Azrieli
College of Engineering
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Faculty of Computer SCIENCE
Course Machine Learning

Ex3 – Final Project – Decision Tree, Random Forest, AdaBoost

Bot or Not? Turing Test for Code:

Using Machine Learning to Predict Code Authorship Based on Syntax and Style

Submitted by:

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chatGPT chat link: https://chatgpt.com/share/688a75c6-918c-800b-91fb-513255dde9ae

<u>Objective</u>

The objective of this project is to develop and compare three machine learning models <u>implemented from scratch</u>—

- Decision Tree
- Random Forest
- and AdaBoost

For the **binary classification task of <u>distinguishing AI-generated code from human-written code</u>** using the AIGCodeSet dataset.

<u>Introduction</u>

Recent advances in large language models (LLMs) have enabled automated code generation at scale.
However, for applications such as **academic integrity, software provenance, plagiarism detection, security,** and **software quality**,
<u>it is crucial to reliably detect AI-generated code.</u>

In this project, we explore the use of machine learning to classify whether a given piece of code was written by a human or generated by an LLM.
We formulated this as a binary classification problem and tested a range of models—including both custom implementations and comparable models from scikit-learn.

Throughout this process, we aimed to identify what approaches work best and understand the unique challenges involved in treating code as data.

<u>Dataset</u>

<u>Source:</u>

- https://huggingface.co/datasets/basakdemirok/AIGCodeSet

Content:

- The AIGCodeSet dataset is a large collection of Python code snippets designed to support research on distinguishing human-written code from code generated by artificial intelligence.
- It contains a total of 7,583 code samples — 4,755 written by humans and collected from IBM’s CodeNet platform, and 2,828 generated by several AI models (Gemini, LLaMA, and Codestral).

Features:

- The dataset contain several features that were extracted from the raw code by the authors -
    1. Total number of lines.
    2. Number of non-empty code lines.
    3. Number of functions in the code.
    4. Number of blank lines.
    5. Embeddings of the code
- However, we chose to extract features ourselves in order to:
    - Expand the number of features
    - Improve reliability
    - Enhance interpretability and explainability

Labels:

- The dataset contains labels for each sample, indicating whether human or LLM wrote the code
- The original dataset had several types of LLM produced code:
    1. Generated from scratch
    2. LLM fixed human code with runtime error
    3. LLM fixed human code with syntax error

For simplicity—and in line with our objectives—we focused only on the LLM-generated-from-scratch vs. human-written code.

Importing the dataset:

In [129…

```
from datasets import load_dataset

def import_db(dataset_path):
    dataset = load_dataset(dataset_path, split="train") #loading
    dataset = dataset.remove_columns(['problem_id', 'ada_embedding', 'submission_id
    return dataset.to_pandas() #return the dataset as pandas dataframe

df = import_db("basakdemirok/AIGCodeSet")
```

Preprocessing

- **Cleaning the data** - For simplicity, and in line with our objectives—we focused only on the LLM-generated-from-scratch vs. human-written code. Therefore, we filtered the data to match out objectives.

In [130…

```
import numpy as np
human_vs_generated_df = df[np.logical_or(df.status_in_folder == 'Generate', df.labe
```

- **re-naming lables** - we converted the classes from (1, 0) to (1, -1), mainly to simplify the implementation of our customized AdaBoost model, where:
  - 1: LLM
  - -1: Human

In [131…

```
human_vs_generated_df['label'] = human_vs_generated_df['label'].replace(0, -1)
```

- **Feature Engineering** - Since raw code is hard to feed directly into a classifier, and from reasons mentioned earlier regarding original features from dataset - we extracted a set of handcrafted features from each code snippet. These features reflect various characteristics of the code's structure, style, and content — things that might help distinguish between human and AI-written code. We chose various text based features from our personal experience, and augmented the features with additional features suggested by ChatGPT.

