vader-analysis

February 18, 2024

1 Analyzing the scraped data with pandas and mlflow

[413]:
```
# MLflow
import mlflow
from mlflow.models import infer_signature

# MLflow model
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Visualizations
import matplotlib.pyplot as plt

# math functions
import numpy as np

# read CSV file
import os
import glob

# data frames
import pandas as pd

# regexes
import re
```

[414]:
```
# https://medium.com/bitgrit-data-science-publication/
↪sentiment-analysis-on-reddit-tech-news-with-python-cbaddb8e9bb6

# Load Libraries

import pandas as pd
import numpy as np
```

```
# misc
import datetime as dt
from pprint import pprint
from itertools import chain

# reddit crawler
import praw

# sentiment analysis
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.tokenize import word_tokenize, RegexpTokenizer # tokenize words
from nltk.corpus import stopwords

# visualization
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams["figure.figsize"] = (10, 8) # default plot size
import seaborn as sns
sns.set(style='whitegrid', palette='Dark2')
from wordcloud import WordCloud

# Downloading NLTK's databases
nltk.download('vader_lexicon') # get lexicons data
nltk.download('punkt') # for tokenizer
nltk.download('stopwords')
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\georg\AppData\Roaming\nltk_data…
[nltk_data]   Package vader_lexicon is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\georg\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\georg\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[414]: True

1.1 Load dataset in pandas

[415]:
```
# future warnings
import warnings
warnings.filterwarnings("ignore")

# Use the Reddit dataset
topics_dict = { "date":[],
```

```
                 "title":[],
                 "author":[],
                 "stickied":[],
                 "upvote_ratio":[],
                 "score":[],
                 "id":[],
                 "url":[],
                 "num_comments": [],
                 "created": [],
                 "body":[]}
df = pd.DataFrame()
running_total = 0
for fname in glob.glob(os.path.abspath('./data/*.meta')):
    metadata = pd.read_csv(fname)

for fname in glob.glob(os.path.abspath('./data/**/*.csv')):
    _df=pd.read_csv(fname)
    _df['query'] = os.path.splitext(os.path.basename(fname))[0]
    subreddit = os.path.basename(os.path.dirname(fname))
    _df['subreddit'] = subreddit
    _df['score_weighted'] = _df['score'] /␣
 ↪metadata[metadata['name']==subreddit]['subscribers'].iloc[0]
    _df['num_comments_weighted'] = _df['num_comments'] /␣
 ↪metadata[metadata['name']==subreddit]['subscribers'].iloc[0]
    df = df.append(_df.copy(), ignore_index=True)
    running_total+=len(_df)
    #print(fname)
    #print(running_total)
    #break #DEBUG
print(running_total)

# remove duplicate posts
df.set_index("id", inplace=True)

# setup the created datetime
df['created_date'] = pd.to_datetime(df['created'], unit='s')
```

62622

1.2 Run sentiment analysis

[416]:
```
# Clean data

#Create a function to clean the tweets
def cleanTxt(text):
    text = re.sub(r'@[A-Za-z0-9]+', '', text) #Remove @mentions replace with␣
 ↪blank
```

```
    text = re.sub(r'#', '', text) #Remove the '#' symbol, replace with blank
    text = re.sub(r'RT[\s]+', '', text) #Removing RT, replace with blank
    text = re.sub(r'https?:\/\/\S+', '', text) #Remove the hyperlinks
    text = re.sub(r':', '', text) # Remove :
    return text

#Next we have to remove emoji & Unicode from the Tweet data.
def remove_emoji(string):
    emoji_pattern = re.compile("["
    u"\U0001F600-\U0001F64F" # emoticons
    u"\U0001F300-\U0001F5FF" # symbols & pictographs
    u"\U0001F680-\U0001F6FF" # transport & map symbols
    u"\U0001F1E0-\U0001F1FF" # flags (iOS)
    u"\U00002500-\U00002BEF" # chinese char
    u"\U00002702-\U000027B0"
    u"\U00002702-\U000027B0"
    u"\U000024C2-\U0001F251"
    u"\U0001f926-\U0001f937"
    u"\U00010000-\U0010ffff"
    u"\u2640-\u2642"
    u"\u2600-\u2B55"
    u"\u200d"
    u"\u23cf"
    u"\u23e9"
    u"\u231a"
    u"\ufe0f" # dingbats
    u"\u3030"
    "]+", flags=re.UNICODE)
    return emoji_pattern.sub(r'', string)
```

[417]:
```
# remove rows without a comment body
df.dropna(subset='body', how="any", inplace=True)

df['clean'] = df['body'].apply(lambda x: remove_emoji(cleanTxt(x)))
```

[418]:
```
def vader_sentiment(dataset):
    # VADER sentiment analysis
    sid = SentimentIntensityAnalyzer()

    dataset[['pos', 'neg', 'neu', 'compound']] = dataset['clean'].apply(lambda␣
 ↪text: pd.Series(sid.polarity_scores(text)))

    # Threshold conditions determine the value of the sentiment of the text
    THRESHOLD = 0.2
    conditions = [
        (dataset['compound'] <= -THRESHOLD),
        (dataset['compound'] > -THRESHOLD) & (dataset['compound'] < THRESHOLD),
```

```
        (dataset['compound'] >= THRESHOLD),
        ]
    values = ["neg", "neu", "pos"]
    dataset['label'] = np.select(conditions, values)

    # Convert all sentiment columns to numeric type
    dataset[['pos', 'neg', 'neu', 'compound']] = dataset[['pos', 'neg', 'neu',␣
 ↪'compound']].apply(pd.to_numeric, errors='coerce')
```

1.3 Filtering dataset for GPT3 and GPT4

[419]:
```
# converting created dates from reddit API into human readable format
from datetime import datetime

# Define the date range for GPT-3 hype analysis
gpt3_start = datetime(2022, 11, 1)
gpt3_end = datetime(2023, 1, 31)

# Define the date range for GPT-3 hype analysis
gpt4_start = datetime(2023, 2, 15)
gpt4_launch =  datetime(2023, 3, 14)
gpt4_end = datetime(2023, 5, 15)

# get the distance of the date to the GPT-4 launch date
df['launch_distance'] = abs(gpt4_launch - df['created_date'])
df['launch_distance_f'] = df['launch_distance'] / pd.to_timedelta(1, unit='D')

# Filter datasets
df_gpt3 = df[(df['created_date'] >= gpt3_start) & (df['created_date'] <=␣
 ↪gpt3_end)]

# Split at gpt4_launch date
df_gpt4_before = df[(df['created_date'] >= gpt4_start) & (df['created_date'] <␣
 ↪gpt4_launch)]
df_gpt4_after = df[(df['created_date'] >= gpt4_launch) & (df['created_date'] <=␣
 ↪gpt4_end)]

# apply vader sentiment to matched datasets
vader_sentiment(df_gpt3)
vader_sentiment(df_gpt4_before)
vader_sentiment(df_gpt4_after)
```

[420]:
```
df_gpt3.describe() #3936 count
df_gpt4_before.describe() #1821 count
df_gpt4_after.describe() #10384 count
```

[420]:

```
        Unnamed: 0  upvote_ratio         score  num_comments       created  \
count  7186.000000   7186.000000   7186.000000   7186.000000  7.186000e+03
mean   1308.272474      0.907897   2590.818954    424.175758  1.681434e+09
std     791.959025      0.101435   4686.361973    741.385185  1.476895e+06
min       1.000000      0.250000      0.000000      0.000000  1.678839e+09
25%     838.000000      0.880000     26.000000      8.000000  1.680216e+09
50%    1170.000000      0.940000    186.000000     70.000000  1.681472e+09
75%    1756.000000      0.980000   3085.000000    456.000000  1.682701e+09
max    3450.000000      1.000000  22371.000000   3835.000000  1.684078e+09

       score_weighted  num_comments_weighted              launch_distance  \
count     7186.000000            7186.000000                         7186
mean         0.006916               0.001127  31 days 01:06:15.650013916
std          0.018835               0.003005  17 days 02:14:54.726580965
min          0.000000               0.000000              1 days 00:12:18
25%          0.000027               0.000007             16 days 22:40:29
50%          0.000211               0.000065             31 days 11:33:56
75%          0.003298               0.000594             45 days 17:01:49
max          0.150882               0.025865             61 days 15:20:13

       launch_distance_f          pos          neg          neu     compound
count        7186.000000  7186.000000  7186.000000  7186.000000  7186.000000
mean           31.046014     0.045888     0.840807     0.113014     0.608252
std            17.093689     0.064766     0.098919     0.073173     0.580954
min             1.008542     0.000000     0.000000     0.000000    -0.998100
25%            16.944780     0.005000     0.807000     0.079000     0.422300
50%            31.481898     0.037000     0.855000     0.107000     0.929900
75%            45.709595     0.056000     0.894000     0.138000     0.993800
max            61.639039     0.565000     1.000000     0.510000     0.999800
```

[421]:

```
# Features to measure with MLflow
feature_names = ['launch_distance_f', 'num_comments_weighted', 'stickied',␣
 ↪'upvote_ratio', 'created', 'compound', 'pos', 'neg', 'neu']
# Target MLflow value
target_name = 'score_weighted'

# these variables should be represented as log of the original values
log_variables = ['score_weighted','num_comments', 'launch_distance_f',␣
 ↪'created']
# These features are disabled. Stickied items throw off the counts.
for feature in ['stickied']: feature_names.remove(feature)

def clean_dataset(dataset, csv_name, inplace=True):
    global log_variables, feature_names, target_name
    if inplace is True:
        _dataset = dataset
    else:
```

```
        _dataset = dataset.copy()
    for variable in log_variables:
        # Rename the variables to log_[variable] in the datasets
        log_variable = 'log_'+variable
        if target_name == variable:
            target_name = log_variable
        elif variable in feature_names:
            feature_names[feature_names.index(variable)] = log_variable
        _dataset[log_variable] = _dataset[variable].apply(lambda value: np.
 ↪log(value+1))
    _dataset.dropna(subset=feature_names, how="any", inplace=True)
    _dataset.dropna(subset=target_name, how="any", inplace=True)

    ## Output file to csv
    _dataset.to_csv('/'.join(['output', csv_name + '.csv']))
    return _dataset

clean_dataset(df_gpt3, 'gpt3')
clean_dataset(df_gpt4_before, 'gpt4-before')
clean_dataset(df_gpt4_after, 'gpt4-after')

print(f"feature_names={feature_names}")
print(f"target_name={target_name}")
```

```
feature_names=['log_launch_distance_f', 'num_comments_weighted', 'upvote_ratio',
'log_created', 'compound', 'pos', 'neg', 'neu']
target_name=log_score_weighted
```

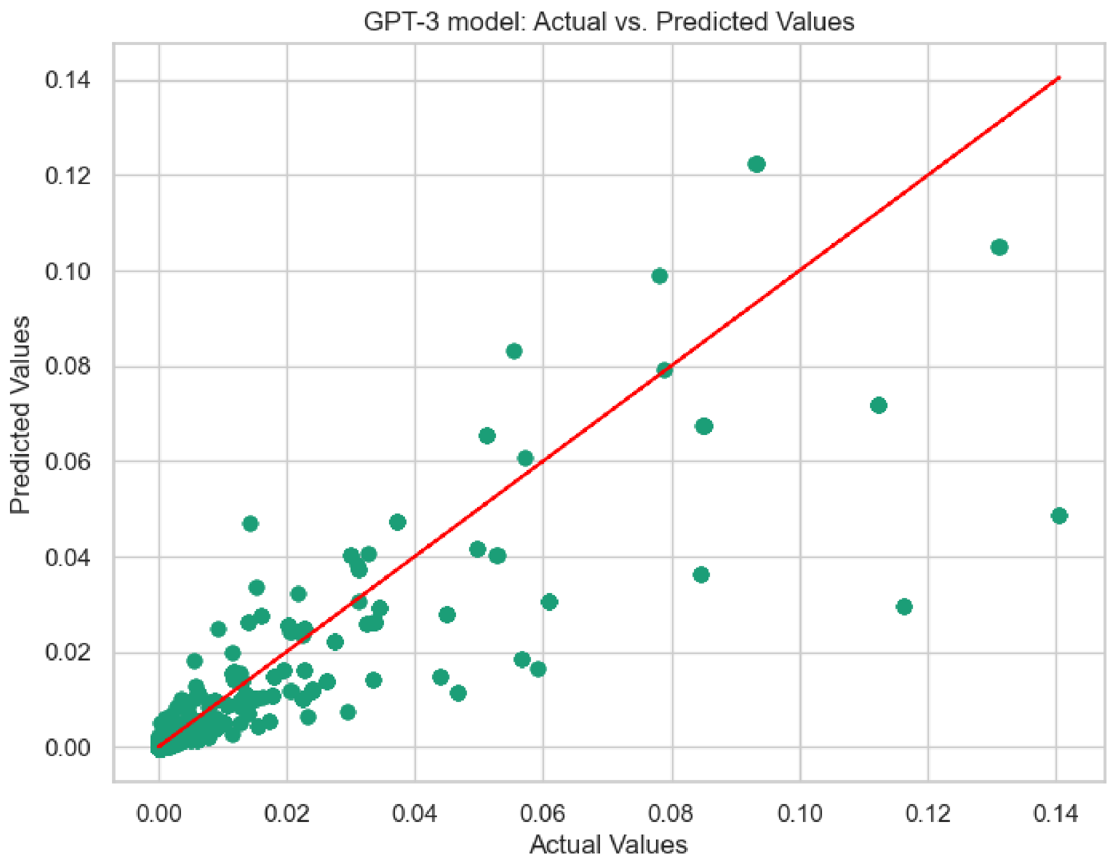
[422]:
```
# Enable automatic logging to MLflow
mlflow.set_experiment("Reddit GPT Hype")
mlflow.autolog()

