Score Visualisation

February 8, 2022

[ ]:
```python
import matplotlib.pyplot as plt
import matplotlib
import numpy as np
import pandas as pd
from IPython.display import display, HTML
import math


df_scores = pd.read_csv("../output/model_comparisons.csv")
df_scores = df_scores.loc[~df_scores["is_random"]]
df_scores = df_scores.drop(columns=["is_random"])

#trash all topics separate
df_scores = df_scores[df_scores["Name"].str.contains("topics_separate=False")]

#print(df_scores.head(10).to_string())

# Append ratio column
pref = "_ratio="
df_scores["ratio"] = df_scores['Name'].apply(lambda x: x[(x.
↪find(pref)+len(pref)):(x.find(pref)+len(pref)+3)])
#print(df_scores["Name"].iloc[0])
df_scores["ratio"] = df_scores["ratio"].astype(float)


def annot_max(x,y, ax=None, do_max=True):
    xmax = x[np.argmax(y)] if do_max else x[np.argmin(y)]

    ymax = y.max() if do_max else y.min()

    text= "x={:.3f}, y={:.3f}".format(xmax, ymax)
    if not ax:
        ax=plt.gca()
    bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
    arrowprops=dict(arrowstyle="->",connectionstyle="angle,angleA=0,angleB=60")
    kw = dict(xycoords='data',textcoords="axes fraction",
              arrowprops=arrowprops, bbox=bbox_props, ha="right", va="top")
```

```
    ax.annotate(text, xy=(xmax, ymax), xytext=(1.3,0.75), **kw)
```

[ ]:
```
print(df_scores["ratio"].unique())
print(len(df_scores[df_scores["ratio"] ==0.2]))
print(df_scores["Name"].iloc[0])
```

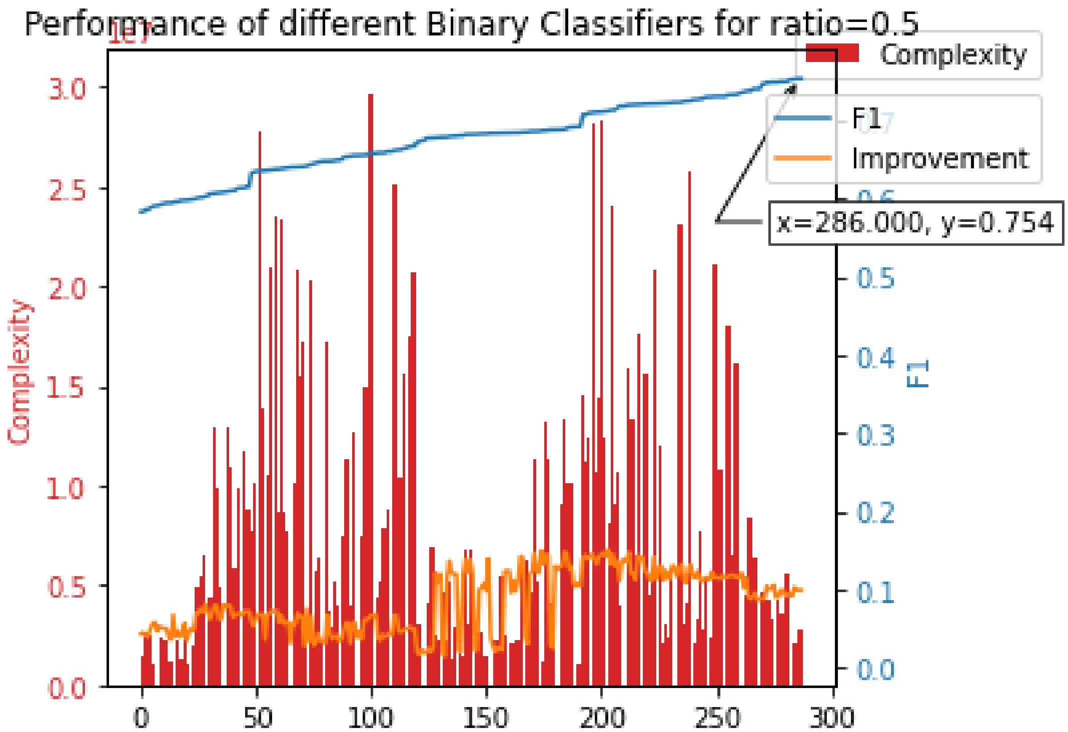
```
[0.5 0.3 0.2]
480
xgboost_norm=0_weighted_title_prepend_sampling=down_topics_separate=False_predic
t=ratio_mapping=opposite_ratio=0.5_wo_metadata_use_liwc_use_mf_requirements={'po
st_num_comments': 0, 'post_score': 0, 'post_ratio': 0}_random_y=False
```

[ ]:
```
params = {
    # normalised: 0 = only "abs", 1 = only "norm", 2 = norm and abs
    "norm": [0,1,2],
    # weighted_vals: whether votes should be weighted by comment score
    "weighted": [True, False],
    # title_prepend: whether to use the title prepended or standalone dataset
    "title_prepend": [True,False ],
    # sampling_vals: which type of sampling should be done ("up", "down",␣
  ↪"none")
    "sampling": ["up", "down", "none"],
    # if each topic should be analysed separately
    "topics_separate": [False],
    # should we predict "class" (classification for binary) or "ratio"␣
  ↪(regression for AHR)
    "predict": ["class","ratio", ],
    # should we "clip" negative votes or map them to the "opposite"
    "mapping": ["opposite", "clip"],
    # which most extreme AHR or YTA_ratio we want to predict 0.3, 0.2, 0.1, 0.05
    "ratio": [0.5,0.3, 0.2,],
    # wheter we should include metadata columns (e.g. post_score,␣
  ↪account_karam, link_karma) set MANUALLY
    "wo_metadata": [True, False],
    # wheter we should use the old or new reactions (reactions_YTA, NTA)
    "new_reactions": [False],
    "use_liwc": [True],  # wheter we use liwc features
    "use_mf": [True],  # whether we use moral foundation features
    "requirements": [True, False],
}

df_reg = df_scores.loc[df_scores["is_regression"]]
df_bin = df_scores.loc[~df_scores["is_regression"]]

df_reg = df_reg.sort_values(by='Score', ascending=False)
df_bin = df_bin.sort_values(by='Score', ascending=True)
```

```python
for df_iter in [df_bin, df_reg]:
    clf_type = "Regressors" if df_iter.iloc[0]["is_regression"] else "Binary Classifiers"
    for rto in params["ratio"]:
        df = df_iter.loc[df_iter["ratio"]==rto]
        if len(df)==0:
            continue


        #x_ticks = df["Name"]
        x_loc = range(len(df))
        fig, ax1 = plt.subplots()

        color = 'tab:red'
        ax1.set_ylabel('Complexity', color=color)  # we already handled the x-label with ax1
        ax1.bar(x_loc, df["Complexity"], color=color, )
        ax1.tick_params(axis='y', labelcolor=color)
        #ax1.set_xticks(x_loc)
        #ax1.set_xticklabels(x_ticks, rotation = 90)

        ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis

        color = 'tab:blue'
        ax2.set_ylabel('ME' if df.iloc[0]["is_regression"] else "F1", color=color)
        ax2.plot(x_loc, df["Score"], color='tab:blue',)
        ax2.plot(x_loc, df["Improvement"], color='tab:orange')
        ax2.tick_params(axis='y', labelcolor=color)
        annot_max(x_loc, df["Score"], ax=ax2, do_max = not df.iloc[0]["is_regression"])

        ax1.legend(['Complexity'], bbox_to_anchor=(1.3, 1.05))
        ax2.legend(['ME' if df.iloc[0]["is_regression"] else "F1", 'Improvement'], bbox_to_anchor=(1.3, 0.95))
        fig.tight_layout()  # otherwise the right y-label is slightly clipped

        plt.title(f"Performance of different {clf_type} for ratio={rto}")
        plt.show()
        plt.savefig(f'{clf_type}_ratio={rto}.png')
        print(f"Best run: {df['Name'].iloc[len(df)-1]}, \n{df['Score'].iloc[len(df)-1]}")
        plt.clf()
```