In [132…

```
import pandas as pd
import re
import ast
from spellchecker import SpellChecker
spell = SpellChecker()
```

```
def extract_features_from_code(code):

    lines = code.split('\n')
    num_lines = len(lines)
    num_comment_lines = sum(1 for line in lines if '#' in line)
    comment_ratio = num_comment_lines / num_lines if num_lines > 0 else 0
    comment_text = ' '.join(re.findall(r'#.*', code))
    comment_words = re.findall(r'\b\w+\b', comment_text.lower())
    misspelled = spell.unknown(comment_words)
    num_misspelled = len(misspelled)
    total_comment_words = len(comment_words)
    misspelling_ratio = num_misspelled / total_comment_words if total_comment_words

    #Get rid of comments - (makes further regex extractions easier...)
    new_lines = []
    for line in lines:
        new_lines.append(line.split("#")[0])
    lines = new_lines
    code = '\n'.join(lines)

    num_blank_lines = sum(1 for line in lines if line.strip() == '')
    num_functions = len(re.findall(r'^\s*def\s', code, re.MULTILINE))
    num_classes = len(re.findall(r'^\s*class\s', code, re.MULTILINE))
    num_loops = len(re.findall(r'\b(for|while)\b', code))
    num_try = len(re.findall(r'\b(try:)\b', code))
    num_conditionals = len(re.findall(r'\b(if|elif|else)\b', code))
    num_imports = len(re.findall(r'^\s*(import|from)\s', code, re.MULTILINE))
    has_main_guard = int('if __name__ == "__main__"' in code)
    num_assignments = len(re.findall(r'^(?!\s*#)\s*\w+\s*=.*$', code, re.MULTILINE)
    avg_line_length = sum(len(line) for line in lines) / num_lines if num_lines > 0
    indentation_levels = [len(re.match(r'^\s*', line).group(0)) for line in lines i
    max_indent_depth = max(indentation_levels) if indentation_levels else 0
    tab_vs_space = {
        'tabs': sum(1 for line in lines if line.startswith('\t')),
        'spaces': sum(1 for line in lines if line.startswith(' '))
    }
    ends_with_space = sum(1 for line in lines if line.endswith(' '))
    camel_case_count = len(re.findall(r'\b[a-z]+[A-Z][a-zA-Z]*\b', code))  #example
    snake_case_count = len(re.findall(r'\b[a-z]+(_[a-z]+)+\b', code))      #example
    has_docstring = int(bool(re.search(r'""".*?"""', code, re.DOTALL)))


    return_type_hints = len(re.findall(r'def\s+\w+\s*\([^)]*\)\s*->\s*[\w\[\], ]+:'
    param_type_hints = len(re.findall(r'def\s+\w+\s*\(([^)]*:\s*[\w\[\], ]+[^)]*)\)
    generic_names = len(re.findall(r'\b(foo|bar|baz|lorem|ipsum|qux|quux|xyz)\b', c
    num_prints = len(re.findall(r'(?<!#)[ \t]*print\s*\(', code))
    num_fstrings = len(re.findall(r'''(?<!#)[ \t]*f(['"])(?:\\.|[^\\])*?\1''', code
    list_comprehensions = len(re.findall(r'\[[^\]]*for\s+\w+\s+in\s+[^\]]+\]', code


    return {
        'num_lines': num_lines,
        'num_blank_lines': num_blank_lines,
        'num_comment_lines': num_comment_lines,
        'comment_ratio': comment_ratio,
        'num_functions': num_functions,
        'num_classes': num_classes,
        'num_loops': num_loops,
        'num_conditionals': num_conditionals,
        'num_imports': num_imports,
        'has_main_guard': has_main_guard,
        'num_assignments': num_assignments,
        'avg_line_length': avg_line_length,
        'max_indent_depth': max_indent_depth,
        'indent_uses_tabs': tab_vs_space['tabs'],
        'indent_uses_spaces': tab_vs_space['spaces'],
        'ends_with_space':ends_with_space,
        'camel_case_count': camel_case_count,
        'snake_case_count': snake_case_count,
        'has_docstring': has_docstring,
        'num_misspelled': num_misspelled,
        'misspelling_ratio': misspelling_ratio,
        'list_comprehensions':list_comprehensions,
        'num_fstrings':num_fstrings,
        'num_prints':num_prints,
        'generic_names':generic_names,
        'param_type_hints':param_type_hints,
        'return_type_hints':return_type_hints
    }

def extract_features_df(df, code_col='code'):
    features = df[code_col].apply(extract_features_from_code)
    features_df = pd.DataFrame(features.tolist())
    return pd.concat([df, features_df], axis=1), features_df.columns


# the new DF with our new generated features - generated from col 'code' in human_v
df_features, new_features_names = extract_features_df(human_vs_generated_df,'code')
```

- **Inspecting the data** - check for missing values, feature scales, class imbalance (by counting samples per category), observe correlations, and consider removing potentially redundant features.

- Missing values and data types
  - No missing values to handle
  - all features are numerical

In [133…
```
df_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5696 entries, 0 to 5695
Data columns (total 32 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   index                5696 non-null   int64  
 1   status_in_folder     5696 non-null   object 
 2   LLM                  5696 non-null   object 
 3   code                 5696 non-null   object 
 4   label                5696 non-null   int64  
 5   num_lines            5696 non-null   int64  
 6   num_blank_lines      5696 non-null   int64  
 7   num_comment_lines    5696 non-null   int64  
 8   comment_ratio        5696 non-null   float64
 9   num_functions        5696 non-null   int64  
 10  num_classes          5696 non-null   int64  
 11  num_loops            5696 non-null   int64  
 12  num_conditionals     5696 non-null   int64  
 13  num_imports          5696 non-null   int64  
 14  has_main_guard       5696 non-null   int64  
 15  num_assignments      5696 non-null   int64  
 16  avg_line_length      5696 non-null   float64
 17  max_indent_depth     5696 non-null   int64  
 18  indent_uses_tabs     5696 non-null   int64  
 19  indent_uses_spaces   5696 non-null   int64  
 20  ends_with_space      5696 non-null   int64  
 21  camel_case_count     5696 non-null   int64  
 22  snake_case_count     5696 non-null   int64  
 23  has_docstring        5696 non-null   int64  
 24  num_misspelled       5696 non-null   int64  
 25  misspelling_ratio    5696 non-null   float64
 26  list_comprehensions  5696 non-null   int64  
 27  num_fstrings         5696 non-null   int64  
 28  num_prints           5696 non-null   int64  
 29  generic_names        5696 non-null   int64  
 30  param_type_hints     5696 non-null   int64  
 31  return_type_hints    5696 non-null   int64  
dtypes: float64(3), int64(26), object(3)
memory usage: 1.4+ MB
```