def trim_dataset(dataset, q_lower = 0, q_upper = 1):
    global target_name
    quantile = target_name
    _dataset = dataset.copy()
    # Trim dataset by the quantile for the target for training
    _dataset = _dataset[(_dataset['stickied'] == False)]
    _q_lower = _dataset[quantile].quantile(q_lower)
    _q_upper = _dataset[quantile].quantile(q_upper)
    _dataset = _dataset[(_dataset[quantile] >= _q_lower) &
                        (_dataset[quantile] <= _q_upper)]
    return _dataset

def model_testing(dataset, test):
    _dataset = dataset.copy()
    _test = test.copy()
```

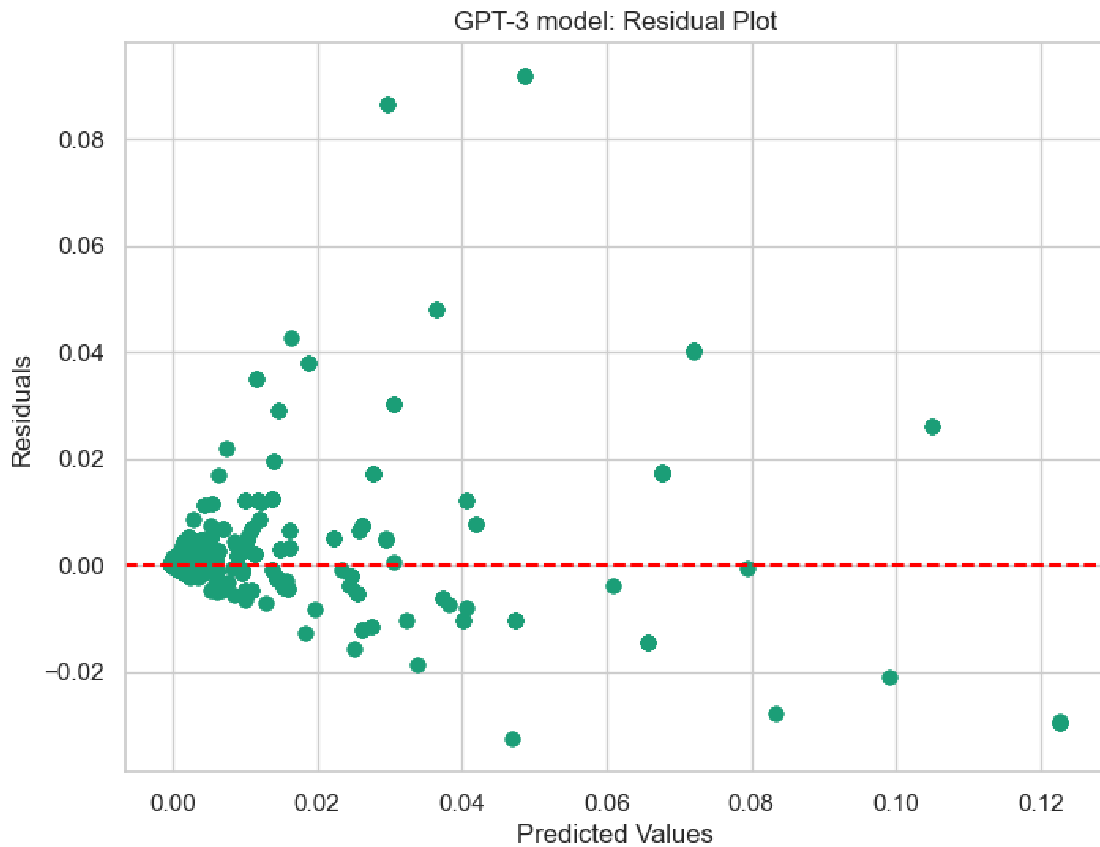
```
    # Trim upper and lower quantiles
    _dataset = trim_dataset(_dataset)
    _test = trim_dataset(_test)
    # Sort values for displaying in graph
    _dataset = dataset
    _test = _test
    # Set X features and y targets
    X_test = _test.loc[:, _test.columns[:,None] == feature_names]
    y_test = _test.loc[:, _test.columns == target_name].values
    X = _dataset.loc[:, _dataset.columns[:,None] == feature_names]
    y = _dataset.loc[:, _dataset.columns == target_name].values

    lr_params =  {}
    lr = LinearRegression(**lr_params)

    # MLflow triggers logging automatically upon model fitting
    lr.fit(X, y)
    y_pred = lr.predict(X_test)

    return {'X': X, 'y': y, 'X_test': X_test, 'y_actual': y_test, 'y_pred':␣
↪y_pred, 'coef': lr.coef_}

gpt3_model = model_testing(df_gpt3, df_gpt4_after)
#gpt3_model_same = model_testing(df_gpt3, df_gpt3)
gpt4_model = model_testing(df_gpt4_before, df_gpt4_after)
#gpt4_model_same = model_testing(df_gpt4_before, df_gpt4_before)
```

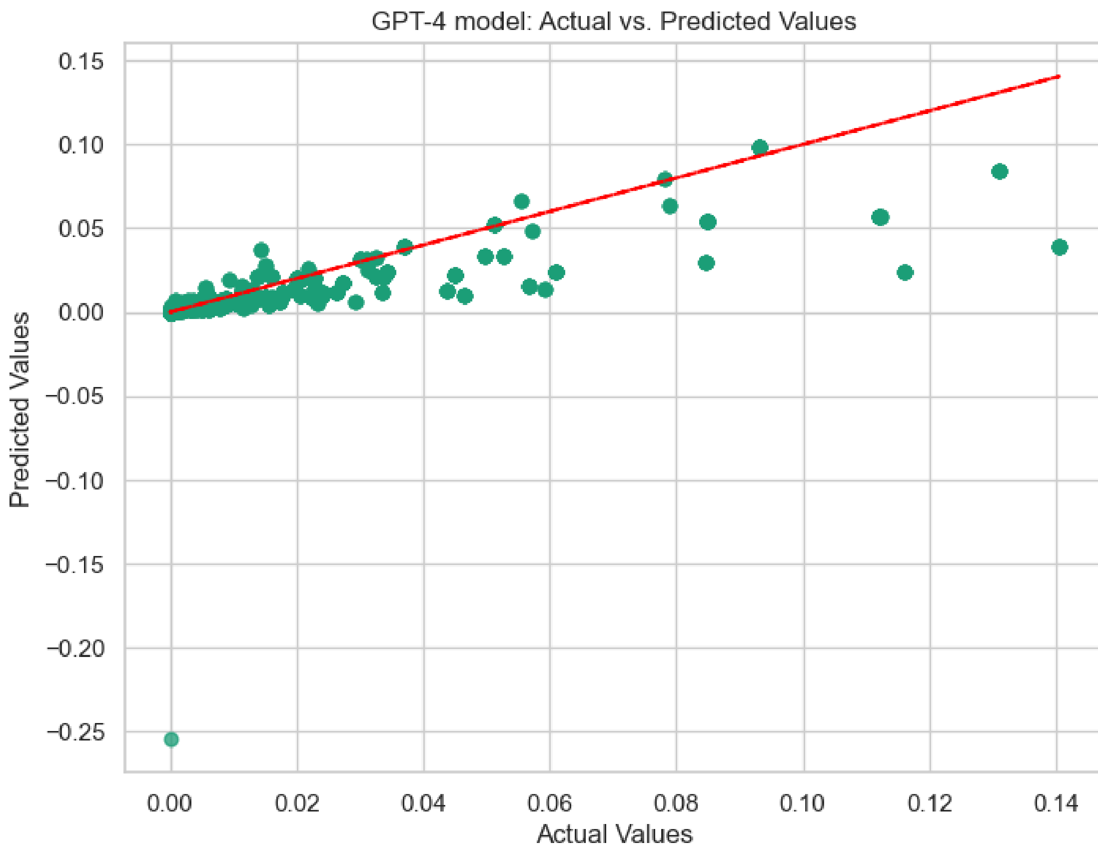
```
2024/02/18 23:32:23 INFO mlflow.tracking.fluent: Autologging successfully
enabled for sklearn.
2024/02/18 23:32:23 INFO mlflow.utils.autologging_utils: Created MLflow
autologging run with ID '83ee2c426aa94ceeabb3610f02946dfd', which will track
hyperparameters, performance metrics, model artifacts, and lineage information
for the current sklearn workflow
2024/02/18 23:32:26 INFO mlflow.utils.autologging_utils: Created MLflow
autologging run with ID 'cabf724c29804869a39f294af34a2630', which will track
hyperparameters, performance metrics, model artifacts, and lineage information
for the current sklearn workflow
```

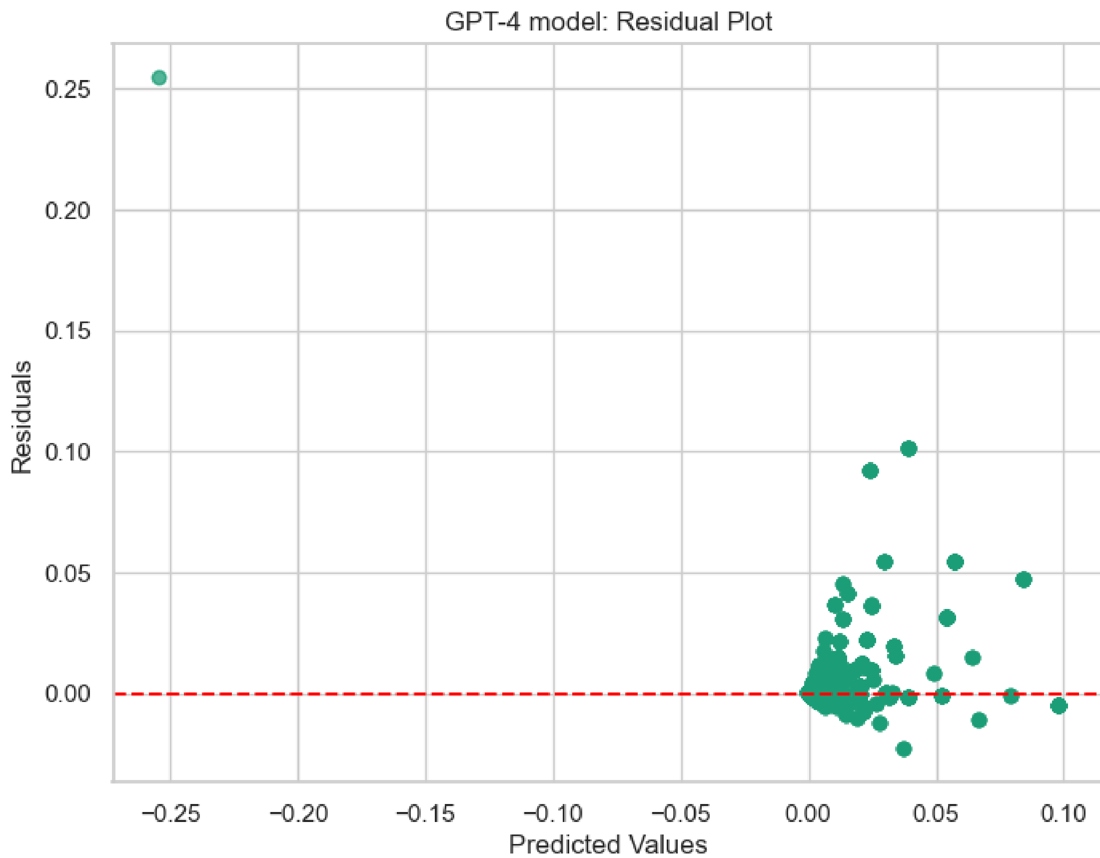
[423]:
```
def plot_accuracy(model, name):
    actual_values = model['y_actual']
    predicted_values = model['y_pred']