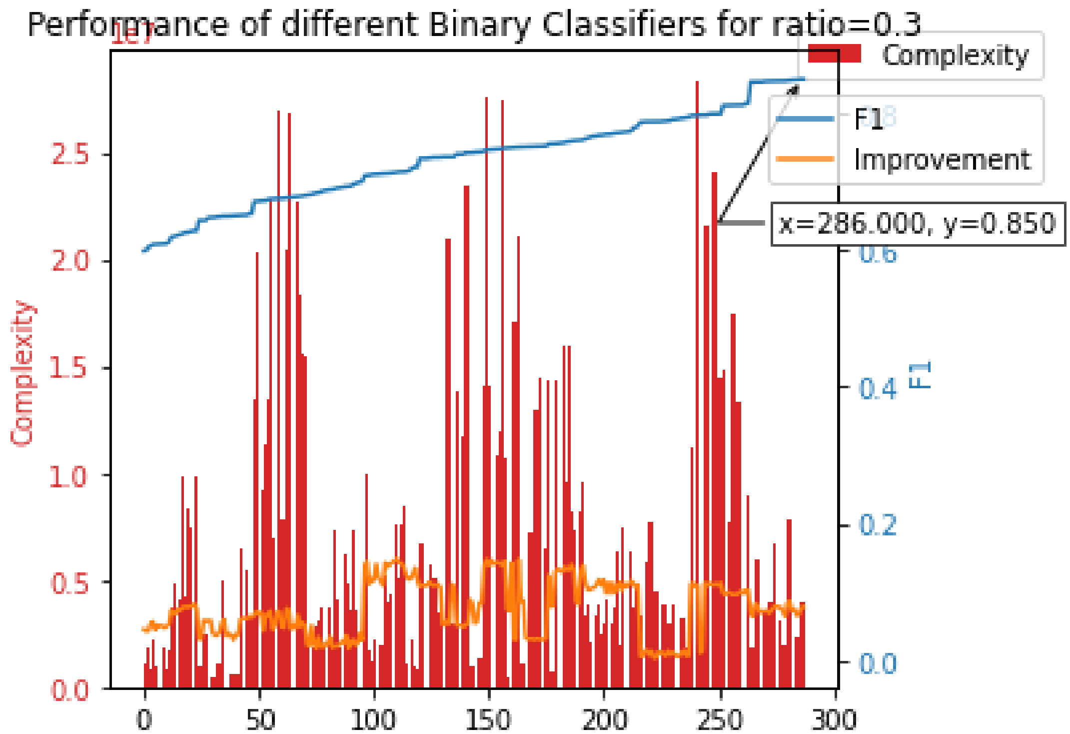
```
    param_impact = []
    for k in params:
        for v in params[k]:
            #which features we ignore
            if k in ["predict", "use_liwc", "use_mf", "new_reactions", "topics_separate"]:
                continue

            if k == "requirements":
                param_str = f"{k}"
                df_tmp = df_iter[df_iter["Name"].str.contains("post_score': 10")] if v else df_iter[~df_iter["Name"].str.contains("post_score': 0")]
            elif type(v) == bool:
                param_str ="_"+k
                if not v:
                    param_str+="=False"
                    df_tmp = df_iter[df_iter["Name"].str.contains(param_str)]
                else:
                    param_str+="_"
                    df_tmp = df_iter[df_iter["Name"].str.contains(param_str)]
            else:
                param_str = f"_{k}={v}_"
                df_tmp = df_iter[df_iter["Name"].str.contains(param_str)]


            best_score = df_tmp["Score"].min() if df.iloc[0]["is_regression"] else df_tmp["Score"].max()
            #worst_score = df_tmp["Score"].max() if df.iloc[0]["is_regression"] else df_tmp["Score"].min()


            if param_str[0]=="_":
                param_str =param_str[1:]
            if param_str[-1]=="_":
                param_str =param_str[:-1]
            if "requirements" in param_str:
                param_str+="="+str(v)

            param_impact.append([param_str, df_tmp["Score"].mean(),best_score, df_tmp["Improvement"].mean()])


    df_impact = pd.DataFrame(param_impact, columns=["Name", "Mean score", "Best score", "Mean improvement"])
```

```
    df_impact = df_impact.sort_values(by='Mean score', ascending=df.
↪iloc[0]["is_regression"])
    print(clf_type)
    display(HTML(df_impact.to_html()))
```



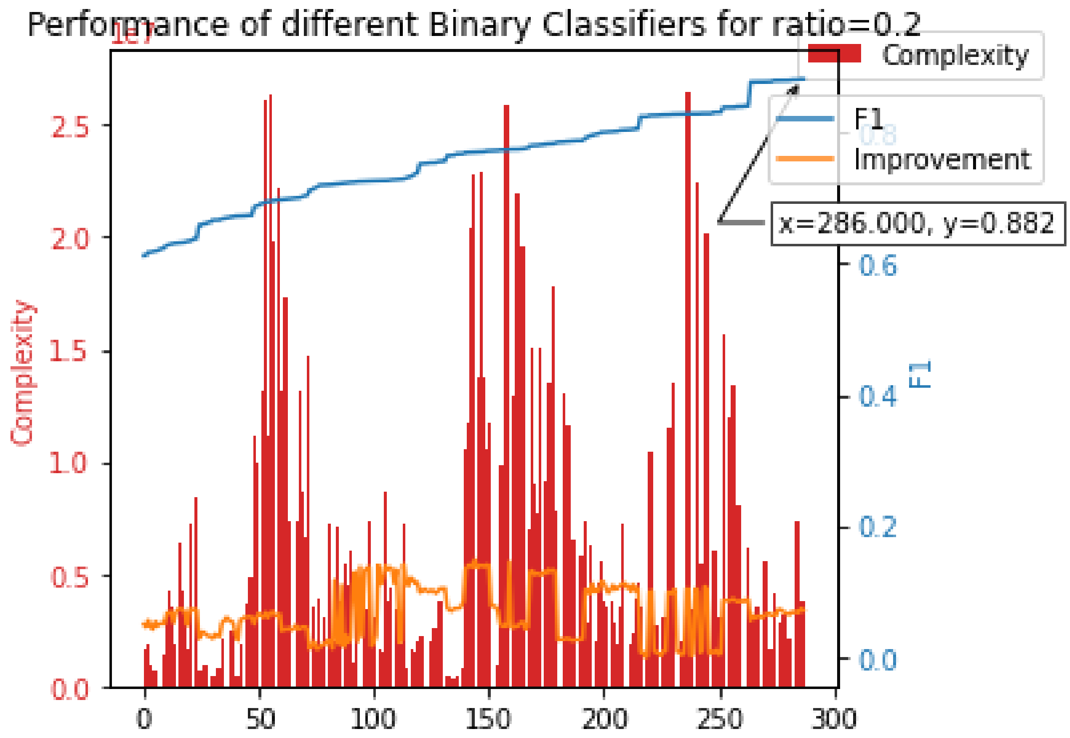

```
Best run: xgboost_norm=2_weighted=False_title_prepend_sampling=none_topics_separ
ate=False_predict=class_mapping=clip_ratio=0.5_wo_metadata=False_use_liwc_use_mf
_requirements={'post_num_comments': 10, 'post_score': 10, 'post_ratio':
0.7}_random_y=False,
0.7535519283565387
```

```
<Figure size 432x288 with 0 Axes>
```




```
Best run: xgboost_norm=2_weighted=False_title_prepend_sampling=up_topics_separat
e=False_predict=class_mapping=clip_ratio=0.3_wo_metadata=False_use_liwc_use_mf_r
equirements={'post_num_comments': 10, 'post_score': 10, 'post_ratio':
0.7}_random_y=False,
0.8502771941689505
```

