone to mistake because the processes are automated.
- In a production environment, this is the only way to do machine learning end to end.
- Pipeline enhances the lazy evaluation. So this is a very natural choice in Spark. The pipeline is even more important for big data.

Grid-search and cross-validation

Usually, there are many hyperparameters in a model of selection and some combination of those parameters might give the best result. Tuning them requires checking all possible combinations of the hyperparameter. Doing them manually is a tedious bookkeeping task. Fortunately, there is a grid search option available in Spark like in Sci-kit learn.

When doing the grid search we need to validate the model using a separate dataset that was not used to train the data. So far we used customized validation set for comparison between different models. Usually, Spark would be handling very big data. For big data, the train-validation split can be sufficient. For small datasets like this, however, cross-validation is preferred over the train-validation split. Coss-validation is available in Spark. We will use five-fold cross-validation for better model selection.

We use CrossValidator available in Spark ML for the cross-validation. CrossValidator accepts estimatorParamMaps in which we can pass a grid search object built with ParamGridBuilder which is also available in Spark ML.

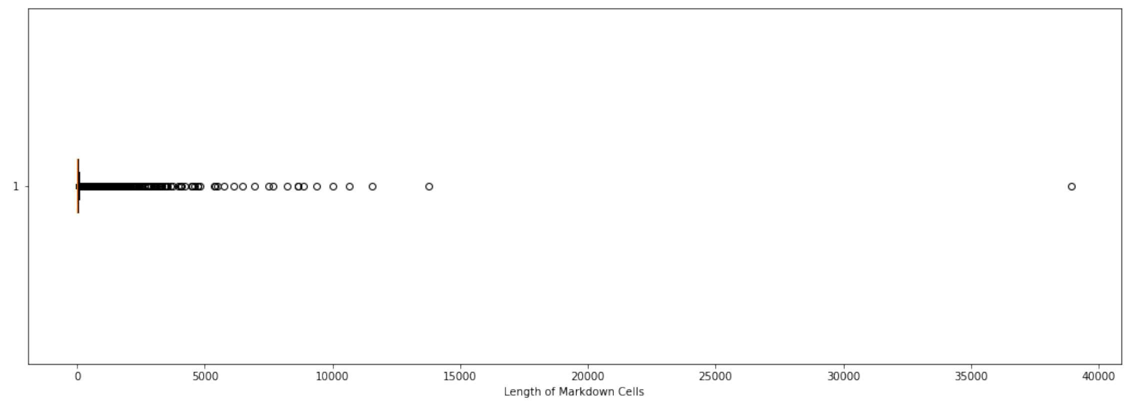
We have chosen a random forest for our submission model. We test three hyperparameters from the random forest: number of trees, minimum information

Markdown Cells Length Distribution :

[13]:
```
mkd_lengths = np.array([len(mkd_df ["source"][i].split()) for i in␣
 ↪range(len(mkd_df))])
print(f'\033[94m Min Markdown Cells Length = ', min(mkd_lengths))
print(f'\033[94m Mean Markdown cells Length = ', round(np.mean(mkd_lengths),2))
print(f'\033[94m Max Markdown Cells Length = ', max(mkd_lengths))
```

```
Min Markdown Cells Length =  1
Mean Markdown cells Length =  29.42
Max Markdown Cells Length =  38939
```

[14]:
```
fig,ax= plt.subplots(figsize= (18,6))
plt.boxplot(mkd_lengths, vert = False)
plt.xlabel("Length of Markdown Cells");
```



Markdown Cells WordCloud :

[15]:
```
# # show words cloud
# wordcloud_notes = wordcloud.WordCloud(stopwords=wordcloud.STOPWORDS,␣
 ↪max_font_size=120, max_words=5000,
#                         width = 600, height = 400,
#                         background_color='white').generate("".
 ↪join(mkd_df["source"][:1000]))
# fig, ax = plt.subplots(figsize=(14,10))
# ax.imshow(wordcloud_notes, interpolation='bilinear')
# ax.set_axis_off()
# plt.imshow(wordcloud_notes);
```

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Code and Markdown cells Length After Cleaning :