    # Scatter plot of actual versus predicted values
    plt.figure(figsize=(8, 6))
    plt.scatter(actual_values, predicted_values, alpha=0.5)
    plt.plot(actual_values, actual_values, color='red', linestyle='--')
    plt.xlabel("Actual Values")
```

```
    plt.ylabel("Predicted Values")
    plt.title(name + ": Actual vs. Predicted Values")
    plt.grid(True)
    plt.show()

    # Residual plot
    residuals = actual_values - predicted_values
    plt.figure(figsize=(8, 6))
    plt.scatter(predicted_values, residuals, alpha=0.5)
    plt.axhline(y=0, color='red', linestyle='--')
    plt.xlabel("Predicted Values")
    plt.ylabel("Residuals")
    plt.title(name + ": Residual Plot")
    plt.grid(True)
    plt.show()

    # Coefficient plot (if coefficients are available in the MLflow run)
    if "coefficients" in model:
        coefficients = model["coef"]
        plt.figure(figsize=(8, 6))
        sns.barplot(x=coefficients.index, y=coefficients.values)
        plt.xlabel("Independent Variables")
        plt.ylabel("Coefficients")
        plt.title("Coefficient Plot")
        plt.xticks(rotation=45)
        plt.grid(True)
        plt.show()
plot_accuracy(model=gpt3_model, name='GPT-3 model')
plot_accuracy(model=gpt4_model, name='GPT-4 model')
```


GPT-3 model: Actual vs. Predicted Values
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Predicted Values
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
Actual Values

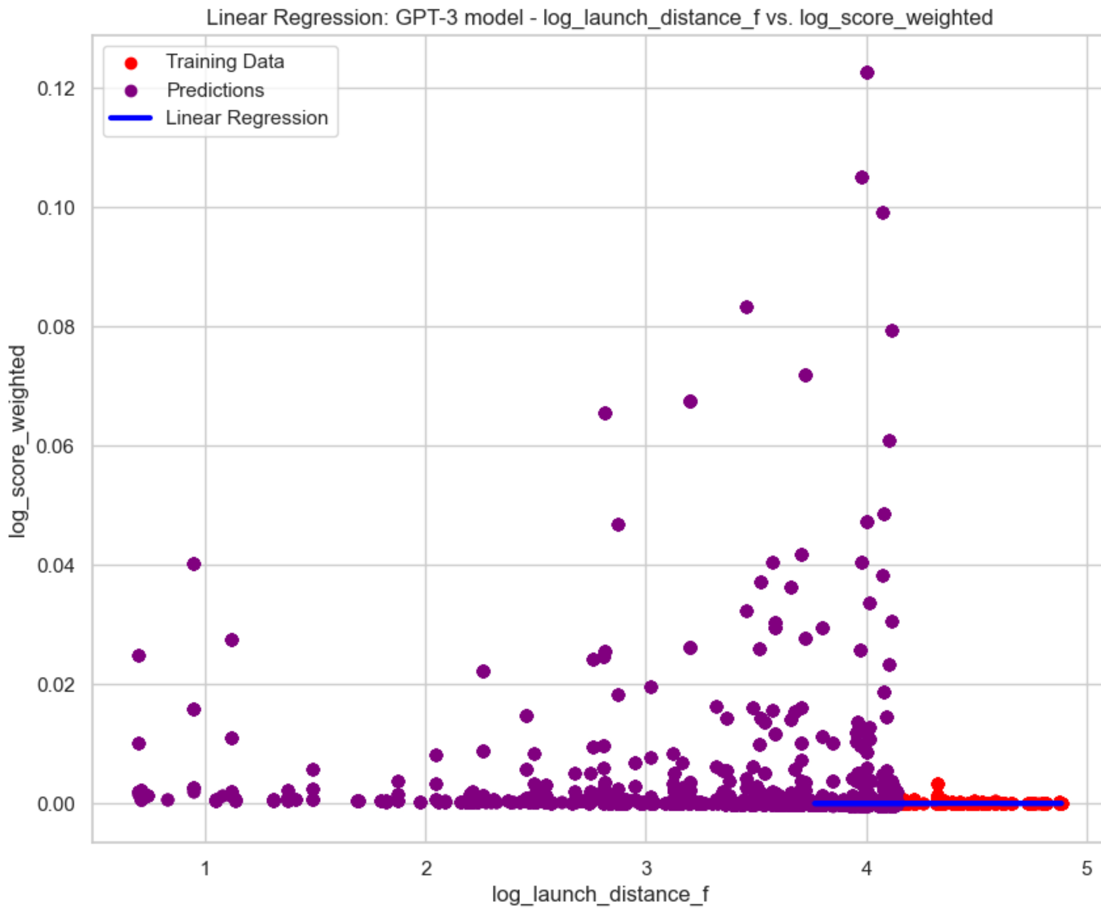

GPT-3 model: Residual Plot
Residuals
0.08
0.06
0.04
0.02
0.00
−0.02
0.00
0.02
0.04
0.06
0.08
0.10
0.12
Predicted Values


GPT-4 model: Actual vs. Predicted Values
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
Predicted Values
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
Actual Values

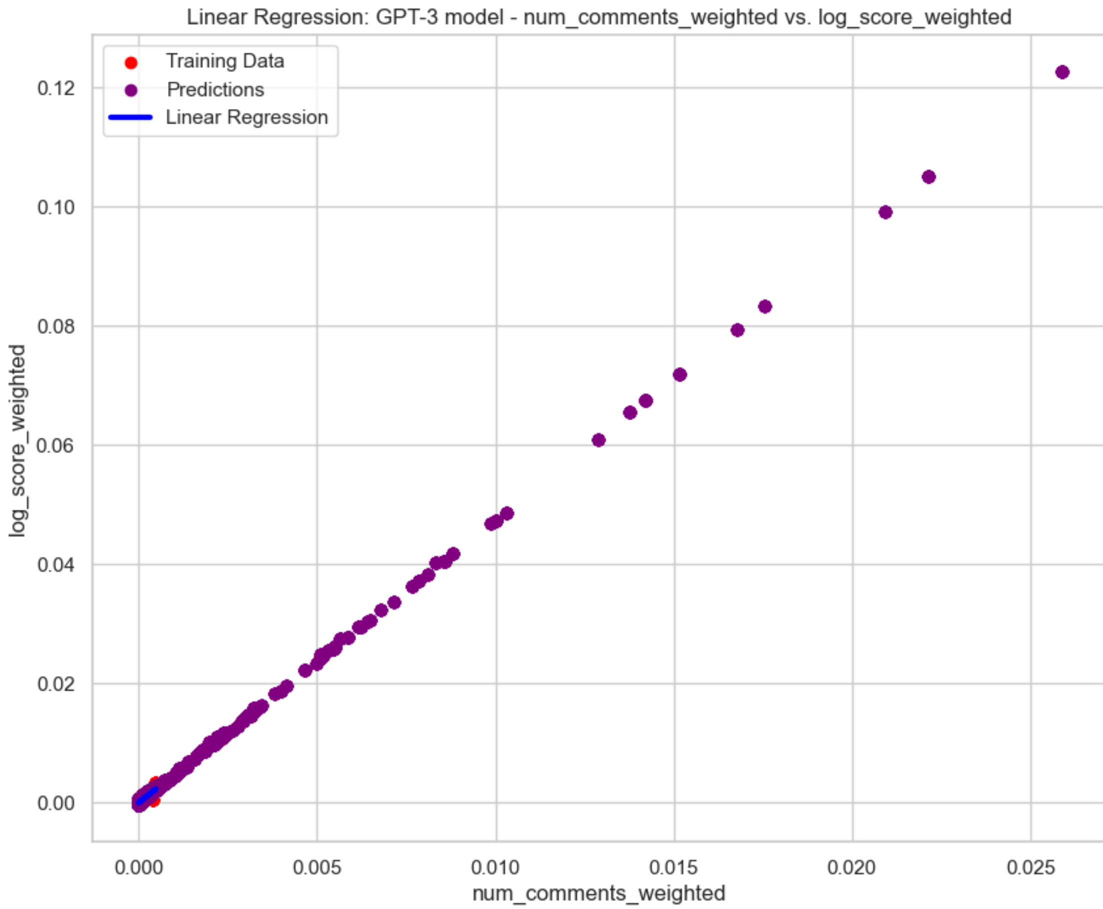


[426]:
```python
def plot_features(model, name):
    for coef in feature_names:
        print(f"{coef}={model['coef'][0][feature_names.index(coef)]}")
        feature = coef
        plt.scatter(model['X'][feature], model['y'], color='red',␣
 ↪label='Training Data')
        plt.scatter(model['X_test'][feature], model['y_pred'], color='purple',␣
 ↪label='Predictions')
        y_fit = model['X'][feature] * model['coef'][0][feature_names.
 ↪index(feature)]
        plt.plot(model['X'][feature], y_fit, color='blue', linewidth=3,␣
 ↪label='Linear Regression')
        plt.xlabel(f"{feature}")
        plt.ylabel(f"{target_name}")
        plt.title(f"Linear Regression: {name} - {feature} vs. {target_name}")
        plt.legend()
        plt.show()
plot_features(model=gpt3_model, name='GPT-3 model')
plot_features(model=gpt4_model, name='GPT-4 model')
```

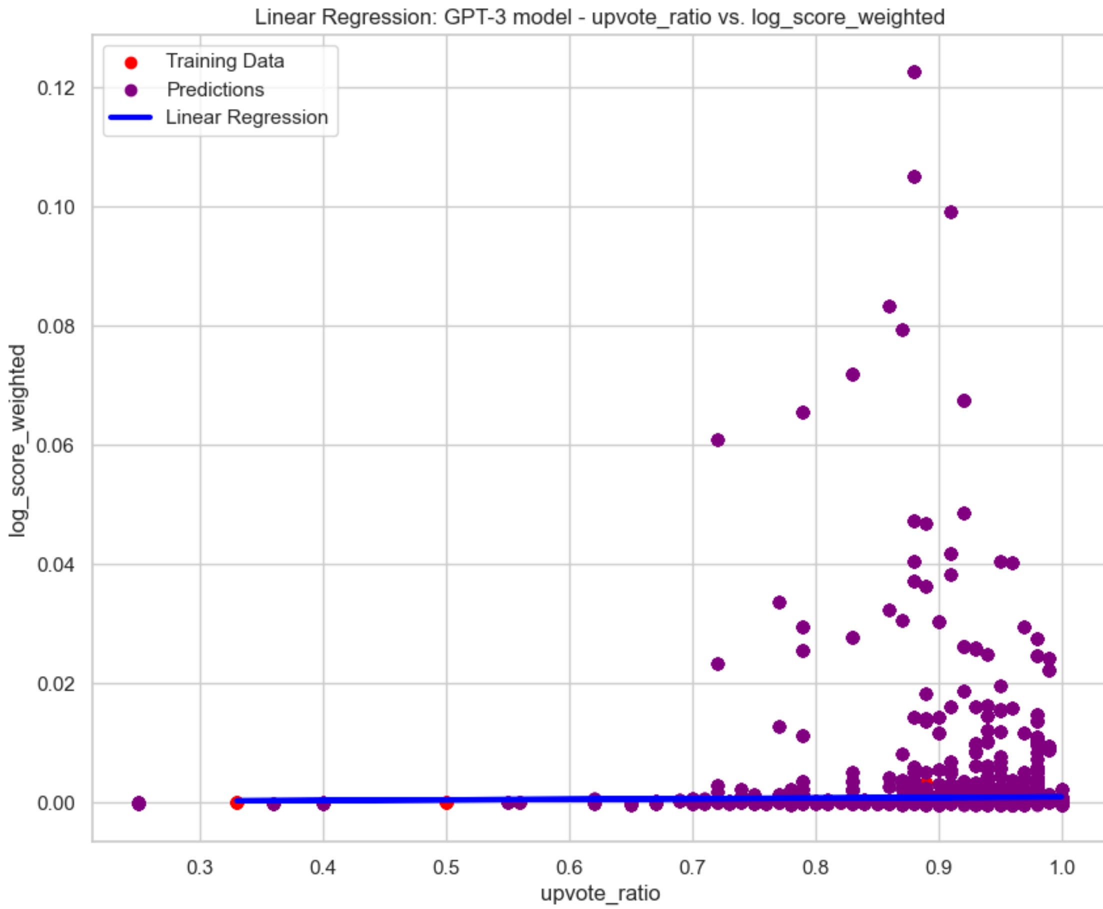
log_launch_distance_f=1.4401203089229048e-05



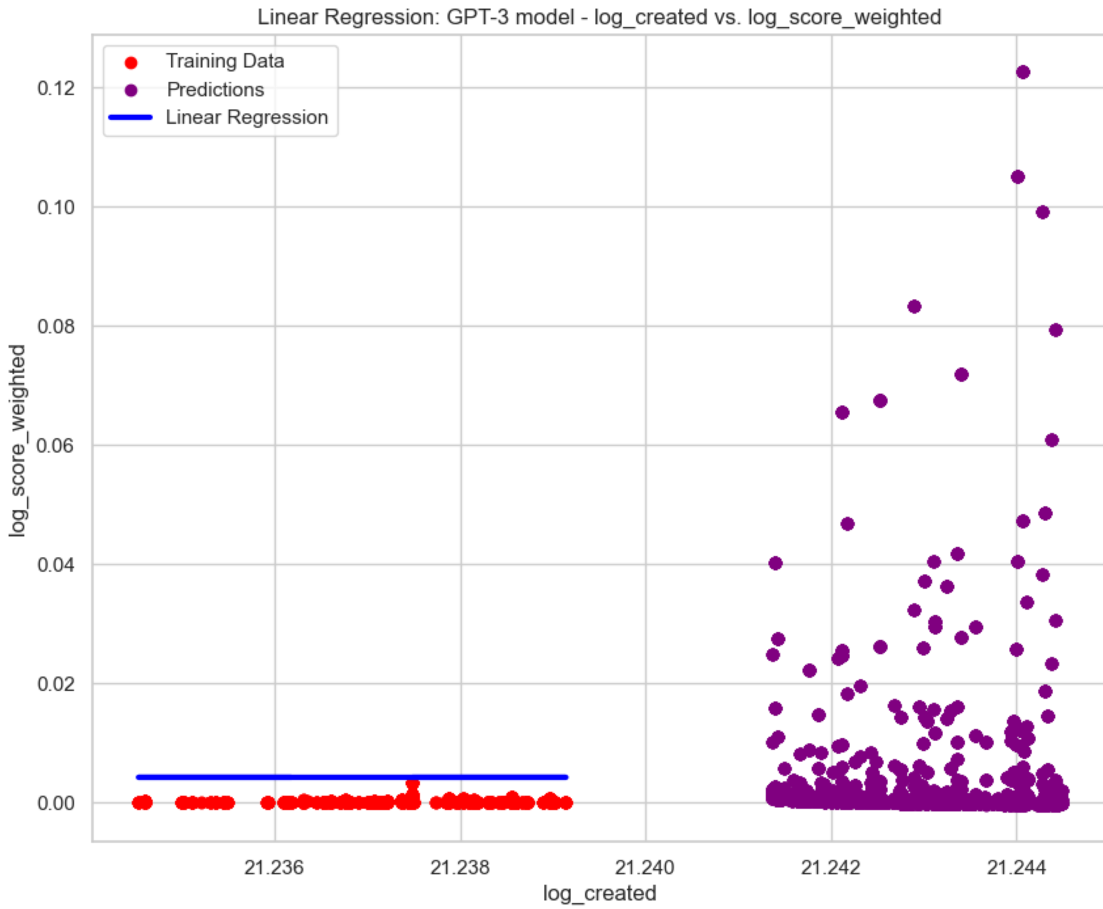
num_comments_weighted=4.7497015333104216



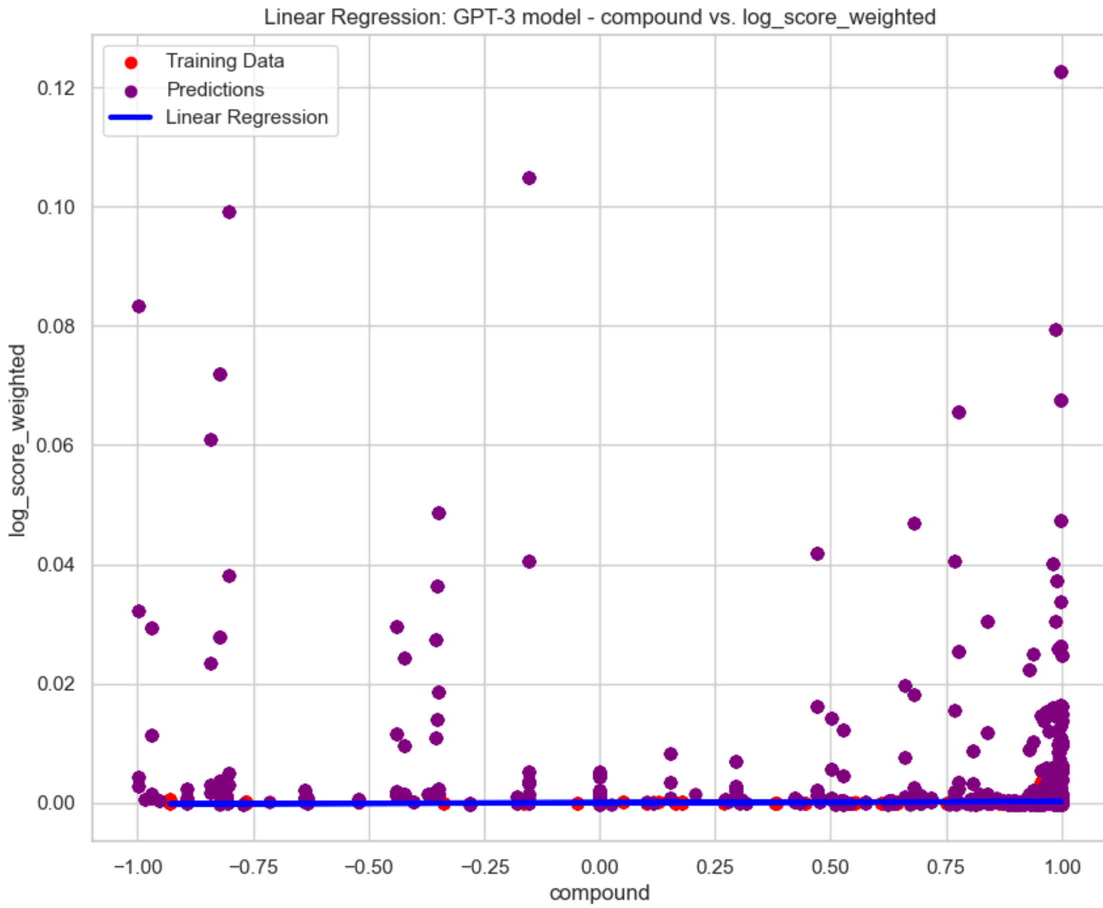