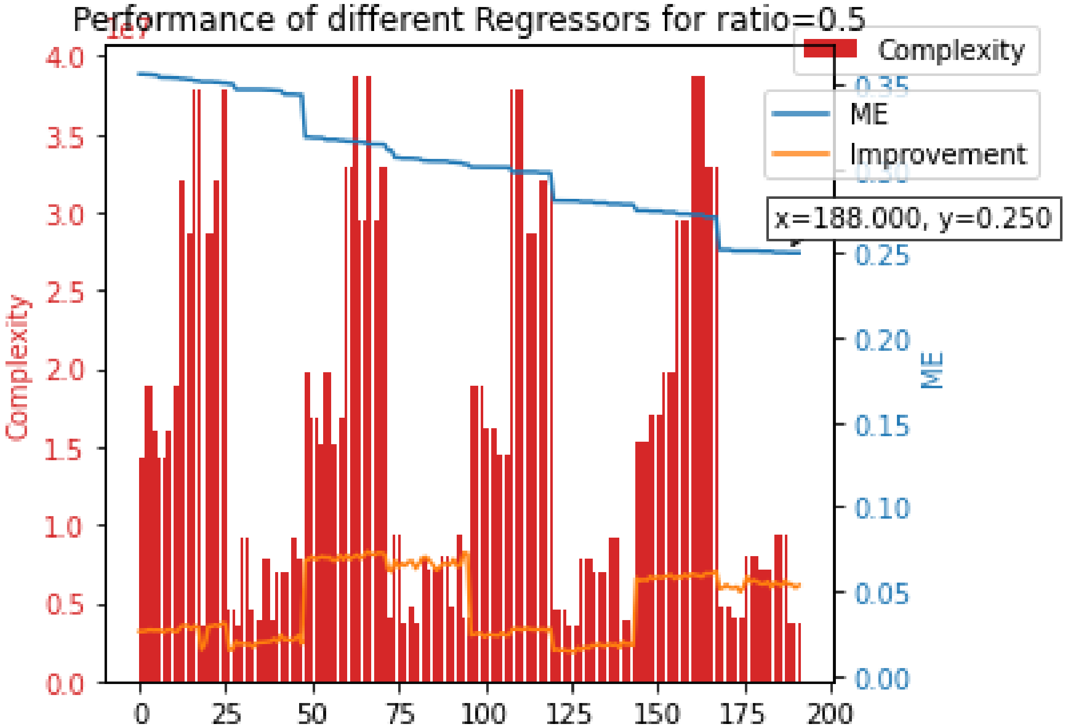
```
<Figure size 432x288 with 0 Axes>
```




```
Best run: xgboost_norm=2_weighted=False_title_prepend_sampling=up_topics_separat
e=False_predict=class_mapping=opposite_ratio=0.2_wo_metadata=False_use_liwc_use_
mf_requirements={'post_num_comments': 10, 'post_score': 10, 'post_ratio':
0.7}_random_y=False,
0.88171621108376
Binary Classifiers
```

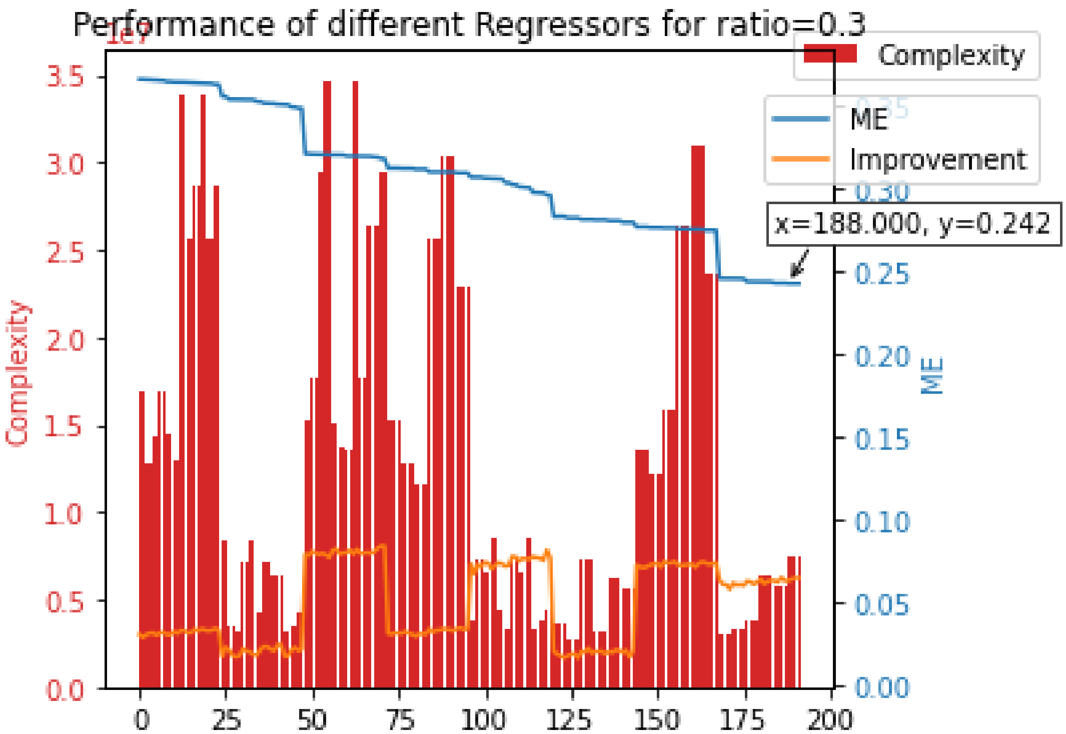
```
<IPython.core.display.HTML object>
```

```
<Figure size 432x288 with 0 Axes>
```



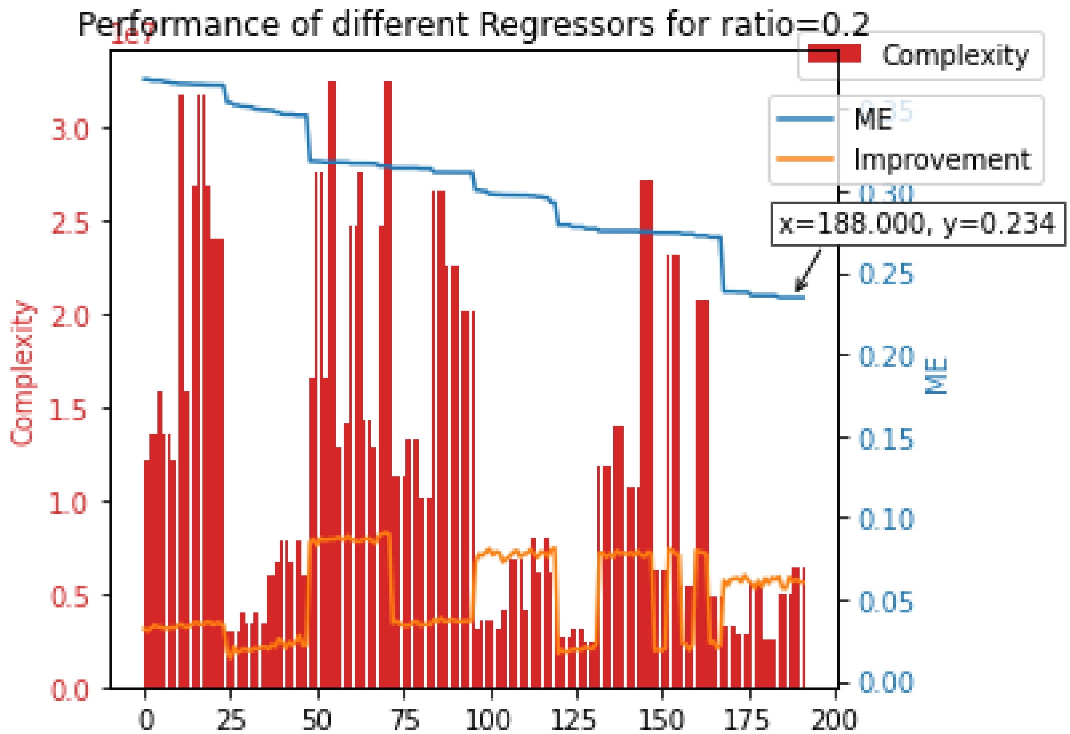

```
Best run: xgboost_norm=0_weighted=False_title_prepend_sampling=none_topics_separ
ate=False_predict=ratio_mapping=opposite_ratio=0.5_wo_metadata=False_use_liwc_us
e_mf_requirements={'post_num_comments': 10, 'post_score': 10, 'post_ratio':
0.7}_random_y=False,
0.2503177133966368
```

```
<Figure size 432x288 with 0 Axes>
```