[16]:

```
####Source: https://www.kaggle.com/code/parulpandey/
↪eda-and-preprocessing-for-bert

# text preprocessing helper functions

def clean_text(text):
    '''Make text lowercase, remove text in square brackets,remove links,remove␣
↪punctuation
    and remove words containing numbers.'''
    text = text.lower()
    text = text.strip()
    text = re.sub('\[.*?\]', '', text)
    text = re.sub('https?://\S+|www\.\S+', '', text)
    text = re.sub('<.*?>+', '', text)
    text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
    text = re.sub('\n', '', text)
    text = re.sub('\w*\d\w*', '', text)
    return text

def text_preprocessing(text):
    """
    Cleaning and parsing the text.

    """
    tokenizer = nltk.tokenize.RegexpTokenizer(r'\w+')
    nopunc = clean_text(text)
    tokenized_text = tokenizer.tokenize(nopunc)
    combined_text = ' '.join(tokenized_text)
    return combined_text

# code text preprocessing helped functions

def clean_code(text):
    '''Make text lowercase, remove text in square brackets,remove links,remove␣
↪punctuation
    and remove words containing numbers.'''
    text = text.replace('[', ' ').replace(']', ' ').replace('(', ' ').
↪replace(')', ' ').replace('{', ' ').replace('}', ' ').replace('=', ' ').
↪replace(',', ' ')
    text = text.lower()
    text = text.replace('_', '')
    text = text.replace('\n', ' ')
    text = text.replace('.', ' ')
    text = re.sub(r'".*"', ' ', text)
    text = re.sub(r"'.*'", ' ', text)
    text = re.sub("^\d+\s|\s\d+\s|\s\d+$", ' ', text)
    text = re.sub(' +', ' ', text)
```

```
    text = text.strip()
    return text

def code_preprocessing(text):
    """
    Cleaning and parsing the text.

    """
    tokenizer = nltk.tokenize.RegexpTokenizer(r'\w+')
    nopunc = clean_code(text)
    tokenized_text = tokenizer.tokenize(nopunc)
    combined_text = ' '.join(tokenized_text)
    return combined_text
```

[17]:
```
markdowns = df[df['cell_type'] == 'markdown']
codes = df[df['cell_type'] == 'code']
```