- Scaling:
  - Significant differences in feature scales detected – **We will normalize the data.**

In [134…
```
df_features.describe()
```

Out[134…

	index	label	num_lines	num_blank_lines	num_comment_lines	comm
count	5696.000000	5696.000000	5696.000000	5696.000000	5696.000000	56
mean	4581.038448	-0.669593	22.091643	4.440836	1.197858	
std	1910.698301	0.742794	23.571162	6.806933	3.819041	
min	1.000000	-1.000000	1.000000	0.000000	0.000000	
25%	3310.750000	-1.000000	9.000000	1.000000	0.000000	
50%	4734.500000	-1.000000	16.000000	2.000000	0.000000	
75%	6158.250000	-1.000000	28.000000	6.000000	0.000000	
max	7582.000000	1.000000	571.000000	144.000000	98.000000	

8 rows × 29 columns

In [135…

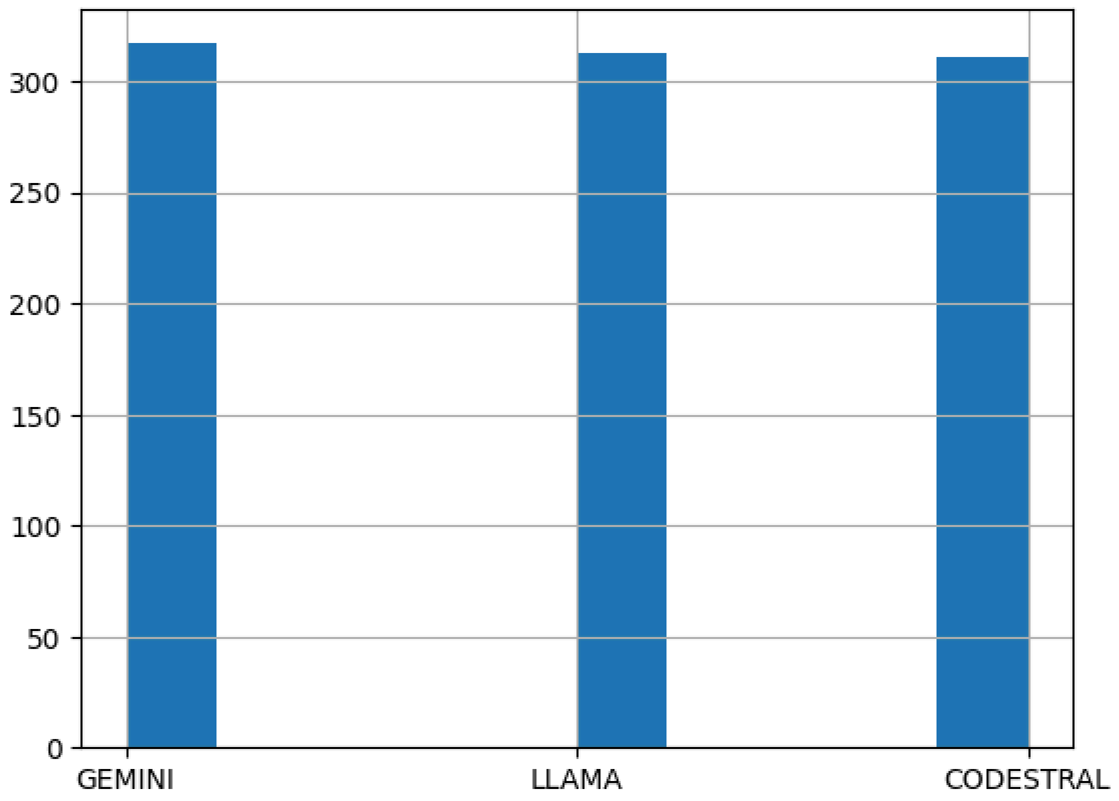
```
#####normlize with Z-score:#####
df_features[new_features_names] = (df_features[new_features_names] - df_features[ne
```

- Imbalanced data:
  - The data is balanced across different LLM models.
  - However, it is imbalanced between human and LLM-generated code: 4755 vs. 941 samples. This imbalance can cause models to become biased toward the majority class, leading to poor performance on the minority class. **We will address this by upsampling the minority class (LLM-generated code) through sampling with replacement to equalize class sizes.**