Best run: xgboost_norm=2_weighted=False_title_prepend=False_sampling=none_topics_separate=False_predict=ratio_mapping=clip_ratio=0.3_wo_metadata=False_use_liwc_use_mf_requirements={'post_num_comments': 10, 'post_score': 10, 'post_ratio': 0.7}_random_y=False,
0.2424255713398038

<Figure size 432x288 with 0 Axes>




```
Best run: xgboost_norm=2_weighted=False_title_prepend=False_sampling=none_topics
_separate=False_predict=ratio_mapping=clip_ratio=0.2_wo_metadata=False_use_liwc_
use_mf_requirements={'post_num_comments': 10, 'post_score': 10, 'post_ratio':
0.7}_random_y=False,
0.2344733809988172
Regressors

<IPython.core.display.HTML object>

<Figure size 432x288 with 0 Axes>
```

[ ]:
```
# INSPECT FEATURES
```

[ ]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestClassifier,␣
 ↪GradientBoostingClassifier, RandomForestRegressor
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
from tune_sklearn import TuneGridSearchCV
from sklearn import preprocessing
import sys
import matplotlib.pyplot as plt
import xgboost as xgb
```

```python
import shap
from sklearn import metrics
import json
import multiprocessing
import itertools as it
from tqdm import tqdm

TRIAL_RUN = False
OUTPUT_DIR = "./output/"
DATASETS_DIR = "../datasets/"




def get_data(params):
    prepend_csv = "prepend_done.csv"
    standalone_csv = "standalone_done.csv"

    if params["title_prepend"]:
        df = load_wo_cols(DATASETS_DIR+prepend_csv, params)
    else:
        df = load_wo_cols(DATASETS_DIR+standalone_csv, params)

    if params["new_reactions"]:
        new_react = "id_to_reactions_new.csv"
        df_reactions = pd.read_csv(DATASETS_DIR+new_react)
        df = df.merge(df_reactions, left_on="post_id", right_on="post_id",
                      validate="1:1", suffixes=('', '_DROP')).filter(regex='^(?!
 ↪.*_DROP)')

    if params["norm"] < 2:
        df = df[df.columns.drop(
            list(df.filter(regex="_abs" if params["norm"] == 1 else "_norm")))]

    keys = ["info", "yta", "nah", "esh", "nta"]
    weight = "weighted_" if params["weighted"] else ""
    values = ["reactions_"+weight+k.upper() for k in keys]
    acros = dict(zip(keys, values))

    dfs = []
    if params["topics_separate"] > 0:

        topic_min = df["topic_nr"].min()
        topic_max = df["topic_nr"].max()
        #print(f"Data split by topic ({topic_min}, {topic_max})")

        for i in range(topic_min, topic_max+1):
```

```
            dfs.append(df.loc[df["topic_nr"] == i])
    else:
        dfs = [df]


    return dfs, acros


def load_wo_cols(path, params, remove_cols=[], verbose=False):
    cols_to_remove = ["post_text", "Unnamed: 0", "Unnamed: 1", "Unnamed: 2",␣
↪"Unnamed: 0.1",
                      "Unnamed: 0.1.1", "liwc_post_id", "foundations_post_id",
                      "foundations_title_post_id", "liwc_title_post_id",␣
↪"post_created_utc"]+remove_cols
    metadata = ["speaker_account_comment_karma", "post_num_comments",␣
↪"speaker_account_age",
                "speaker_account_link_karma", "post_ups", "post_downs",␣
↪"post_score", "reactions_is_devil", "reactions_is_angel","post_ratio"]
    # removed "post_ratio" from metadata b.c. used for weights

    removed = []
    df = pd.read_csv(path, nrows=10)
    cols_to_read = list(df.columns)

    # remove metadata
    if params["wo_metadata"]:
        cols_to_remove = cols_to_remove+metadata

    if params["new_reactions"]:
        cols_to_remove = cols_to_remove + \
            list(filter(lambda x: "reaction" in x and not "reaction_is" in x,␣
↪cols_to_read))

    # remove liwc
    if not params["use_liwc"]:
        cols_to_remove = cols_to_remove + \
            list(filter(lambda x: "liwc_" in x, cols_to_read))

    # remove moral foundations
    if not params["use_mf"]:
        cols_to_remove = cols_to_remove + \
            list(filter(lambda x: "foundations_" in x, cols_to_read))

    # post requirements setup
    cols_to_remove = [
        x for x in cols_to_remove if x not in list(params["requirements"].
↪keys())]
```

```
    if verbose:
        print(cols_to_read)
    for col in cols_to_remove:
        if col in cols_to_read:
            cols_to_read.remove(col)
            removed.append(col)

    #print(f"Removed {removed} from {path.split('/')[-1]}")
    #print("ONLY USING 10k lines")
    df = pd.read_csv(path, usecols=cols_to_read,nrows = 100000 if TRIAL_RUN␣
↪else None)

    # delte posts that don't meet requirements
    nr_rows_pre_req = len(df)
    for k, v in params["requirements"].items():
        df = df.loc[(df[k] >= v), :]
    # remove cols required for "requirements"
    if params["wo_metadata"]:
        to_drop = set(list(params["requirements"].keys()))
        in_list = set(list(df.columns))
        will_drop = list(to_drop.intersection(in_list))
        df = df.drop(columns=will_drop)
        removed += will_drop



    # print(
    #     f"Removed {int(100*(nr_rows_pre_req-len(df))/len(df))}% due to␣
↪requirements, Now {len(df)} posts remain.")
    # Check values in df
    # df.describe().loc[['min','max']].to_csv("min_max.csv",index=False)
    return df


def sampling(X_train, y_train, params, indices=[], verbose=False):
    df_len_old = len(X_train)
    if verbose:
        print(f"{params['sampling']}-sampling for {params['predict']}")

    if params["sampling"] == "none":
        X_train_ret = X_train
        y_train_ret = y_train

    if verbose:
        print("Original Y distribution on training set")
        _ = plt.hist(y_train, bins='auto')
```

```
        plt.show()

    if params["predict"] == "ratio":
        if params["sampling"] == "up":
            raise Exception("Upsampling with regression is not feasible ")
        elif params["sampling"] == "down":
            # downsampling
            bucket_ranges = [x/10 for x in list(range(0, 11))]
            bucket_counter = []