[18]:
```
codes['source_clean'] = codes['source'].apply(str).apply(lambda x:␣
 ↪code_preprocessing(x))
markdowns['source_clean'] = markdowns['source'].apply(str).apply(lambda x:␣
 ↪text_preprocessing(x))
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:2:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

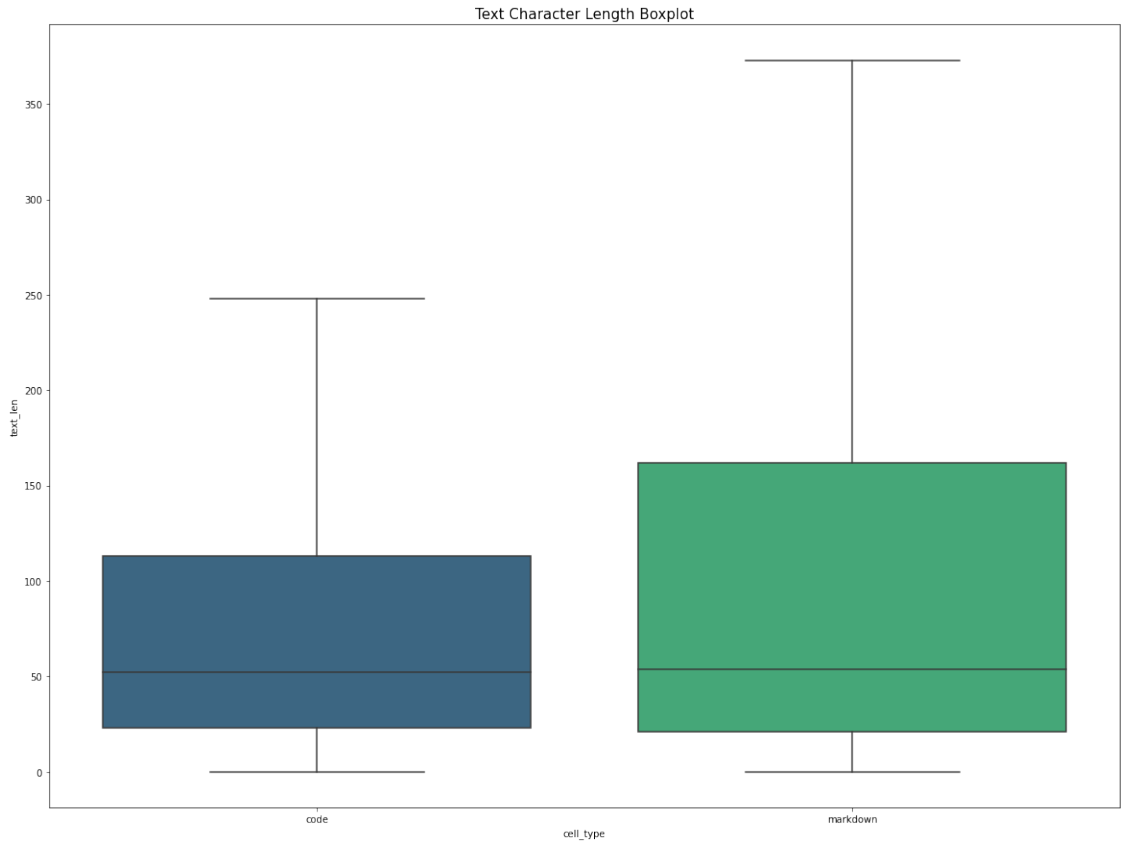
[19]:
```
train = pd.concat([codes, markdowns], ignore_index = True)
del codes, markdowns
_ = gc.collect()
```

[20]:
```
train['text_len'] = train['source_clean'].astype(str).apply(len)
train['text_word_count'] = train['source_clean'].apply(lambda x: len(str(x).
    ↪split()))
```

[21]:
```
# markdowns = train[train['cell_type'] == 'markdown']
# codes = train[train['cell_type'] == 'code']
```

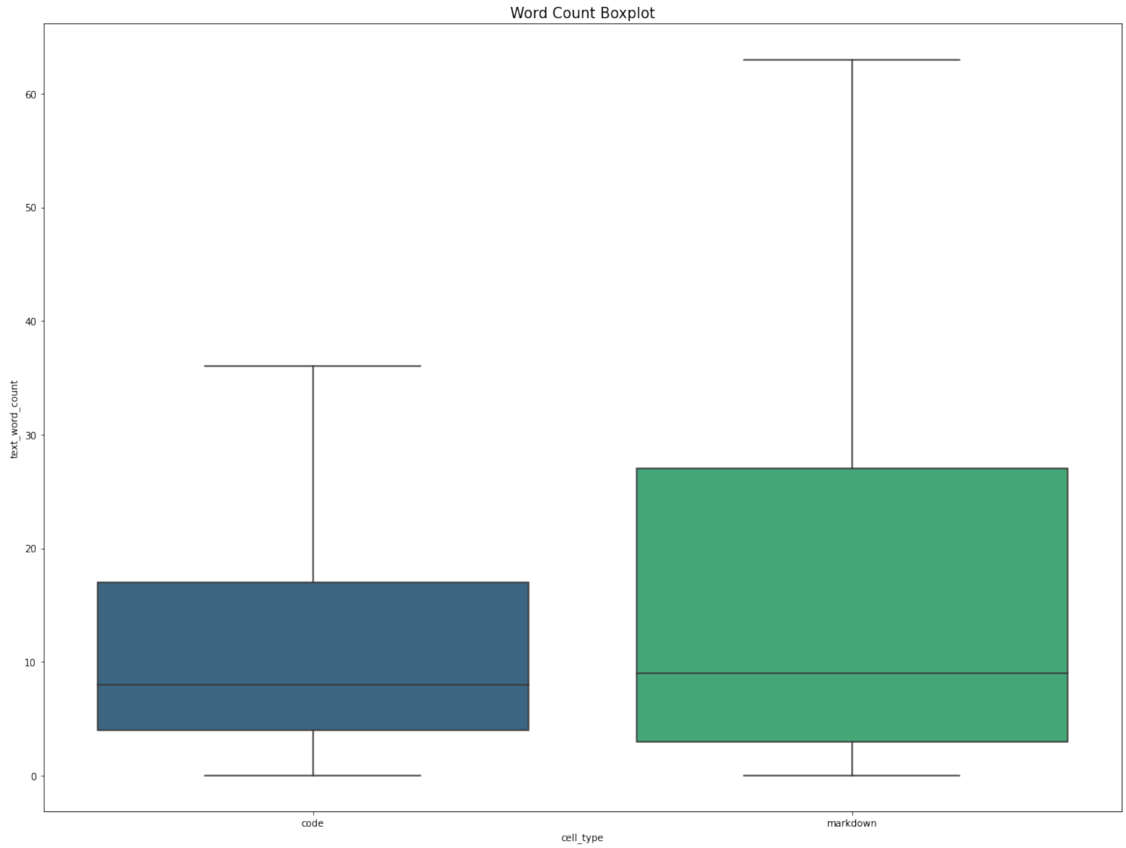
[22]:
```
fig, ax = plt.subplots(figsize=(20, 15))