In [136…

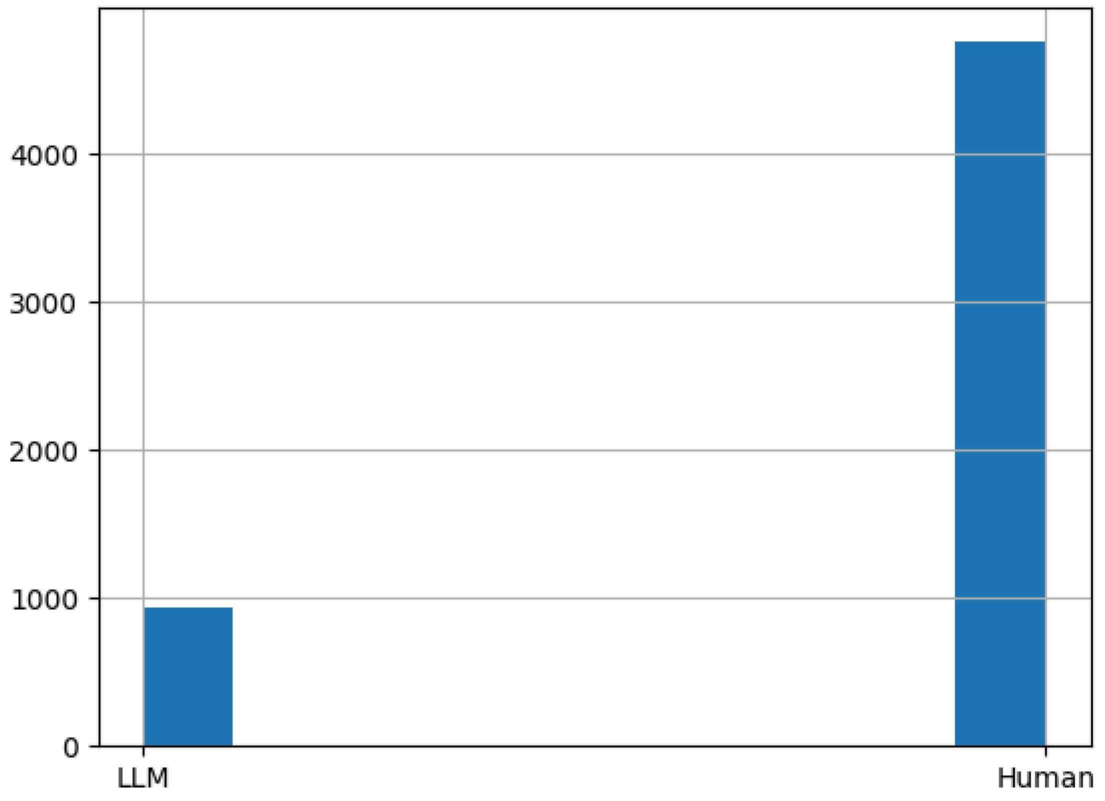
```
df_features[df_features['LLM'] != 'Human']['LLM'].hist()
print(f"Data is balanced between different LLM models")
```

```
Data is balanced between defferent LLM models
```



In [137…
```
df_features['label'].apply(lambda x: 'Human' if x==-1 else 'LLM').hist()
```

Out[137…
```
<Axes: >
```



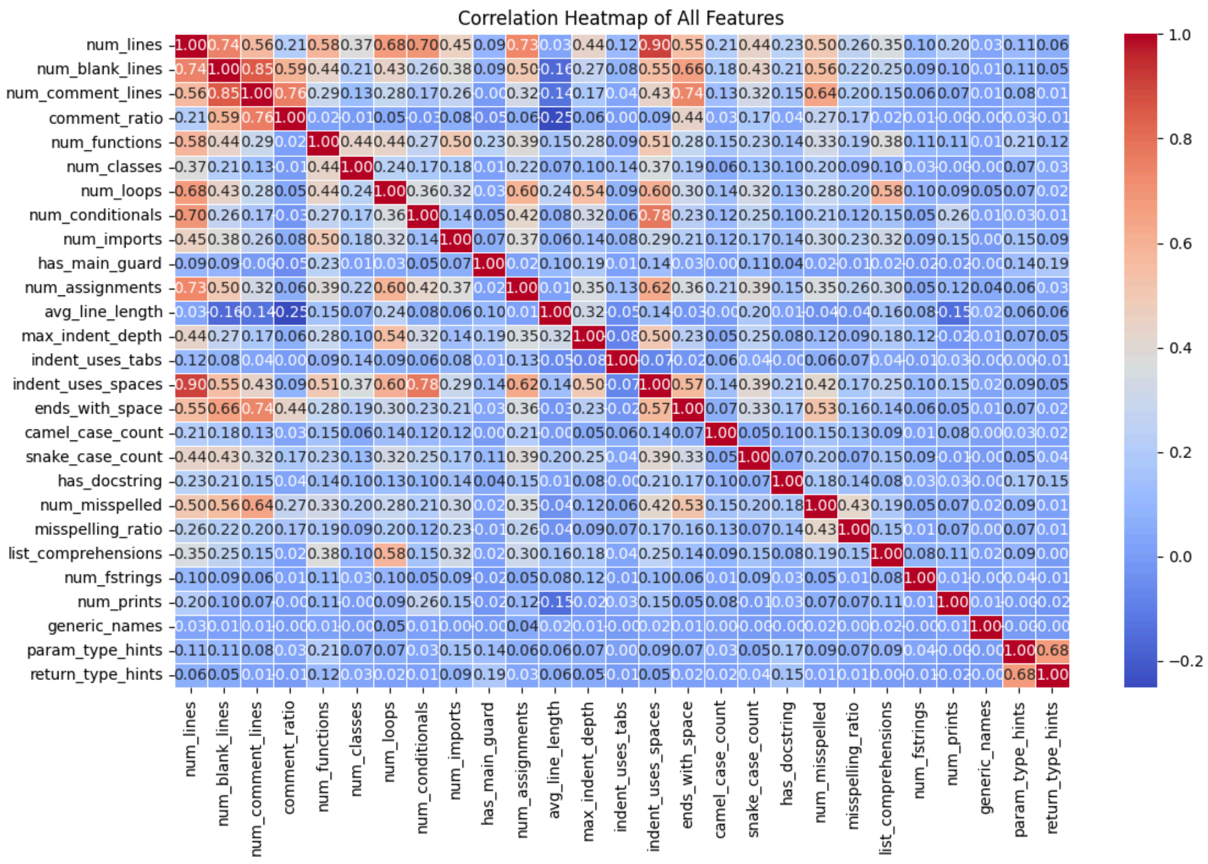
In [138…
```
#####handle  imbalanced data:#####
```

```
from sklearn.utils import resample

#returns the most frequent label - in our case its Human(-1)
majority_class = df_features["label"].value_counts().idxmax()

# Separate classes to 2 seperated df's
df_majority = df_features[df_features["label"] == majority_class]
df_minority = df_features[df_features["label"] == -majority_class]

# Oversample minority class
df_minority_upsampled = resample(df_minority, replace=True, n_samples=len(df_majori

# Combine back
df_balanced = pd.concat([df_majority, df_minority_upsampled])
```