            X_train_tmp = X_train
            y_train_tmp = y_train.reshape((len(y_train), 1))
            dummy_feat_name = [str(int) for int in range(X_train_tmp.shape[1])]
            feat_names_to_sample = dummy_feat_name+["Y"]
            data_to_sample = np.append(X_train_tmp, y_train_tmp, 1)
            df_to_sample = pd.DataFrame(
                data_to_sample, columns=feat_names_to_sample)

            # Get bucket sizes
            for i in range(len(bucket_ranges)):
                if bucket_ranges[i] == 1:
                    continue
                orig_size = len(df_to_sample.loc[(bucket_ranges[i] <=␣
↪df_to_sample['Y']) & (
                    df_to_sample['Y'] <= bucket_ranges[i+1])])
                bucket_counter.append(orig_size)

            # We only downsample buckets that are > 2* bucket mean => 2*bucket␣
↪mean
            bucket_max = int(np.mean(bucket_counter)*1.5)
            for j in range(len(bucket_counter)):
                if bucket_counter[j] > bucket_max:
                    if verbose:
                        print(
                            f"Bucket {bucket_ranges[j]}-{bucket_ranges[j+1]}␣
↪has {bucket_counter[j]}>{bucket_max}")
                    df_bkt = df_to_sample.loc[(bucket_ranges[j] <=␣
↪df_to_sample['Y']) & (
                        df_to_sample['Y'] <= bucket_ranges[j+1])]
                    df_bkt_smpl = df_bkt.sample(
                        n=max(int(bucket_max),len(df_bkt)), replace=False,␣
↪random_state=42)
                    df_to_sample.loc[(bucket_ranges[j] <= df_to_sample['Y']) & (
                        df_to_sample['Y'] <= bucket_ranges[j+1])] = df_bkt_smpl

            df_to_sample = df_to_sample.dropna()
            y_train = df_to_sample["Y"]
```

```
            df_to_sample = df_to_sample.drop(columns=["Y"])

            X_train = df_to_sample.to_numpy()
            X_train_ret = X_train
            y_train_ret = y_train

    elif params["predict"] == "class":
        df_y = pd.DataFrame(data={"Y": y_train})

        if len(indices) > 0:
            if verbose:
                print(f"Using {len(indices)} indices")
        else:
            indices = range(len(indices))

        # Get list of indices for classes that are in the indices array
        c0_idx = pd.Series(df_y.loc[df_y["Y"] == 0].index.values)
        c0_idx = c0_idx[c0_idx.isin(indices)]
        c1_idx = pd.Series(df_y.loc[df_y["Y"] == 1].index.values)
        c1_idx = c1_idx[c1_idx.isin(indices)]

        if verbose:
            print(f"    Y=0: {c0_idx.shape}")
            print(f"    Y=1: {c1_idx.shape}")

        if params["sampling"] == "up":
            # upsample
            if len(c0_idx) >= len(c1_idx):
                n = len(c0_idx)
                c1_idx_sampeled = c1_idx.sample(
                    n=n, random_state=1, replace=len(c1_idx) < n).values
                c0_idx_sampeled = c0_idx.values
                if verbose:
                    print(f"Upsampling Y=1 with {n} samples")

            elif len(c0_idx) < len(c1_idx):
                n = len(c1_idx)
                c0_idx_sampeled = c0_idx.sample(
                    n=n, random_state=1, replace=len(c0_idx) < n).values
                c1_idx_sampeled = c1_idx.values
                if verbose:
                    print(f"Upsampling Y=0 with {n} samples")

        elif params["sampling"] == "down":
            # downsample
            if len(c0_idx) >= len(c1_idx):
                n = len(c1_idx)
```

```
                c0_idx_sampeled = c0_idx.sample(
                    n=n, random_state=1, replace=len(c0_idx) < n).values
                c1_idx_sampeled = c1_idx.values
                if verbose:
                    print(f"Downsampling Y=0 with {n} samples")
            elif len(c0_idx) < len(c1_idx):
                n = len(c0_idx)
                c1_idx_sampeled = c1_idx.sample(
                    n=n, random_state=1, replace=len(c1_idx) < n).values
                c0_idx_sampeled = c0_idx.values
                if verbose:
                    print(f"Downsampling Y=1 with {n} samples")
        else:
            c0_idx_sampeled = c0_idx
            c1_idx_sampeled = c1_idx

        all_idx = np.concatenate((c0_idx_sampeled, c1_idx_sampeled), axis=0)

        if verbose:
            df_tmp = df_y.iloc[all_idx]
            print(f"   Y=0: {len(df_tmp.loc[df_tmp['Y']==0])}")
            print(f"   Y=1: {len(df_tmp.loc[df_tmp['Y']==1])}")

        X_train_ret = X_train[all_idx, :]
        y_train_ret = y_train[all_idx]

    # print(df_len_old)
    #print(f"Removed/Added {int(100*(df_len_old-len(y_train_ret))/
 ↪len(y_train_ret))}% due to Sampling, Now {len(y_train_ret)} posts remain.")
    return X_train_ret, y_train_ret


def obj_size_fmt(num):
    if num < 10**3:
        return "{:.2f}{}".format(num, "B")
    elif ((num >= 10**3) & (num < 10**6)):
        return "{:.2f}{}".format(num/(1.024*10**3), "KB")
    elif ((num >= 10**6) & (num < 10**9)):
        return "{:.2f}{}".format(num/(1.024*10**6), "MB")
    else:
        return "{:.2f}{}".format(num/(1.024*10**9), "GB")


def memory_usage():
    memory_usage_by_variable = pd.DataFrame({k: sys.getsizeof(v)
                                              for (k, v) in globals().items()},␣
 ↪index=['Size'])
```

```
    memory_usage_by_variable = memory_usage_by_variable.T
    memory_usage_by_variable = memory_usage_by_variable.sort_values(
        by='Size', ascending=False).head(10)
    memory_usage_by_variable['Size'] = memory_usage_by_variable['Size'].apply(
        lambda x: obj_size_fmt(x))
    return memory_usage_by_variable


def opposite_jdgmt(judg):

    if "NTA" in judg:
        rtn = judg.replace("NTA", "YTA")
    elif "NAH" in judg:
        rtn = judg.replace("NAH", "ESH")
    elif "YTA" in judg:
        rtn = judg.replace("YTA", "NTA")
    elif "ESH" in judg:
        rtn = judg.replace("ESH", "NAH")
    elif "INFO" in judg:
        rtn = judg

    return rtn+"_neg_vals"


def get_vote_counts(df, acros):
    dct = {}
    for acr in list(acros.values()):
        dct[acr] = len(df[acr].to_numpy().nonzero()[0])

    dct["total"] = np.sum(list(dct.values()))
    print(dct)


# mapping is either "clip", meaning negative votes are just set to 0, or␣
↪"opposite", meaning we use the mapping table in "opposite_jdgmt"
def map_negative_values(df, acros, mapping="clip"):

    if mapping == "opposite" or mapping == "map":
        #print("Map = opposite")
        for k in acros.keys():
            acr = acros[k]

            if k == "info":
                continue

            # create temporary columns containing zeros and only negative votes␣
↪for each vote type (except info)
```

```
            df[acr+"_neg_vals"] = 0
            df.loc[df[acr] < 0, acr+"_neg_vals"] = df[acr]*-1
            df.loc[df[acr] < 0, acr] = 0

        for k in acros.keys():
            if k == "info":
                continue
            acr = acros[k]
            # set negative values to 0 & add opposite judgement vote
            df[acr] = df[acr] + df[opposite_jdgmt(acr)]

    elif mapping == "clip":
        #print("Map = clip")
        for k in acros.keys():
            acr = acros[k]
            df.loc[df[acr] < 0, acr] = 0

    return df


def get_data_classes(df, acros, ratio=0.5, verbose=False, predict="class",␣
 ↪judgement_weighted=True, mapping="clip"):
    if verbose:
        print(f"df original shape {df.shape}")

    n_rows_old = len(df)