sns.boxplot(data=train,x = 'cell_type', y="text_len", palette = 'viridis',␣
    ↪showfliers = False, ax=ax)
plt.title('Text Character Length Boxplot', size=15)
plt.show()
```



[23]:
```
fig, ax = plt.subplots(figsize=(20, 15))

sns.boxplot(data=train,x = 'cell_type', y="text_word_count", palette =␣
    ↪'viridis', showfliers = False, ax=ax)
plt.title('Word Count Boxplot', size=15)
plt.show()
```



Notebooks Analysis:

 <u>Observations:</u>

- Minimum count for both Code Cells and Markdown cells across all notebooks is 1.
- Mean Code cells count across all notebooks is 30 cells
- Mean Markdown cells count across all notebooks is 15 cells
- Max count of Code cells and Markdown cells across all notebooks is 809 cells and 537 cells respectively.

[24]:
```
## loading code_cell counts from notebooks
notebook_ids = [notebook[:-5] for notebook in os.listdir("../input/AI4Code/
 ↪train")]
code_counts= []
markdown_counts= []
for i in trange(len(notebook_ids)):
    temp_df = df.loc[(notebook_ids[i])]
    code_counts.append((temp_df["cell_type"] == "code").sum())
    markdown_counts.append((temp_df["cell_type"] == "markdown").sum())
```

```
counts_df = pd.DataFrame(data = np.array([notebook_ids, code_counts,␣
↪markdown_counts, ]).T, columns = ["notebook_id", "code_count",␣
↪"markdown_count"])
counts_df["markdown_count"] = counts_df["markdown_count"].astype(str).
↪astype(int)
counts_df["code_count"] = counts_df["code_count"].astype(str).astype(int)
counts_df["total_count"] = counts_df["code_count"] + counts_df["markdown_count"]
print(f'\033[94m Minimum Cell count in any notebook', counts_df["total_count"].
↪min())
print(f'\033[94m Maximum Cell count in any notebook', counts_df["total_count"].
↪max())
print(f'\033[94m Mean of Cell counts across all notebooks',␣
↪round(counts_df["total_count"].mean(), 2 ))
counts_df.head()
```

```
  0%|          | 0/139256 [00:00<?, ?it/s]

Minimum Cell count in any notebook 2

Maximum Cell count in any notebook 1005

Mean of Cell counts across all notebooks 45.75
```

[24]:

	notebook_id	code_count	markdown_count	total_count
0	8a2564b730a575	11	1	12
1	38d64ca81d4a98	17	20	37
2	051d049a469e47	52	39	91
3	2142dd60936a39	15	10	25
4	6270fcdb7e77f4	18	6	24

0.2.2 Outlier Notebooks Analysis:

[25]:
```
k = 100
top_k = counts_df.sort_values(by = ["total_count"], ascending=False)[:k]
fig = px.bar(data_frame=top_k,
             x = "notebook_id" ,
             y = [ "code_count", "markdown_count"],
             color_discrete_sequence=['#DE3163', '#58D68D']

            )
fig.update_layout(
    title={
        'text': "Cell Type Count analysis for top 100 cell count␣
↪notebooks(OUTLIERS)",
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
```

```
    xaxis_title="Notebook ID",
    yaxis_title="Count",
    template="plotly_white"

)
fig.update_traces(marker_line_color='black',
                  marker_line_width=0.9,opacity = 0.9)
fig.show()
```

Code Cell Count Analysis:

[26]:
```
print(f'\033[94m Minimum Code Cell count in any notebook',␣
 ↪counts_df["code_count"].min())
print(f'\033[94m Maximum Code Cell count in any notebook',␣
 ↪counts_df["code_count"].max())
print(f'\033[94m Mean of Code Cell counts across all notebooks',␣
 ↪round(counts_df["code_count"].mean(), 2 ))
```

```
Minimum Code Cell count in any notebook 1

Maximum Code Cell count in any notebook 809

Mean of Code Cell counts across all notebooks 30.19
```

0.2.3 Code Cell Count Distribution across all notebooks:

[27]:
```
fig = px.histogram(data_frame=counts_df,
                   x= "code_count",
                   color_discrete_sequence=["#DE3163"],
                   marginal="violin")
fig.update_layout(
    title={
        'text': "Code Cell Count Distribution",
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
    xaxis_title="Code Cells",
    yaxis_title="Count",
    showlegend=False,
    template="plotly_white"
)
fig.show()
fig = px.histogram(data_frame=counts_df[counts_df["code_count"]<100],
                   x= "code_count",
                   color_discrete_sequence=["#58D68D"],
                   marginal="violin")
fig.update_layout(
    title={
```