- Correlated features:
  - This revealed strong correlations (>=0.85 - that are likely redundant features)
    - num_comment_lines ↔ num_blank_lines: 0.85
    - num_lines ↔ indent_uses_spaces: 0.90
  - **We decided not to drop - "indent_uses_spaces" and "num_blank_lines" after seeing that it did not improve the results**

In [139…

```
import seaborn as sns
import matplotlib.pyplot as plt
# Compute correlation matrix
corr = df_balanced[new_features_names].corr()
# Plot heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(corr, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.5)
plt.title("Correlation Heatmap of All Features")
plt.tight_layout()
plt.show()
```



In [141…

```
### drop highly correlated features and redundant columns then reset index###
# clean_df = df_balanced.drop(["indent_uses_spaces", "num_blank_lines",'LLM','statu

#test results without dropping highly correlated columns were better!
clean_df = df_balanced.drop(['LLM','status_in_folder','index','code'], axis=1).rese
```

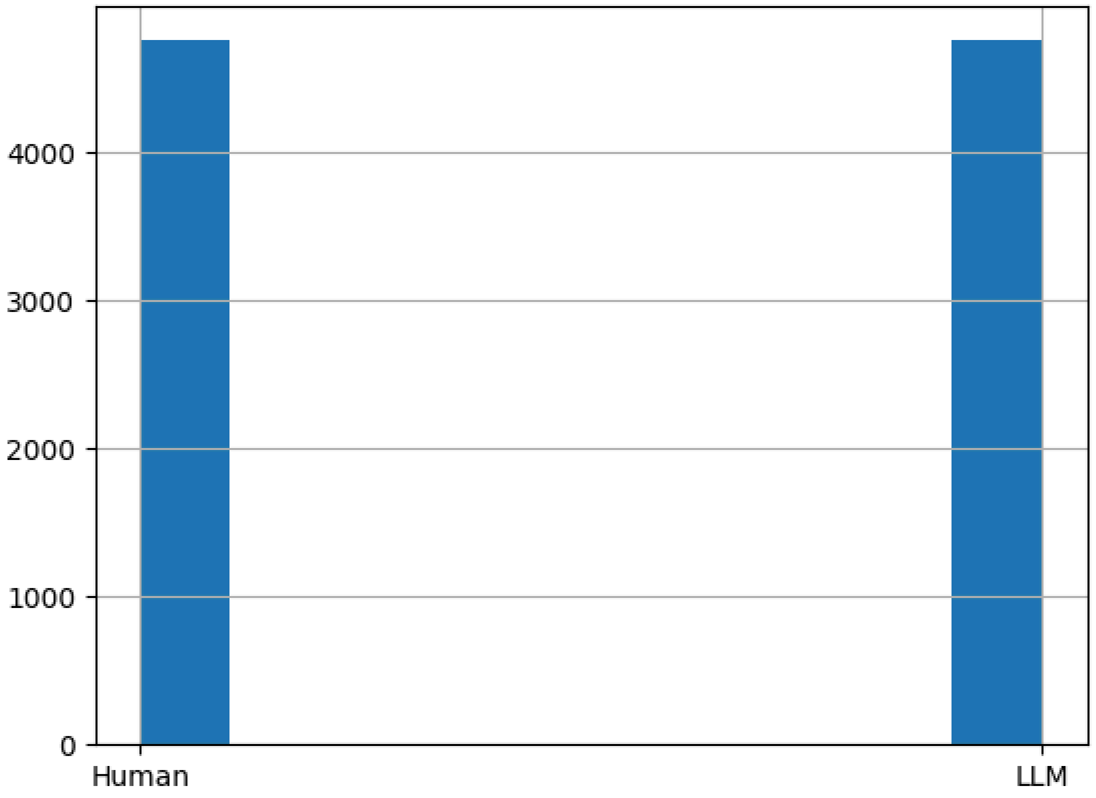
Sneak peek after Preprocessing

In [142…

```
#######check if balanced obtained and check remaining number of observations after
clean_df['label'].apply(lambda x: 'Human' if x==-1 else 'LLM').hist()
```