    # Map negative judgements to opposing judgement, if we are not simply␣
 ↪counting each comment as one vote (i.e. if judgement_weighted = True)
    # i.e. YTA<->NTA, ESH<->NAH
    if judgement_weighted:
        df = map_negative_values(df, acros, mapping=mapping)

    if predict == "class":
        # We only look at YTA and NTA
        df["YTA_ratio"] = df[acros["yta"]] / \
            (df[acros["info"]] + df[acros["yta"]] +
             df[acros["nah"]]+df[acros["esh"]]+df[acros["nta"]])

        # drop all rows where the majority is not YTA or NTA
        df = df.loc[((df[acros["yta"]] > df[acros["info"]]) & (df[acros["yta"]]␣
 ↪> df[acros["nah"]]) & (df[acros["yta"]] > df[acros["esh"]])) | (
            (df[acros["nta"]] > df[acros["info"]]) & (df[acros["nta"]] >␣
 ↪df[acros["nah"]]) & (df["reactions_weighted_NTA"] > df[acros["esh"]]))]
        if verbose:
            print(f"Drop all rows where majority is not YTA or NTA {df.shape}")
```

```
        # drop all rows that are not "extreme" enough
        df = df.loc[(1-ratio <= df["YTA_ratio"]) | (df["YTA_ratio"] <= ratio)]

        #print(
        #    f"Removed {int(100*( (n_rows_old-len(df)) / n_rows_old) )}% due to agreement ratio, Now {len(df)} posts remain.")

        # specifc classes & drop unnecesarry
        # YTA = Class 1, NTA = class 0
        df["Y"] = np.where(df[acros["yta"]] > df[acros["nta"]], 1,  0)
        smp_weights = None
        if verbose:
            print(df.shape)

    elif predict == "ratio":
        # Y = asshole ratio(AHR) = (YTA+ESH)/(YTA+ESH+NTA+NAH)
        # drop posts w.o. votes
        tmp = df[acros["yta"]] + df[acros["nah"]] + \
            df[acros["esh"]]+df[acros["nta"]]
        tmp = tmp[tmp != 0]
        tmp = (df[acros["yta"]]+df[acros["esh"]])/tmp
        df["Y"] = tmp

        n_rows_old = len(df)
        df = df.loc[(1-ratio <= df["Y"]) | (df["Y"] <= ratio)]
        smp_weights = None
        # print(
        #    f"Removed {int(100*(n_rows_old-len(df))/len(df))}% of posts b.c. not enough agreement. Now {df.shape}")

    if np.min(df["Y"]) < 0 or np.max(df["Y"]) > 1:
        raise Exception("Y value should be in range [0,1]")

    # get list of all columns that contain uppercase vote acronym
    vote_acroynms = list(filter(lambda x: any(
        [acr.upper() in x for acr in list(acros.keys())]), list(df.columns)))
    vote_acroynms += ["post_id"]
    df = df.drop(columns=vote_acroynms)

    if verbose:
        print(df.shape)

    X = df.drop(columns=["Y"])
    y = df["Y"].to_numpy()

    feat_name_lst = list(X.columns)
```

```
    # scaling
    scaler = preprocessing.StandardScaler().fit(X)
    X_scaled = scaler.transform(X)
    return X_scaled, y, feat_name_lst, None#smp_weights.to_numpy()


def get_train_test_split(params, grid_search=False, verbose=False):
    dfs, acros = get_data(params)

    df = dfs[0]
    if len(dfs) > 1:
        print("MORE THAN 1 df")

    df_cpy = df.copy()
    X, y, feat_name_lst,smp_weights = get_data_classes(df_cpy,␣
 ↪ratio=params["ratio"], acros=acros, predict=params["predict"],␣
 ↪judgement_weighted=params["weighted"],
                                                mapping=params["mapping"],␣
 ↪verbose=False)
    if grid_search:
        print("YOU SURE YOU WANT TO BE DOING THIS?")
        return X, y, feat_name_lst

    train, test = train_test_split(
        range(len(X)), test_size=0.33, random_state=42)

    X_train, y_train = sampling(
        X[train], y[train], params, indices=train if params["predict"] ==␣
 ↪"class" else [], verbose=False)

    X_test = X[test, :]
    y_test = y[test]

    if params["random_y"]:
        # Sanity check, i.e. get results for random predition
        #df["Y"] = np.random.randint(0, 1001, size=len(df["Y"]))/1000

        y_test_sum_old = np.sum(y_test[:len(y_test*0.5)])
        np.random.shuffle(y_test)
        y_test_sum_new = np.sum(y_test[:len(y_test*0.5)])
        #if y_test_sum_old == y_test_sum_new:
        #    print("Not truly random values")
        if verbose:
            print(f"USING RANDOM Y\n Was {y_test_sum_old} Is {y_test_sum_new}")

    return X_train, y_train, X_test, y_test, feat_name_lst
```

```python
def get_clf_name(params, clf_type):
    clf_name = clf_type
    for k, v in params.items():
        if isinstance(v, bool) and v:
            clf_name += f"_{k}"
        else:
            clf_name += f"_{k}={v}"
    return clf_name


def get_metrics(y_test, y_pred, params, verbose=True):
    if params["predict"] == "class":
        # testing score
        f1_test = metrics.f1_score(y_test, y_pred, average="weighted")
        acc_test = metrics.accuracy_score(y_test, y_pred)

        if verbose:
            print(f"    Accuracy: {acc_test}\n    F1: {f1_test}")
            print(classification_report(y_test, y_pred, target_names=[
                "Class 0: low AH", "Class 1: high AH"]))
        else:
            return f1_test

    elif params["predict"] == "ratio":
        mean_abs = metrics.mean_absolute_error(y_test, y_pred)
        mean_sqr = metrics.mean_squared_error(y_test, y_pred)
        rmse = metrics.mean_squared_error(y_test, y_pred, squared=False)

        if verbose:
            print(
                f"    Mean absolute: {mean_abs}\n    Mean squared: {mean_sqr}\n    Root Mean Squared: {rmse}")
        else:
            return mean_abs


def get_param_combs(params,sensible=False):
    combinations = list(it.product(*(params[Name] for Name in params)))

    keys = list(params.keys())
    combs = list(map(lambda x: dict(zip(keys, x)), combinations))

    if sensible:
        for dct in combs:
            dct["sensible"] = sensible
```

```
    return combs

# once as best, once sampling comparison
#xgboost_norm=2_weighted=False_title_prepend=False_sampling=none_topics_separate=False_predic
 ↪3_wo_metadata=False_use_liwc_use_mf_requirements={'post_num_comments': 10,␣
 ↪'post_score': 10, 'post_ratio': 0.7}_random_y=False,
parmas_rto_hard = {"norm": 2,
                   "weighted": False,
                   "title_prepend": False,
                   "sampling": "none",
                   "topics_separate": False,
                   "predict": "ratio",
                   "mapping": "clip",
                   "ratio": 0.3,
                   "wo_metadata": True,
                   "new_reactions": False,
                   "use_liwc": True,
                   "use_mf": True,
                   "requirements": True}

# once as best, once sampling comparison
#xgboost_norm=2_weighted=False_title_prepend_sampling=up_topics_separate=False_predict=class_m
 ↪3_wo_metadata=False_use_liwc_use_mf_requirements={'post_num_comments': 10,␣
 ↪'post_score': 10, 'post_ratio': 0.7}_random_y=False,
parmas_class_hard = {"norm": 2,
                   "weighted": False,
                   "title_prepend": True,
                   "sampling": "up",
                   "topics_separate": False,
                   "predict": "class",
                   "mapping": "clip",
                   "ratio": 0.3,
                   "wo_metadata": True,
                   "new_reactions": False,
                   "use_liwc": True,
                   "use_mf": True,
                   "requirements": True}

params_sens = {
    # normalised: 0 = only "abs", 1 = only "norm", 2 = norm and abs
    "norm": [1,],
    # weighted_vals: whether votes should be weighted by comment score
    "weighted": [True],
    # title_prepend: whether to use the title prepended or standalone dataset
    "title_prepend": [True ],
    # sampling_vals: which type of sampling should be done ("up", "down",␣
 ↪"none")
```