```
upvote_ratio=0.0009905129629084186
```



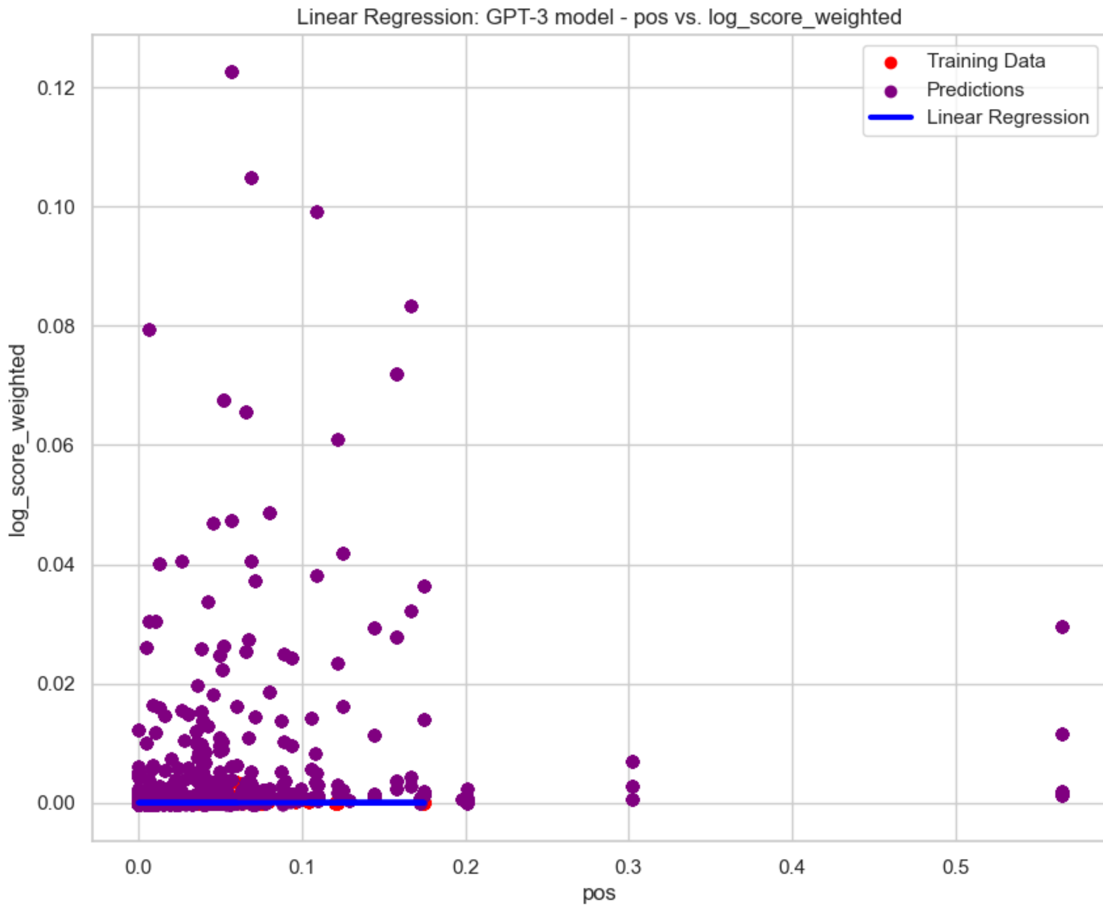

```
log_created=0.0002010309518536424
```



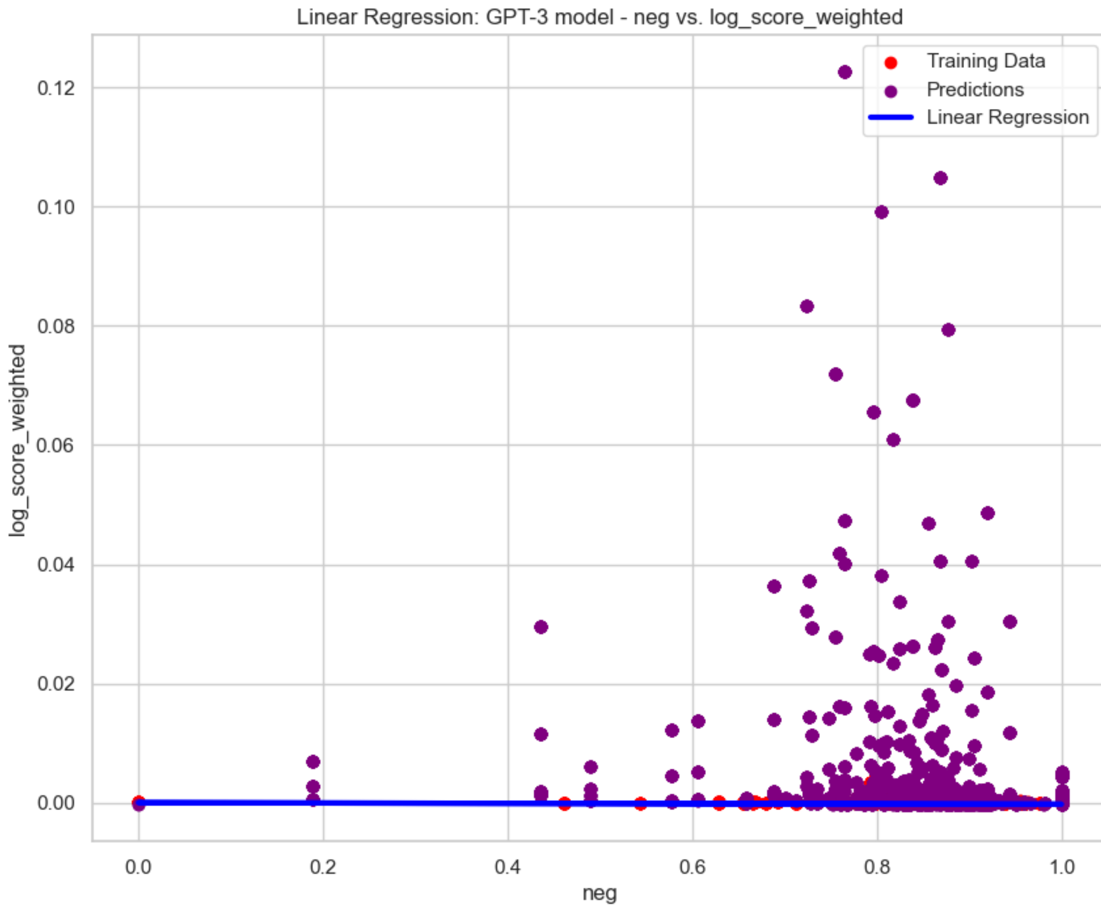