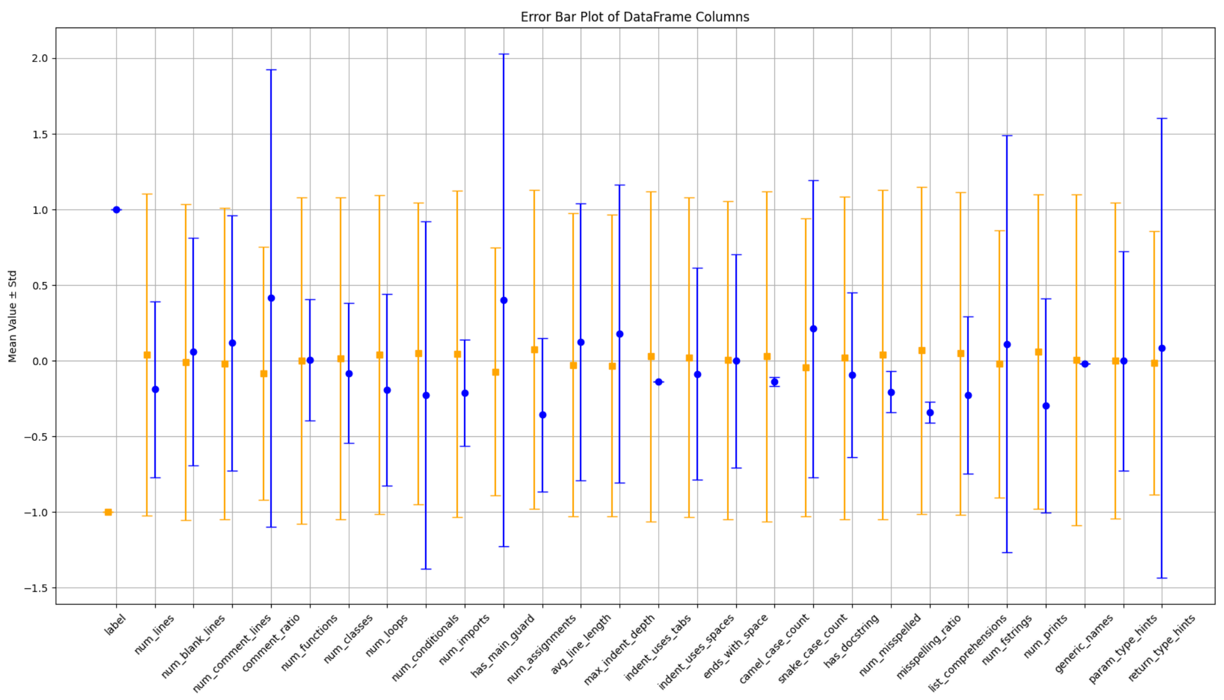
Out[142…

```
<Axes: >
```



In [143…

```
#######check scaling and first notion on how LLM and Human differ in selected featu
means_llm = clean_df[clean_df['label']==1].mean()
stds_llm = clean_df[clean_df['label']==1].std()
means_human =  clean_df[clean_df['label']==-1].mean()
stds_human = clean_df[clean_df['label']==-1].std()
offset = 0.2

plt.figure(figsize=(20, 10))
x = np.arange(len(means_llm))
plt.errorbar(x=x, y=means_llm.values, yerr=stds_llm.values, fmt='o', capsize=5, lin
plt.errorbar(x=x - offset, y=means_human.values, yerr=stds_human.values, fmt='s', c
plt.xticks(ticks=x, labels=means_llm.index, rotation=45)
plt.ylabel("Mean Value ± Std")
plt.title("Error Bar Plot of DataFrame Columns")
plt.grid(True)
plt.show()
```



In [144…

```
##### Show top positive and negative correlations with the target (label) - first n
corr = clean_df.corr()
label_corr = corr['label'].drop('label')  # drop self-correlation
sorted_corr = label_corr.sort_values(ascending=False)


print("Top features positively correlated with label:")
print(sorted_corr[sorted_corr > 0].head(10))

print("\nTop features negatively correlated with label:")
print(sorted_corr[sorted_corr < 0].tail(10))
```

```
Top features positively correlated with label:
comment_ratio        0.199070
has_main_guard       0.179901
snake_case_count     0.128479
max_indent_depth     0.105198
avg_line_length      0.078745
num_comment_lines    0.073579
num_fstrings         0.057093
return_type_hints    0.040887
num_blank_lines      0.039122
num_functions        0.003480
Name: label, dtype: float64

Top features negatively correlated with label:
indent_uses_tabs      -0.108113
num_conditionals      -0.126537
num_lines             -0.132929
num_loops             -0.133022
num_misspelled        -0.157142
num_imports           -0.158286
list_comprehensions   -0.161307
num_prints            -0.195954
num_assignments       -0.252466
misspelling_ratio     -0.258252
Name: label, dtype: float64
```

Splitting the data to train and test

- 80-20 ratio in train-test

In [145…

```
##### Train/test split#####
from sklearn.model_selection import train_test_split

# Separate features and labels
X = clean_df.drop(columns=["label"])
y = clean_df["label"]

# Stratify makes sure the distribution of labels in train and test data is the same
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

Models and Algorithms

To tackle the challenge of distinguishing between human-written and LLM-generated code, we implemented and compared several supervised learning models.
We used both handcrafted implementations and scikit-learn models to explore the performance and learning behavior of each method.

Evaluation and visualizations of the models

- We used standard metrics to evaluate all of our models
- We display a confusion matrix to show where most of the errors are