```
    "sampling": ["none" ],
    # if each topic should be analysed separately
    "topics_separate": [False, ],
    # should we predict "class" (classification for binary) or "ratio"␣
 ↪(regression for AHR)
    "predict": ["class","ratio", ],
    # should we "clip" negative votes or map them to the "opposite"
    "mapping": ["opposite"],
    # which most extreme AHR or YTA_ratio we want to predict 0.3, 0.2, 0.1, 0.05
    "ratio": [0.3, ],
    # wheter we should include metadata columns (e.g. post_score,␣
 ↪account_karam, link_karma) set MANUALLY
    "wo_metadata": [True],
    # wheter we should use the old or new reactions (reactions_YTA, NTA)
    "new_reactions": [False],
    "use_liwc": [True],  # wheter we use liwc features
    "use_mf": [True],  # whether we use moral foundation features
    "requirements": [True],
}

post_requirements = {  # requirement: key >= value in post
    "post_num_comments": 10,
    "post_score": 10,
    "post_ratio": 0.7,
}



# wheter we a random run right now => to compare the actual score with the␣
 ↪random one
random_run = [False]

combs_sensible = get_param_combs(params_sens, sensible=True)
combs = combs_sensible +[parmas_class_hard,parmas_rto_hard]

if TRIAL_RUN:
    print("THIS IS A TRIAL RUN")
    combs = combs[:2]

rankings = {"sensible":{}, "best":{}}
for params_i in tqdm(combs):

    # upsamping not implemented for regression
    if params_i["sampling"] == "up" and params_i["predict"] == "ratio":
        continue

    # handle post requirements
```

```
    if params_i["requirements"]:
        params_i["requirements"] = post_requirements
    else:
        params_i["requirements"] = dict.fromkeys(post_requirements, 0)


    last_random_score = None  # holder variable for last random score
    for is_random in random_run:
        params_i["random_y"] = is_random

        # ADD GPU
        xgboost = xgb.XGBClassifier(verbosity=0, random_state=42,␣
↪use_label_encoder=False, ) if params_i["predict"] == "class" else xgb.
↪XGBRegressor(
            verbosity=0, random_state=42, )

        #xgboost = xgb.XGBClassifier(verbosity=0, random_state=42,␣
↪use_label_encoder=False) if params_i["predict"] == "class" else xgb.
↪XGBRegressor(
        #    verbosity=0, random_state=42)
        classifiers = (xgboost, "xgboost")
        clf_name = get_clf_name(params_i, classifiers[1])
        X_train, y_train, X_test, y_test, feat_name_lst = get_train_test_split(
            params_i)

        smp_weights = None
        xgboost.fit(X_train, y_train, sample_weight=smp_weights)
        y_pred = xgboost.predict(X_test)

        is_regression = params_i["predict"] == "ratio"

        nr_samples = X_train.shape[0]
        nr_features = X_train.shape[1]
        complexity = nr_samples*nr_features
        score = get_metrics(y_test, y_pred, params_i, verbose=False)

        #if SHOW_SHAPLY:
        #explainer = shap.explainers.GPUTree(clf, X_train)
        explainer = shap.explainers.Tree(xgboost, X_train)
        shap_values = explainer(X_train)
        key = "class" if params_i["predict"] == "class" else "ratio"

        print(f'{"SENSIBLE" if "sensible" in params_i else "BEST"}, {key.
↪upper()}')
        print(f'{"F1" if params_i["predict"] == "class" else "ME" }: {score}')
        print(clf_name)
```

```
        shap.summary_plot(shap_values, X_train, feature_names=feat_name_lst,␣
↪max_display=50)

        shap_df = pd.DataFrame(shap_values.values, columns=feat_name_lst)
        vals = np.abs(shap_df.values).mean(0)
        shap_importance = pd.DataFrame(list(zip(feat_name_lst, vals)),␣
↪columns=['col_name', 'feature_importance_vals'])
        shap_importance.sort_values(by=['feature_importance_vals'],␣
↪ascending=False, inplace=True)
        ranking = shap_importance["col_name"].to_list()

        if "sensible" in params_i:
            print("    Setting sensible=",key)
            rankings["sensible"][key]= ranking
        else:
            print("    Setting best=",key)
            rankings["best"][key]= ranking
```

```
 98%|===================| 10570/10770 [00:37<00:00]

SENSIBLE, CLASS
F1: 0.6829634981330016
xgboost_norm=1_weighted_title_prepend_sampling=none_topics_separate=False_predic
t=class_mapping=opposite_ratio=0.3_wo_metadata_new_reactions=False_use_liwc_use_
mf_requirements={'post_num_comments': 10, 'post_score': 10, 'post_ratio':
0.7}_sensible_random_y=False
```


foundations_Parenth
writing_sty_focus_i_poss_norm
liwc_male
writing_sty_focus_i_obj_norm
liwc_motion
writing_sty_self_joy_norm
liwc_female
foundations_Quote
foundations_WC
liwc_home
writing_sty_self_trust_norm
liwc_work
liwc_article
foundations_OtherP
writing_sty_active_norm
liwc_feel
liwc_friend
liwc_i
liwc_anger
writing_sty_aita_avg_location
liwc_leisure
liwc_see
liwc_negate
liwc_ipron
liwc_time
writing_sty_other_joy_norm
liwc_affiliation
liwc_money
liwc_number
writing_sty_positive_norm
writing_sty_other_positive_norm
liwc_prep
liwc_cause
liwc_insight
writing_sty_focus_we_subj_norm
writing_sty_self_negative_norm
liwc_achieve
writing_sty_aita_lst_location
liwc_family
liwc_conj
liwc_discrep
liwc_quant
liwc_focuspast
writing_sty_other_trust_norm
liwc_anx
liwc_Authentic
writing_sty_negative_norm
writing_sty_sadness_norm
writing_sty_self_surprise_norm
writing_sty_anticipation_norm
−0.5
0.0
0.5
1.0
SHAP value (impact on model output)
High
Feature value
Low

```
 25%|          | 1/4 [00:57<02:51, 57.07s/it]

    Setting sensible= class

 99%|===================| 18604/18786 [00:57<00:00]

SENSIBLE, RATIO
ME: 0.35051868332651054
xgboost_norm=1_weighted_title_prepend_sampling=none_topics_separate=False_predic
t=ratio_mapping=opposite_ratio=0.3_wo_metadata_new_reactions=False_use_liwc_use_
mf_requirements={'post_num_comments': 10, 'post_score': 10, 'post_ratio':
0.7}_sensible_random_y=False
```


liwc_female
liwc_motion
liwc_discrep
liwc_Clout
writing_sty_aita_lst_location
liwc_anger
writing_sty_positive_norm
liwc_home
writing_sty_present_norm
writing_sty_disgust_norm
writing_sty_aita_avg_location
writing_sty_focus_i_poss_norm
liwc_informal
liwc_number
liwc_time
liwc_health
liwc_we
liwc_work
liwc_Parenth
writing_sty_other_trust_norm
writing_sty_sent_subjectivity
liwc_see
liwc_negate
foundations_WC
liwc_insight
writing_sty_sent_polarity
writing_sty_self_fear_norm
foundations_Period
writing_sty_sadness_norm
writing_sty_focus_i_obj_norm
liwc_social
writing_sty_fear_norm
writing_sty_active_norm
foundations_Parenth
liwc_drives
liwc_article
liwc_male
writing_sty_self_anger_norm
writing_sty_self_prof
liwc_feel
liwc_focuspast
liwc_quant
liwc_Authentic
liwc_function
liwc_Period
liwc_adj
writing_sty_other_positive_norm
liwc_friend
liwc_ipron
writing_sty_self_negative_norm
−0.1
0.0
0.1
0.2
0.3
0.4
SHAP value (impact on model output)
High
Low
Feature value