```
        'text': "Code Cell Count Distribution (COUNTS < 100 )",
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
    xaxis_title="Code Cells",
    yaxis_title="Count",
    showlegend=False,
    template="plotly_white"
)
fig.show()
```

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Markdown Cell Count Analysis:

```
[28]: print(f'\033[94m Minimum Markdown Cell count in any notebook',␣
       ↪counts_df["markdown_count"].min())
      print(f'\033[94m Maximum Markdown Cell count in any notebook',␣
       ↪counts_df["markdown_count"].max())
      print(f'\033[94m Mean of Markdown Cell counts across all notebooks',␣
       ↪round(counts_df["markdown_count"].mean(), 2 ))
```

```
Minimum Markdown Cell count in any notebook 1

Maximum Markdown Cell count in any notebook 537

Mean of Markdown Cell counts across all notebooks 15.55
```

0.2.4 Markdown Cell Count Distribution across all notebooks:

```
[29]: fig = px.histogram(data_frame=counts_df,
                         x= "markdown_count",
                         color_discrete_sequence=["#DE3163"],
                         marginal="violin")
      fig.update_layout(
          title={
              'text': "Markdown Cell Count Distribution",
              'y':0.95,
              'x':0.5,
              'xanchor': 'center',
              'yanchor': 'top'},
          xaxis_title="Markdown Cells",
          yaxis_title="Count",
          showlegend=False,
          template="plotly_white"
      )

      fig.show()
```

```python
fig = px.histogram(data_frame=counts_df[counts_df["markdown_count"]<100],
                   x= "markdown_count",
                   color_discrete_sequence=["#58D68D"],
                   marginal="violin")
fig.update_layout(
    title={
        'text': "Markdown Cell Count Distribution (COUNTS < 100 )",
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
    xaxis_title="Markdown Cells",
    yaxis_title="Count",
    showlegend=False,
    template="plotly_white"
)
fig.show()
```

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Minimum Cell Count Analysis:

[30]:
```python
either_one = counts_df[(counts_df["markdown_count"] == 1) |␣
↪(counts_df["code_count"] == 1 )]
both_one = counts_df[(counts_df["markdown_count"] == 1) &␣
↪(counts_df["code_count"] == 1 )]
code_count_one = counts_df[counts_df["code_count"] == 1 ]
markdown_count_one  = counts_df[counts_df["markdown_count"] == 1 ]

print(f"\033[94mTotal notebook with either 1 code cell or 1 markdown cell = ",␣
↪len(either_one))
print(f"\033[94mTotal notebook with both 1 code cell and 1 markdown cell = ",␣
↪len(both_one ))
print(f"\033[94mNotebook counts with only 1 code cell  = " ,len(code_count_one))
print(f"\033[94mNotebook counts with only 1 markdown cell  = "␣
↪,len(markdown_count_one))
```