```
In [146…
#######evaluation function#########
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

#initialize dict of evaluations to view summarized at the end
evaluations = {}

def evaluate_model(y_test,y_pred,model_name):
    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("Precision:", precision_score(y_test, y_pred, average='macro'))
    print("Recall:", recall_score(y_test, y_pred, average='macro'))
    print("F1 Score:", f1_score(y_test, y_pred, average='macro'))

    #add to evaluation dict
    evaluations[model_name] = {"Accuracy":accuracy_score(y_test, y_pred),"Precision

    # Compute confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    print("Confusion Matrix:\n", cm)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=np.unique(y_p
    disp.plot(cmap='Blues')
```

Scikit-learn Decision Tree Classifier

- A decision tree is like a flowchart — a series of yes/no questions that help the model make a prediction.
- During training, the model tries different questions (feature-based splits) and checks how well they separate the data into their true classes.
- This is done using a "loss" function based on impurity metrics such as Entropy and Gini:
  - They measure how mixed or pure each group is after a split.
  - Low impurity means the group contains mostly one class (pure).
  - High impurity means the group contains a mix of classes.
- entropy - for 2 classes:
- what is the probability of class 1* how much it is surprising(the more rare - higher value) + same for second class
- $$\text{Entropy} = -\left(p_1 \cdot \log_2(p_1) + p_2 \cdot \log_2(p_2)\right)$$
- gini - for 2 classes:
- p^2 is the Probability that both samples are from the same class.
- it calcs The probability that the two samples do not belong to the same class — i.e., they are mixed.
- $$\text{Gini} = 1 - (p^2 + (1-p)^2)$$

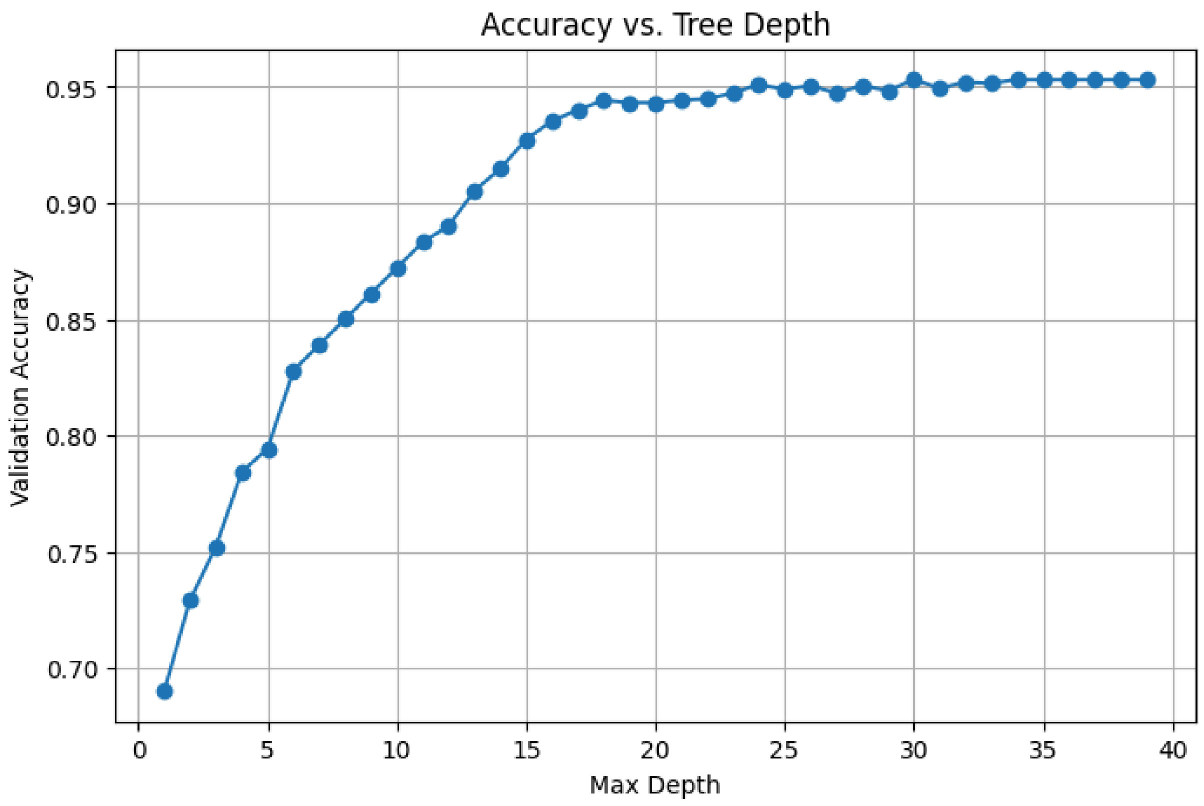
In [147…

```python
from sklearn.tree import DecisionTreeClassifier as DecisionTreeClassifier_sklearn

def sk_decisionTree(X_train, y_train, max_depth=30, criterion='gini'):
    sk_dt_model = DecisionTreeClassifier_sklearn(criterion=criterion, max_depth=max
    sk_dt_model.fit(X_train, y_train)
    return sk_dt_model
```

- Run the function systematically to find best depth:

In [148…