```
 50%|       | 2/4 [02:13<02:16, 68.18s/it]

   Setting sensible= ratio

 98%|===================| 16992/17276 [00:57<00:00]

BEST, CLASS
F1: 0.7937373231799693
xgboost_norm=2_weighted=False_title_prepend_sampling=up_topics_separate=False_pr
edict=class_mapping=clip_ratio=0.3_wo_metadata_new_reactions=False_use_liwc_use_
mf_requirements={'post_num_comments': 10, 'post_score': 10, 'post_ratio':
0.7}_random_y=False
```

liwc_Clout
liwc_female
foundations_Quote
writing_sty_fear_norm
liwc_Dic
liwc_discrep
liwc_home
liwc_relativ
writing_sty_sent_polarity
liwc_adj
liwc_focuspast
liwc_informal
liwc_space
foundations_WC
writing_sty_negative_norm
liwc_differ
liwc_adverb
foundations_Parenth
writing_sty_anticipation_norm
writing_sty_self_positive_norm
liwc_WC
liwc_insight
writing_sty_aita_avg_location
liwc_motion
liwc_leisure
liwc_anger
writing_sty_active_norm
liwc_bio
liwc_prep
writing_sty_focus_i_obj_abs
liwc_number
liwc_friend
writing_sty_focus_he_subj_norm
liwc_pronoun
writing_sty_other_joy_norm
liwc_see
liwc_Authentic
writing_sty_surprise_norm
liwc_affect
liwc_focuspresent
writing_sty_focus_i_obj_norm
liwc_negate
liwc_quant
liwc_drives
liwc_power
writing_sty_focus_i_poss_abs
liwc_male
writing_sty_anticipation_abs
liwc_tentat
liwc_work
−1.5
−1.0
−0.5
0.0
0.5
1.0
SHAP value (impact on model output)
High
Low
Feature value

```
 75%|      | 3/4 [03:29<01:11, 71.75s/it]

    Setting best= class

 99%|===================| 16303/16479 [00:45<00:00]

BEST, RATIO
ME: 0.27888227680325367
xgboost_norm=2_weighted=False_title_prepend=False_sampling=none_topics_separate=
False_predict=ratio_mapping=clip_ratio=0.3_wo_metadata_new_reactions=False_use_l
iwc_use_mf_requirements={'post_num_comments': 10, 'post_score': 10,
'post_ratio': 0.7}_random_y=False
```


liwc_female
liwc_Clout
liwc_Parenth
liwc_discrep
liwc_Authentic
writing_sty_disgust_norm
liwc_sexual
liwc_home
liwc_i
liwc_anger
liwc_bio
liwc_number
liwc_ppron
liwc_informal
writing_sty_aita_lst_location
liwc_work
foundations_QMark
writing_sty_fear_norm
liwc_title_cause
liwc_time
title_writing_sty_disgust_norm
liwc_function
liwc_feel
writing_sty_focus_i_poss_norm
liwc_title_negate
liwc_motion
writing_sty_present_abs
liwc_negate
liwc_affiliation
writing_sty_focus_i_poss_abs
writing_sty_sent_subjectivity
liwc_reward
liwc_focuspresent
liwc_Period
liwc_male
liwc_auxverb
writing_sty_other_joy_norm
writing_sty_other_positive_norm
writing_sty_present_norm
liwc_adverb
writing_sty_other_fear_norm
writing_sty_focus_i_subj_norm
liwc_friend
writing_sty_focus_we_poss_norm
liwc_we
liwc_swear
liwc_anx
liwc_health
liwc_money
writing_sty_self_anger_norm
−0.10 −0.05 0.00 0.05 0.10 0.15 0.20 0.25
SHAP value (impact on model output)
High
Feature value
Low

```
100%|          | 4/4 [04:50<00:00, 72.59s/it]

    Setting best= ratio
```

[ ]:
```
import math
def rbo(list1, list2, p=0.9):
   #https://towardsdatascience.com/
 ↪rbo-v-s-kendall-tau-to-compare-ranked-lists-of-items-8776c5182899
   # tail recursive helper function
   def helper(ret, i, d):
       l1 = set(list1[:i]) if i < len(list1) else set(list1)
       l2 = set(list2[:i]) if i < len(list2) else set(list2)
       a_d = len(l1.intersection(l2))/i
       term = math.pow(p, i) * a_d
       if d == i:
           return ret + term
       return helper(ret + term, i + 1, d)
   k = max(len(list1), len(list2))
   x_k = len(set(list1).intersection(set(list2)))
   summation = helper(0, 1, k)
   return ((float(x_k)/k) * math.pow(p, k)) + ((1-p)/p * summation)

def sum_series(p, d):
   # tail recursive helper function
   def helper(ret, p, d, i):
       term = math.pow(p, i)/i
       if d == i:
           return ret + term
       return helper(ret + term, p, d, i+1)
   return helper(0, p, d, 1)

import collections

def flatten(d, parent_key='', sep='_'):
    items = []
    for k, v in d.items():
        new_key = parent_key + sep + k if parent_key else k
        if isinstance(v, collections.MutableMapping):
            items.extend(flatten(v, new_key, sep=sep).items())
        else:
            items.append((new_key, v))
    return dict(items)

p = 0.98
```

```
d = 20
wrbo1_d = 1 - math.pow(p, d-1) + (((1-p)/p) * d *(np.log(1/(1-p)) -␣
↪sum_series(p, d-1)))

print(f"top {d} ranks account for {wrbo1_d}, usually the would only account for␣
↪{d/50}")


flat_ranking = flatten(rankings)
#only look at top 169 features
for k in flat_ranking:
    flat_ranking[k] = flat_ranking[k][:169]
compare_df = pd.DataFrame.from_dict(flat_ranking)
compare_df = compare_df[["best_class", "sensible_class", "sensible_ratio",␣
↪"best_ratio"]]


rnk_names = list(compare_df.columns)
for i in range(len(rnk_names)):
    if i == 3:
        rbo_cur = rbo(flat_ranking[rnk_names[i]][:50],␣
↪flat_ranking[rnk_names[0]][:50], p=p)
        print(f"Similarity of {rnk_names[0].upper()} and {rnk_names[i].upper()}␣
↪= {round(rbo_cur, 5)}")
    else:
        rbo_cur = rbo(flat_ranking[rnk_names[i]][:50],␣
↪flat_ranking[rnk_names[i+1]][:50], p=p)
        print(f"Similarity of {rnk_names[i].upper()} and {rnk_names[i+1].
↪upper()} = {round(rbo_cur, 5)}")

display(HTML(compare_df.to_html()))
```

```
top 20 ranks account for 0.6095916491370756, usually the would only account for
0.4
Similarity of BEST_CLASS and SENSIBLE_CLASS = 0.36116
Similarity of SENSIBLE_CLASS and SENSIBLE_RATIO = 0.43867
Similarity of SENSIBLE_RATIO and BEST_RATIO = 0.54724
Similarity of BEST_CLASS and BEST_RATIO = 0.37114
```

```
Using or importing the ABCs from 'collections' instead of from 'collections.abc'
is deprecated since Python 3.3, and in 3.9 it will stop working
```

```
<IPython.core.display.HTML object>
```

[ ]:

```
print("hi")
```

```
hi
```

[ ]:
```
compare_df.to_csv("ranking.csv")
```

[ ]:
```

```