```
Total notebook with either 1 code cell or 1 markdown cell =  11426

Total notebook with both 1 code cell and 1 markdown cell =  392

Notebook counts with only 1 code cell  =  737

Notebook counts with only 1 markdown cell  =  11081
```

0.2.5 Code cells count vs Markdown cells count:

[31]:
```
fig = px.scatter(data_frame=counts_df,
                 x = "code_count",
                 y = "markdown_count",
                 size = "code_count",
                 color_discrete_sequence=["#DE3163"])
fig.add_shape(type='line',
                x0=0,
                y0=0,
                x1=800,
                y1=800,
                line=dict(color='Black'),
                xref='x',
                yref='y',name = "X=Y line"
             )
fig.update_layout(
    title={
        'text': "Code Cell Counts vs Markdown Cell Counts",
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
    xaxis_title="Code Cell Counts",
    yaxis_title="Markdown Cell Counts",
    showlegend=False,
    template="plotly_white"
)
fig.show()
```

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[ ]:
```

```

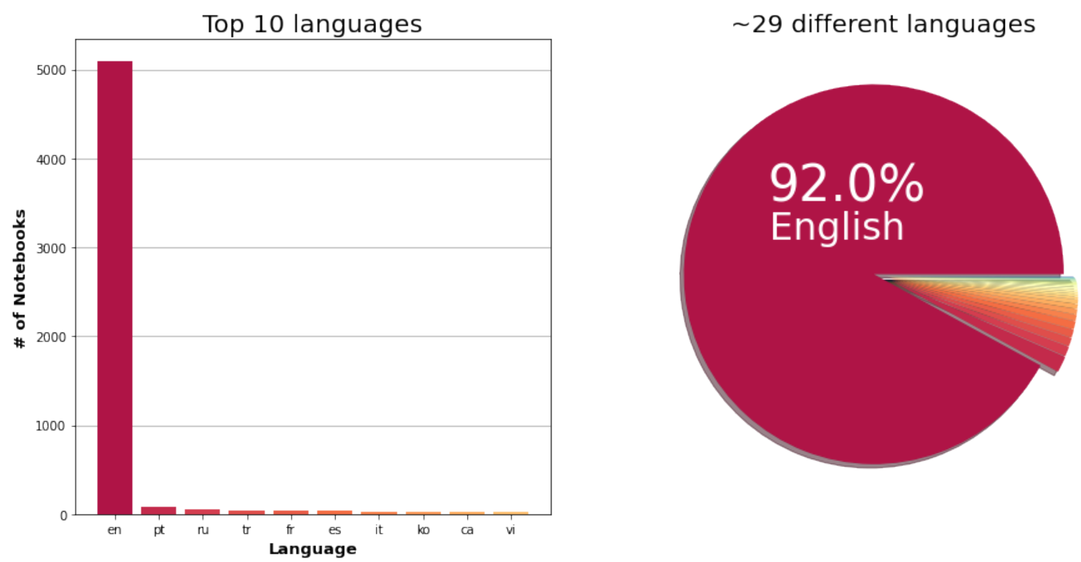
[32]:
```
markdowns_df = df[df["cell_type"]=="markdown"].sample(10000).reset_index()

df_lang = pd.DataFrame(columns=["Count"])
failed_identifications = 0

# Check notebooks
for i, notebook in enumerate(tqdm(markdowns_df.id.unique())):

    # Add probs to df
    prob_df = pd.DataFrame(columns=["Prob"])

    # Look at text within notebook
    for txt in markdowns_df[markdowns_df.id == notebook].source:
```

```python
        # Normalize a bit
        txt = re.sub(r'[^\w]', ' ', txt).strip()

        # Skip too long or too short txt
        if len(txt) > 5000 or len(txt.split(" ")) < 10:
            continue

        try:
            # Detect prob
            lang = detect_langs(txt)

            for l in lang:
                if l.lang in prob_df.index:
                    prob_df.loc[l.lang] = l.prob + prob_df.loc[l.lang]
                else:
                    prob_df.loc[l.lang] = l.prob
        except:
            failed_identifications += 1

    # Add highest prob. lang in notebook to counter
    if len(prob_df) > 0:
        lang = prob_df.sort_values("Prob", ascending=False).index[0]

        if lang in df_lang.index:
             df_lang.loc[lang, "Count"] = 1 + df_lang.loc[lang, "Count"]
        else:
             df_lang.loc[lang, "Count"] = 1

df_lang = df_lang.sort_values("Count", ascending=False)
```

```
  0%|          | 0/9331 [00:00<?, ?it/s]
```

[33]:
```python
colors = sns.color_palette("Spectral", n_colors=len(df_lang))

dt = df_lang.sort_values("Count", ascending=False)

fig, axs = plt.subplots(1, 2, figsize=(15, 7))

explode = np.flip(np.linspace(0, 0.05, len(df_lang)))

axs[1].pie(dt.Count, colors=colors, explode=explode, shadow=True);

top = np.round(dt.Count.en / dt.Count.sum(), 2) * 100
axs[1].text(-0.61, 0.40, f"{top}%", size=40, c="white")
axs[1].text(-0.6, 0.2, f"English", size=30, c="white")
axs[1].set_title(f"~{len(df_lang)} different languages", size=20)
```

```python
axs[0].grid(True, axis="y", zorder=0)
axs[0].bar(df_lang.sort_values("Count", ascending=False).head(10).index,
           df_lang.sort_values("Count", ascending=False).head(10).Count,␣
 ↪color=colors[:10], zorder=3)

axs[0].set_title("Top 10 languages", size=20)
axs[0].set_ylabel("# of Notebooks", size=13, weight="bold")
axs[0].set_xlabel("Language", size=13, weight="bold");
```



[ ]:

```python

```