```
compound=0.00020754435114023195
```



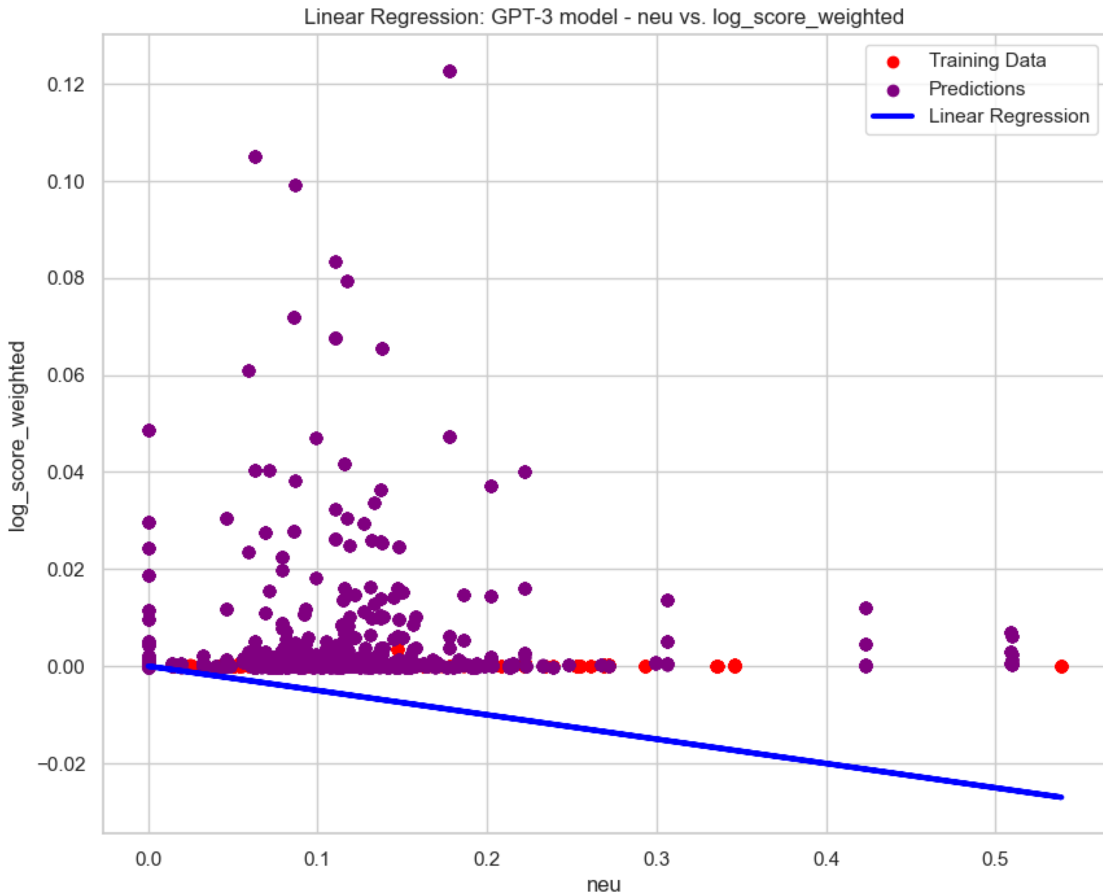

```
pos=1.8977767461151436e-05
```



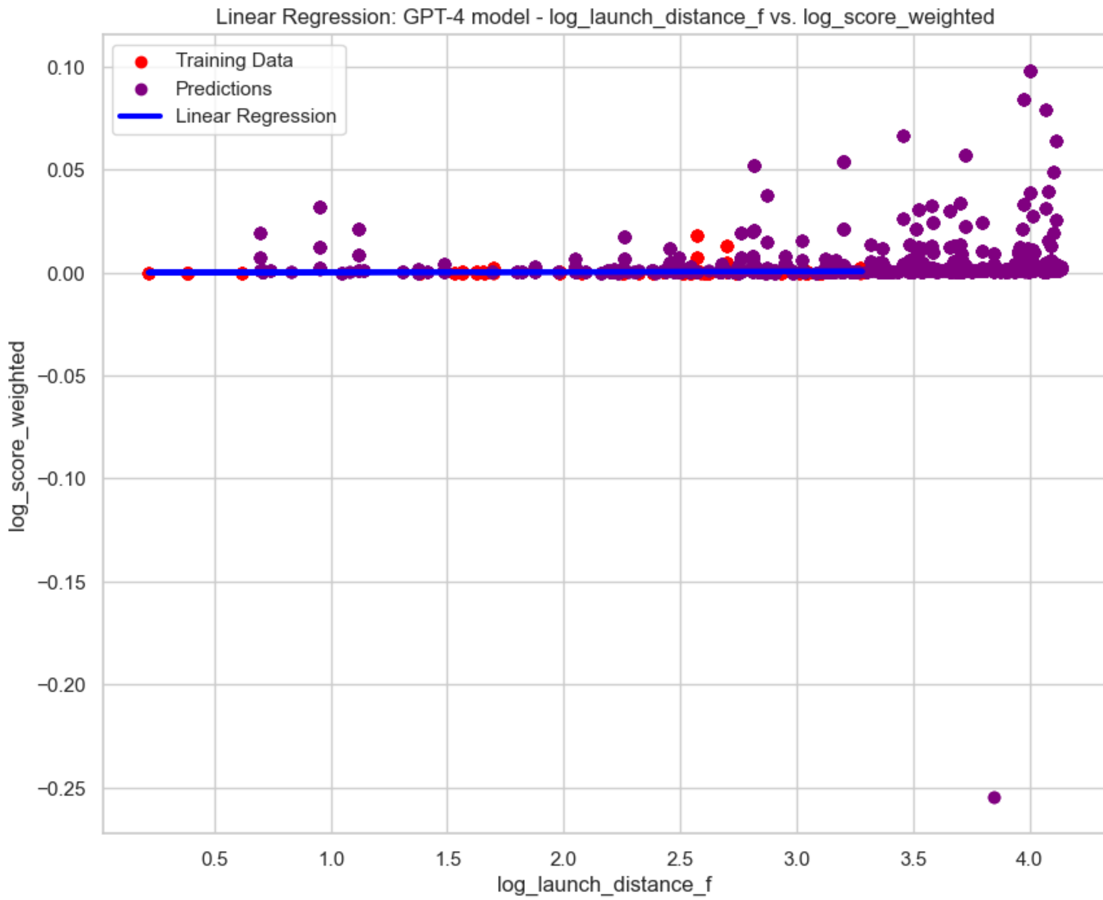
neg=-0.00025694722769253886



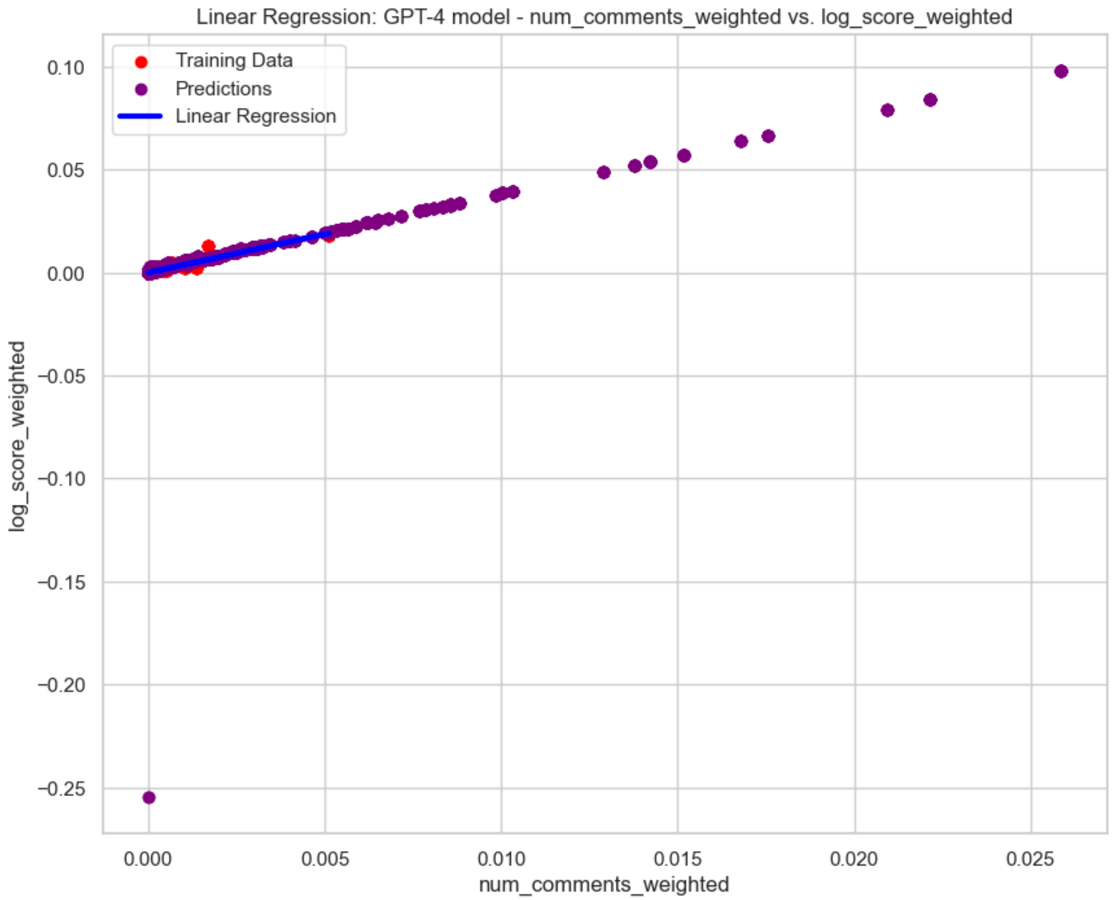

```
neu=-0.050143916791737624
```



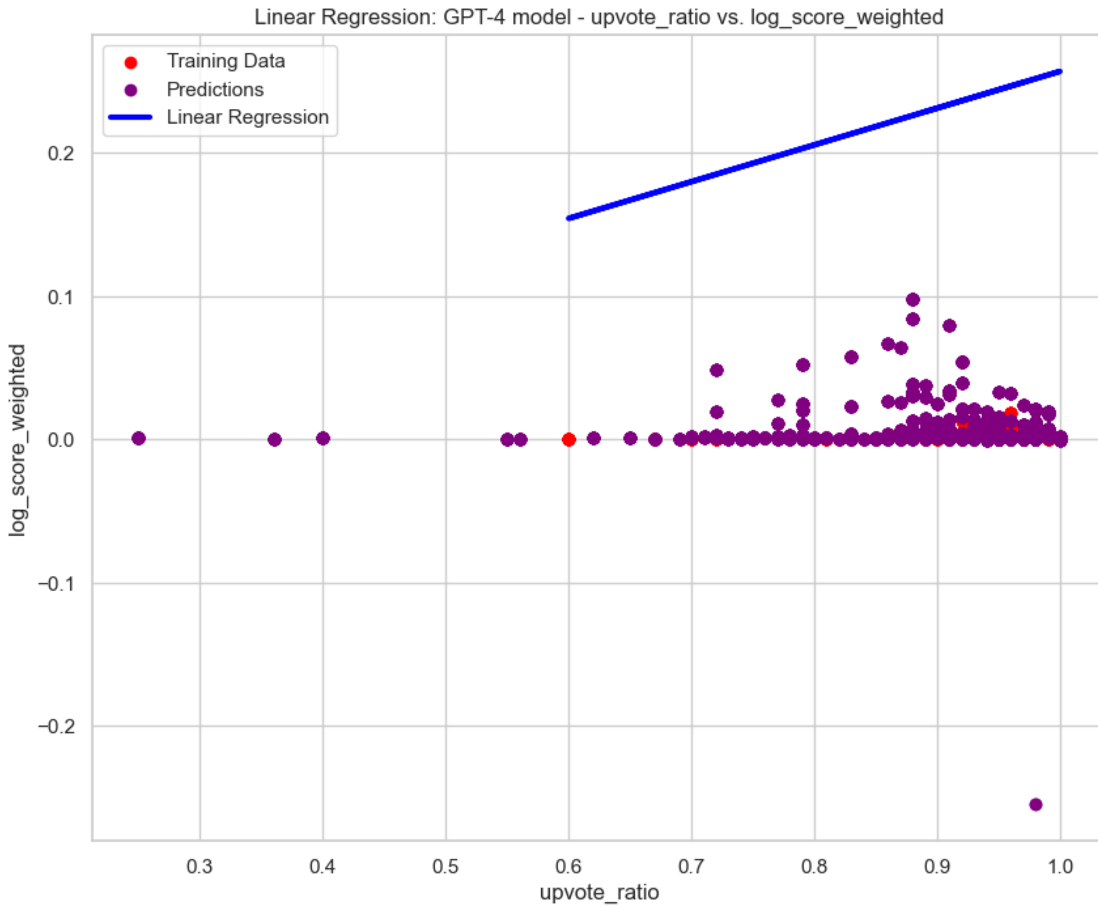
log_launch_distance_f=0.0001688318320620477



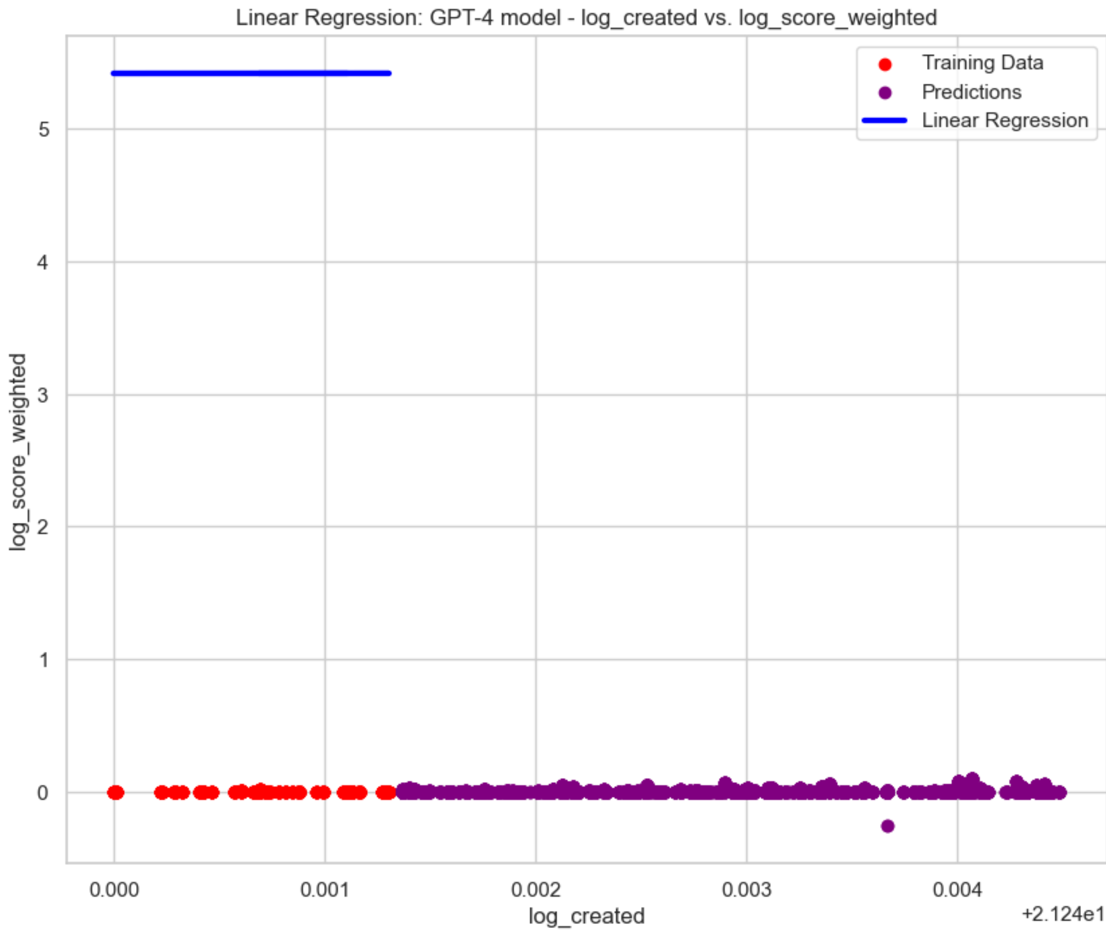
`num_comments_weighted=3.7400639766919372`



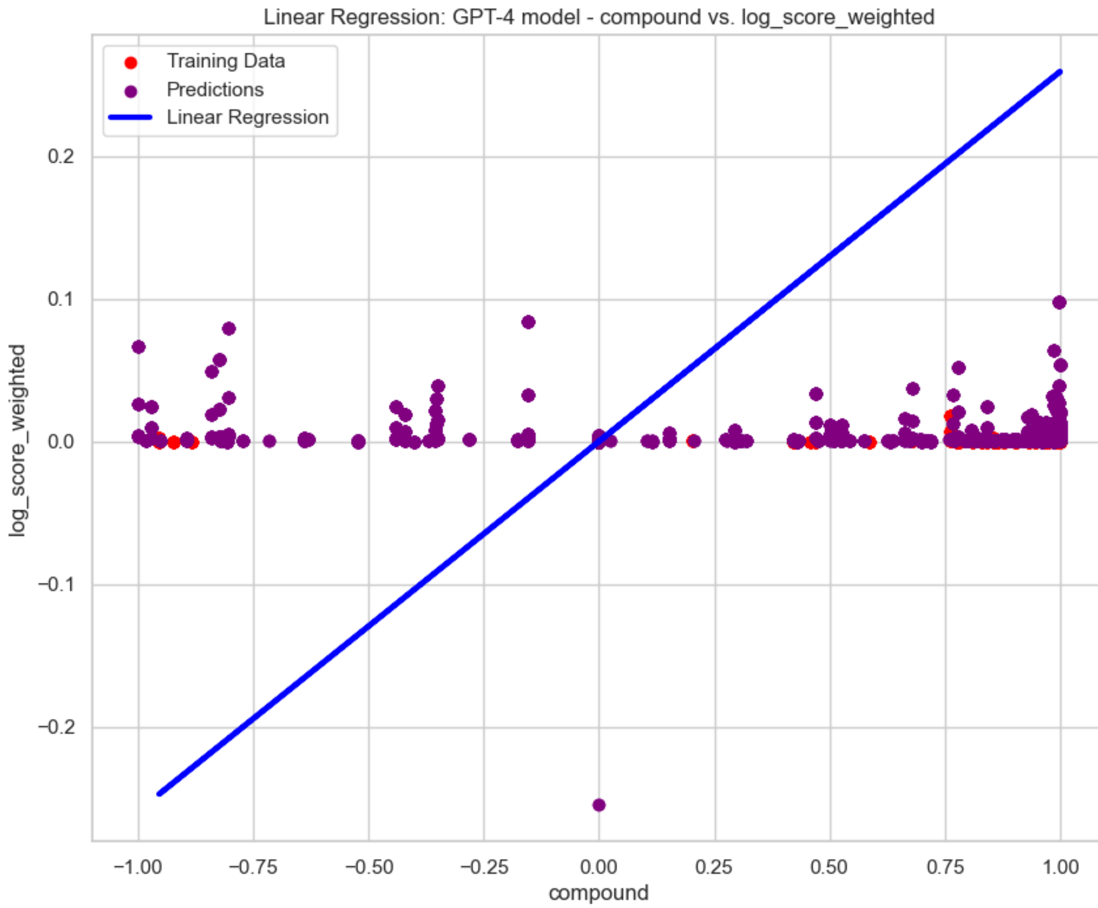
upvote_ratio=0.25666519081571215



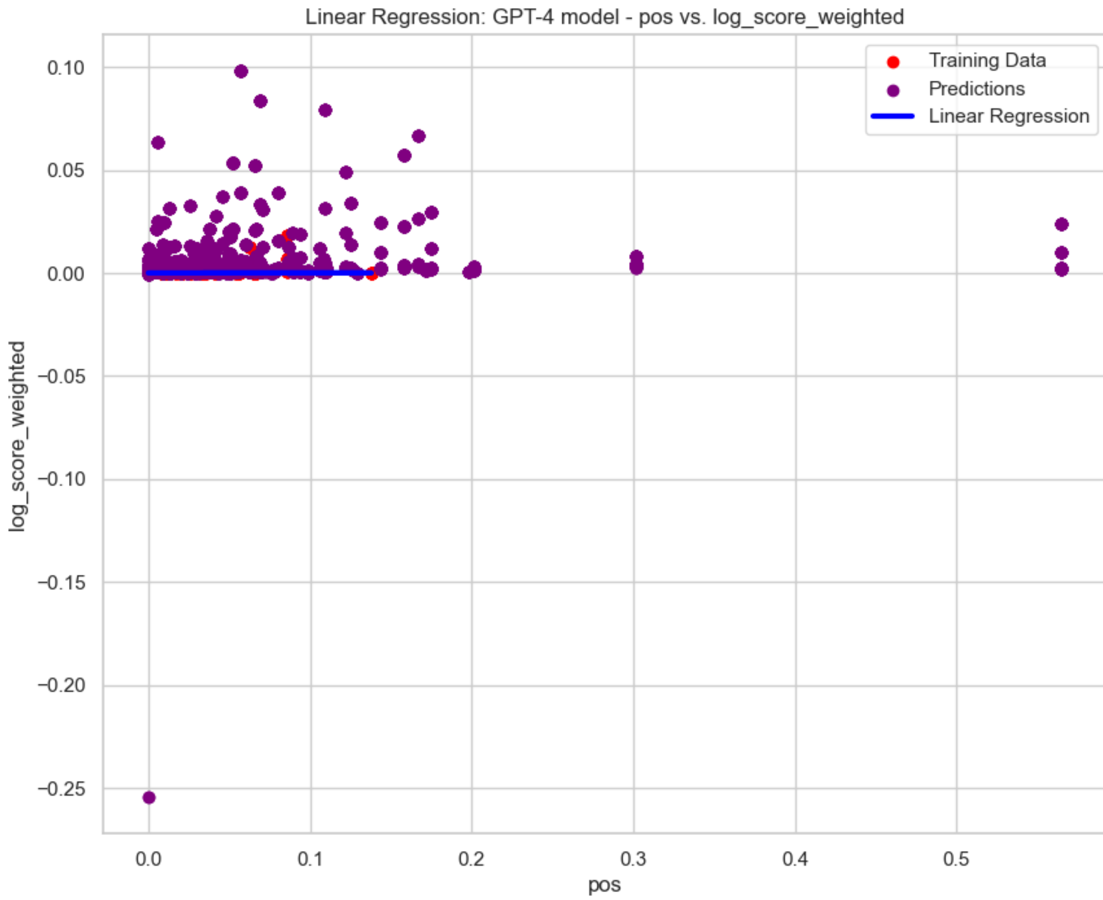

```
log_created=0.254986700298654
```



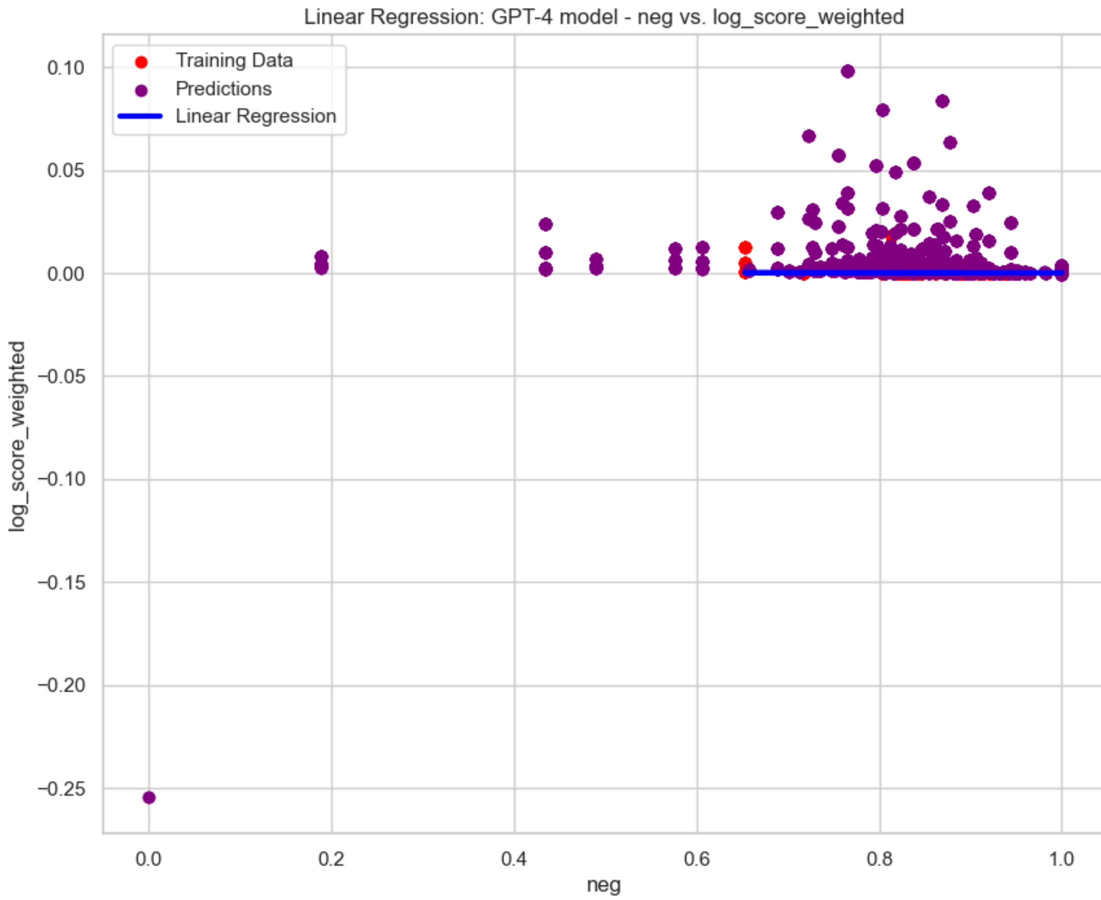
compound=0.2592078505313998



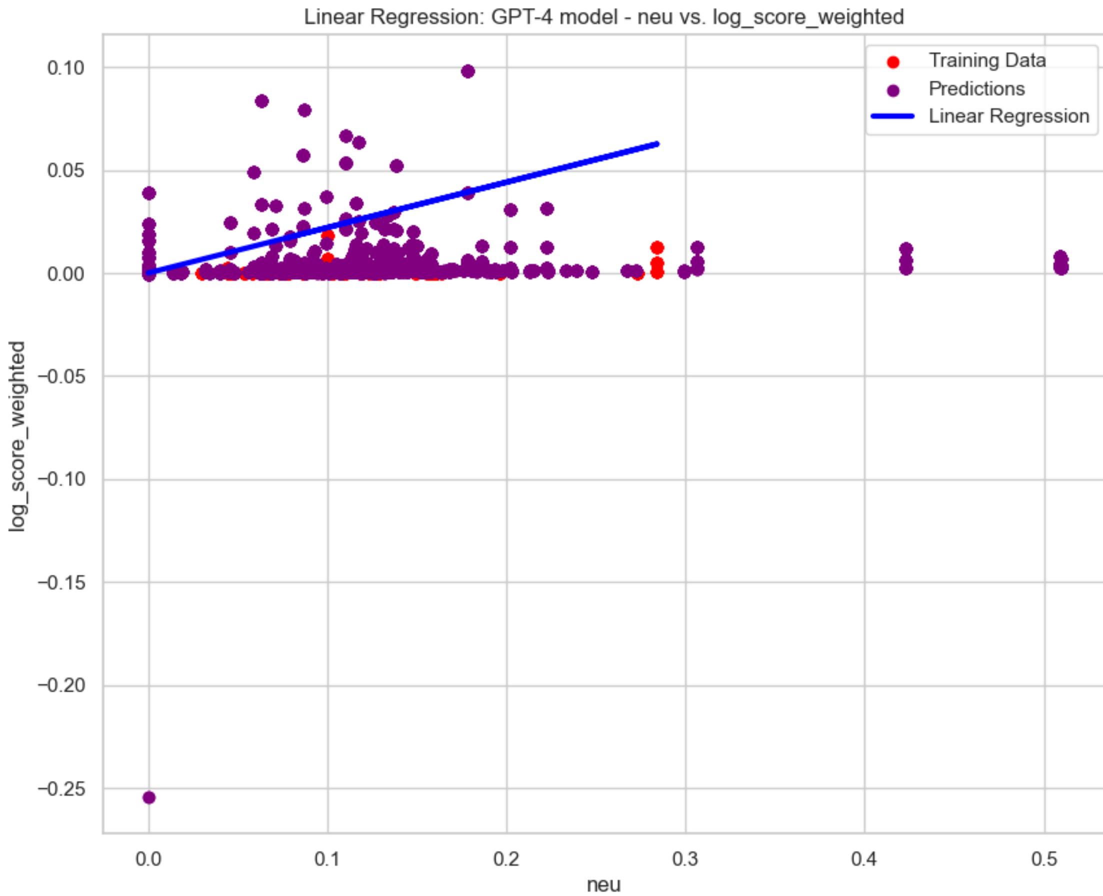

```
pos=3.409054226288788e-05
```




```
neg=8.478550332924328e-05
```

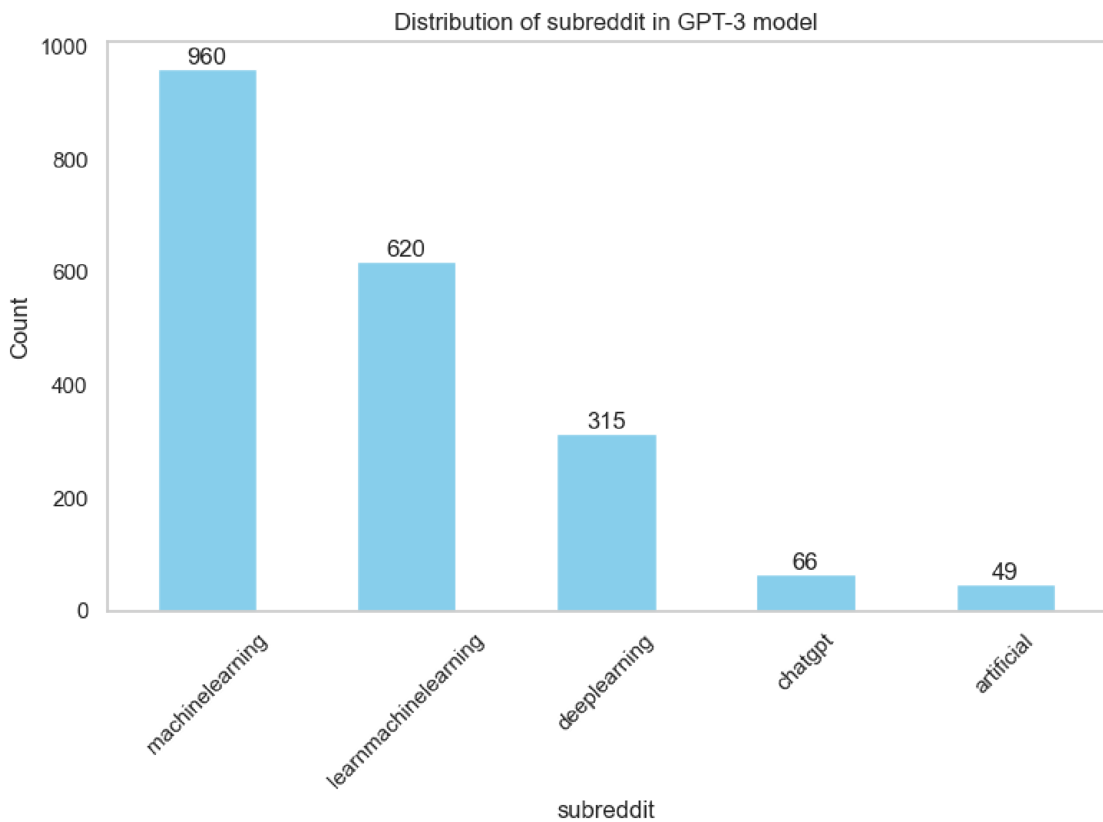


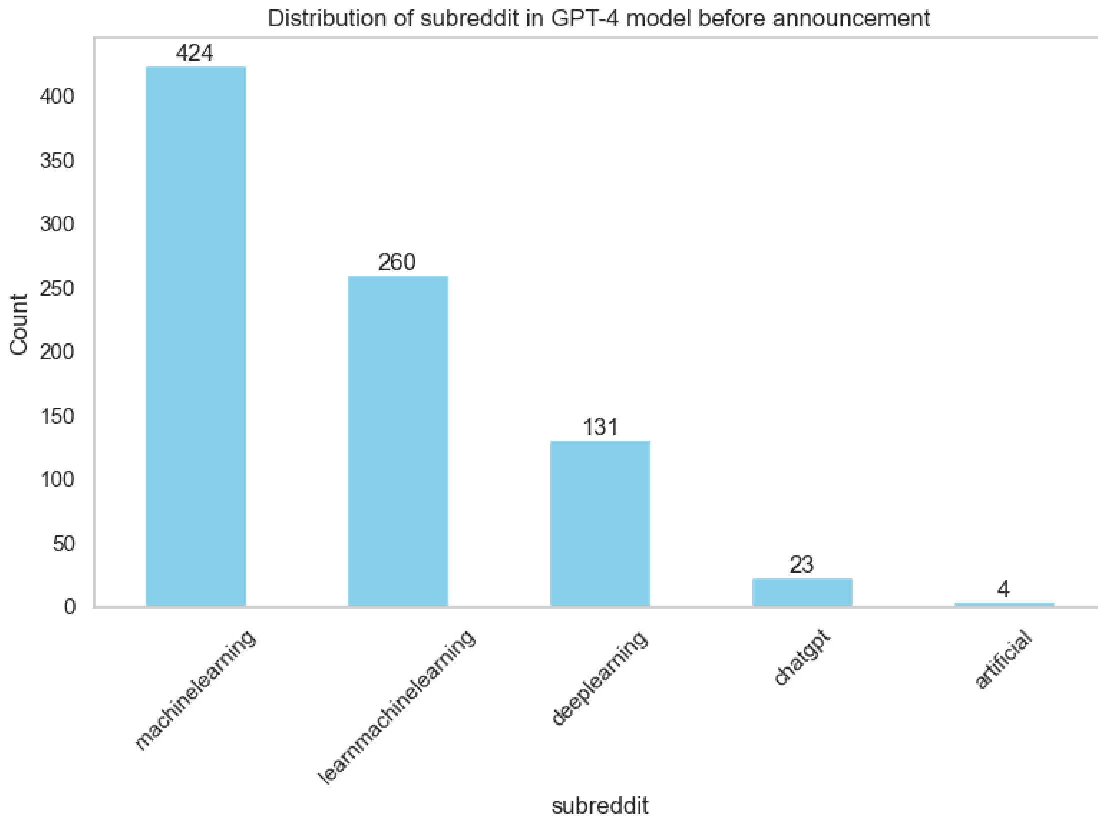
neu=0.22035240722387053

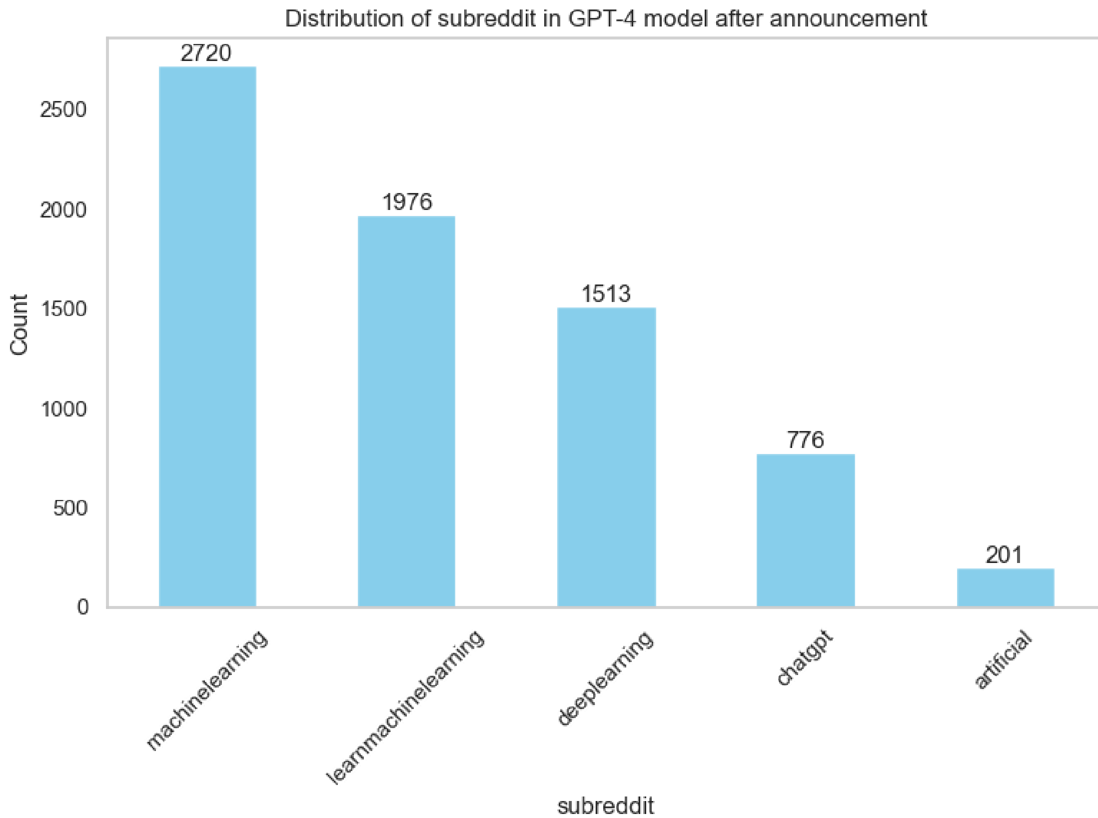


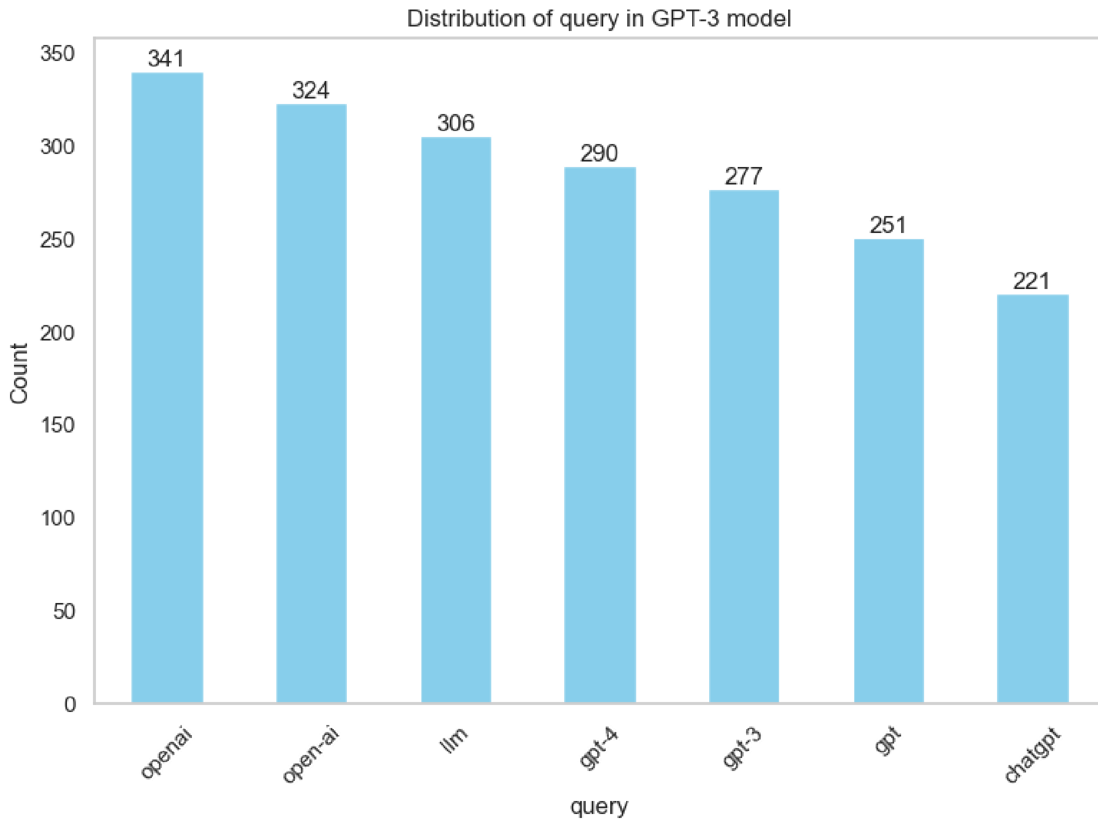
[432]:
```
def plot_distributions(dataset, name, category):
    # Count the occurrences of each category value
    category_counts = dataset[category].value_counts()

    # Plot the distribution as a bar chart
    plt.figure(figsize=(8, 6))
    ax = category_counts.plot(kind='bar', color='skyblue')
    plt.title(f'Distribution of {category} in {name}')
    plt.xlabel(category)
    plt.ylabel('Count')
    plt.xticks(rotation=45)
    plt.grid(axis='y')
    ax.grid(False)  # Remove gridlines


    # Annotate each bar with its count
    for p in ax.patches:
```

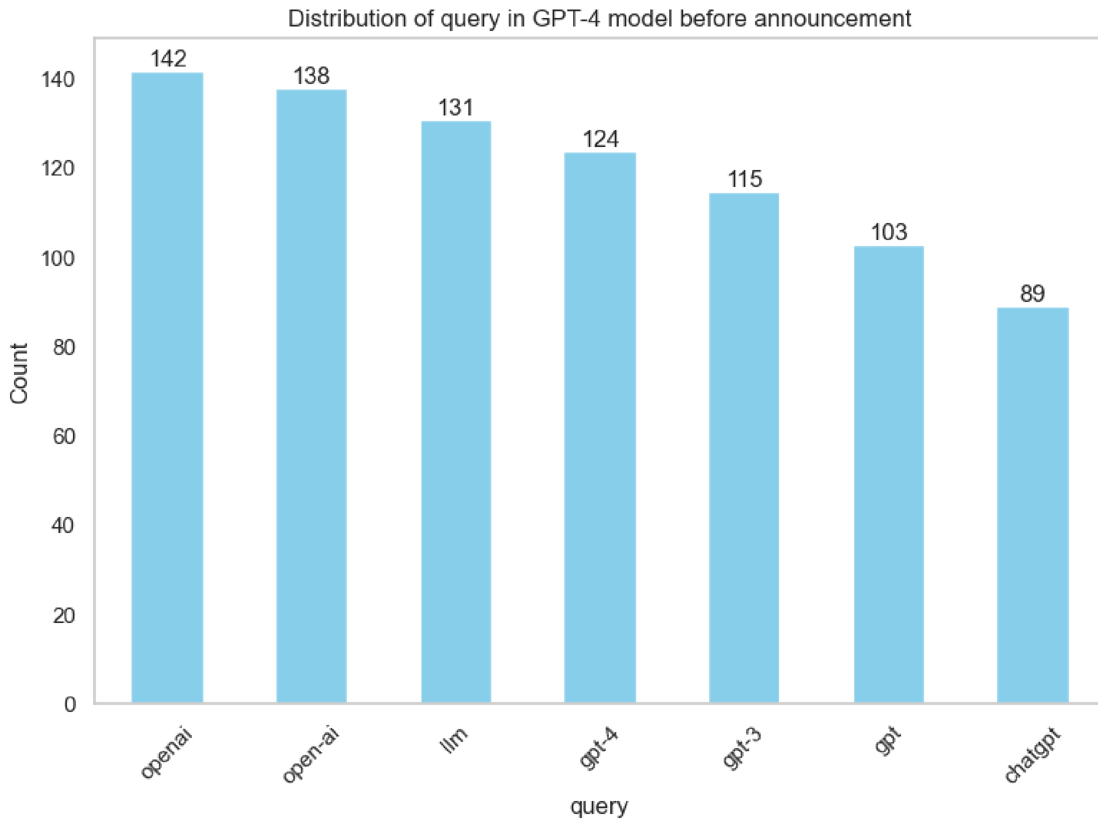
```
        ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2, p.
↪get_height()),
                    ha='center', va='bottom')

    plt.tight_layout()
    plt.show()
for category in ['subreddit', 'query']:
    plot_distributions(dataset=df_gpt3, name='GPT-3 model', category=category)
    plot_distributions(dataset=df_gpt4_before, name='GPT-4 model before␣
↪announcement', category=category)
    plot_distributions(dataset=df_gpt4_after, name='GPT-4 model after␣
↪announcement', category=category)
```



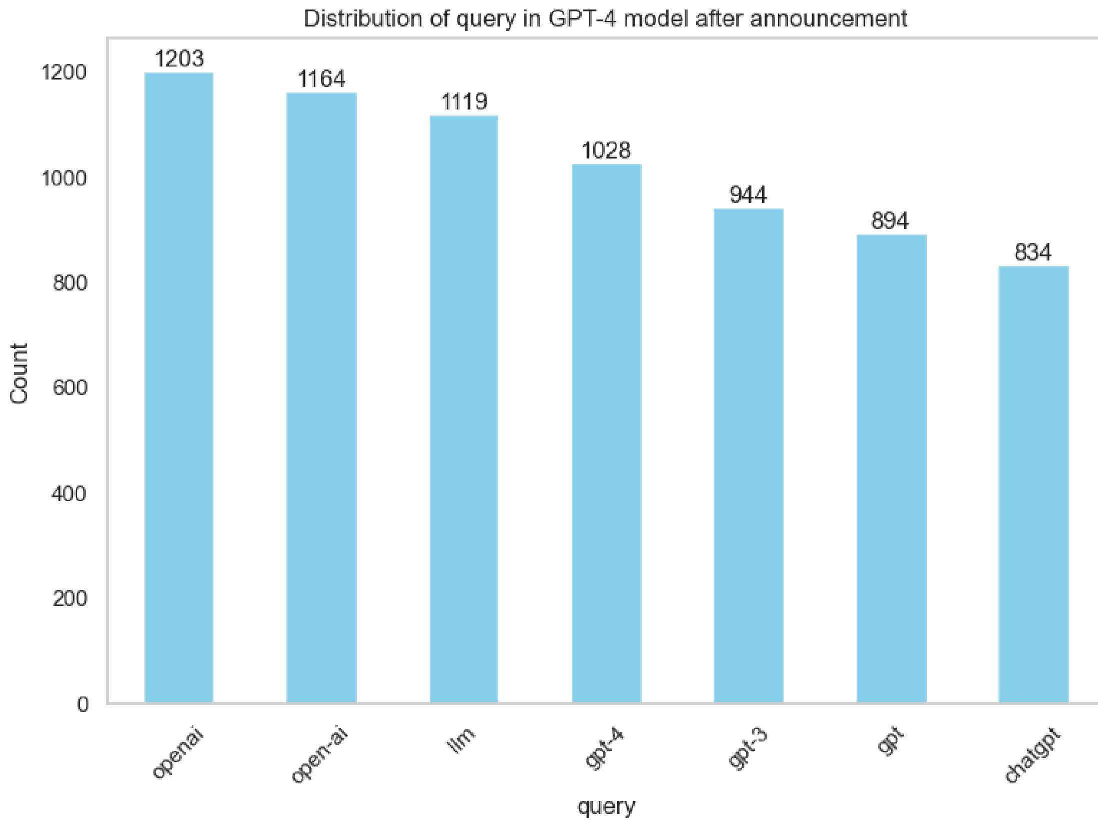

Distribution of subreddit in GPT-4 model before announcement
Count
400
350
300
250
200
150
100
50
0
424
260
131
23
4
machinelearning
learnmachinelearning
deeplearning
chatgpt
artificial
subreddit


Distribution of subreddit in GPT-4 model after announcement
Count
0
500
1000
1500
2000
2500
2720
1976
1513
776
201
machinelearning
learnmachinelearning
deeplearning
chatgpt
artificial
subreddit


Distribution of query in GPT-3 model
Count
query
341
324
306
290
277
251
221
openai
open-ai
llm
gpt-4
gpt-3
gpt
chatgpt
0
50
100
150
200
250
300
350



Distribution of query in GPT-4 model before announcement
Count
query
142
138
131
124
115
103
89
openai
open-ai
llm
gpt-4
gpt-3
gpt
chatgpt
0
20
40
60
80
100
120
140


Distribution of query in GPT-4 model after announcement
Count
0
200
400
600
800
1000
1200
1203
1164
1119
1028
944
894
834
openai
open-ai
llm
gpt-4
gpt-3
gpt
chatgpt
query