```python
from sklearn.metrics import accuracy_score, classification_report
def find_best_depth(X_train, y_train, X_val, y_val, max_depth_range=range(1, 21)):
    from collections import defaultdict
    results = defaultdict(list)

    best_depth = None
    best_accuracy = 0

    for depth in max_depth_range:
        depth_model = sk_decisionTree(X_train, y_train,depth)
        y_pred = depth_model.predict(X_val)

        acc = accuracy_score(y_val, y_pred)
        results["depth"].append(depth)
        results["accuracy"].append(acc)
        if acc > best_accuracy:
            best_accuracy = acc
            best_depth = depth

    # Plotting
    plt.figure(figsize=(8, 5))
    plt.plot(results["depth"], results["accuracy"], marker='o')
    plt.xlabel("Max Depth")
    plt.ylabel("Validation Accuracy")
    plt.title("Accuracy vs. Tree Depth")
    plt.grid(True)
    plt.show()

    print(f"\nBest depth: {best_depth} with accuracy: {best_accuracy:.4f}")
    return best_depth

best_depth = find_best_depth(X_train, y_train, X_test, y_test, max_depth_range=rang
```

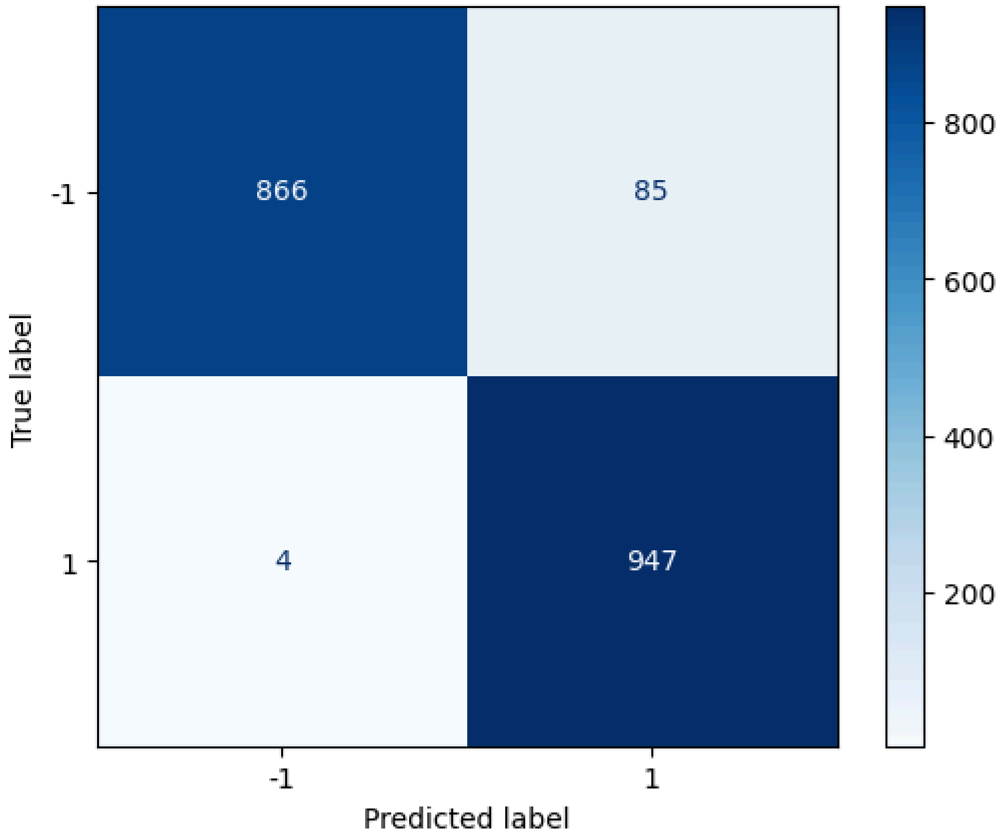


```
Best depth: 30 with accuracy: 0.9532
```

In [149…

```
sk_dt_model = sk_decisionTree(X_train, y_train, best_depth)
#Make Predictions
y_pred = sk_dt_model.predict(X_test)
#Evaluate
evaluate_model(y_test,y_pred, "sk_dt_model")
```

```
Accuracy: 0.9532071503680336
Precision: 0.9565189788826517
Recall: 0.9532071503680337
F1 Score: 0.95312213119589
Confusion Matrix:
 [[866  85]
 [  4 947]]
```



Interpretation

- **Accuracy** - Of all the predictions, 95% were correct.
- **Precision** - Of all predictions labeled as LLM-generated, 96% were correct.
- **Recall** - Of all actual LLM-generated samples, 96% were correctly identified by the model.
- **F1 Score** - A balanced measure of precision and recall. High F1 means the model is both accurate and complete in its predictions.

The model performs very well, with:

- Few mistakes (only 89 total mis-classifications),
- The model is doing better at detecting LLM-generated code — with higher recall and fewer errors.
- It sometimes mistakes Human-written code as LLM-generated, but rarely mistakes LLM code as Human-written.

Decision Tree Classifier - custom implementation

- We implemented a decision tree classifier from scratch, in a way that it was seamlessly usable by the Random Forest and Adaboost models later defined.
- The base unit of the tree is a TreeNode, which represents a junction in the tree
- The tree is built recursively, from root to leaves, adding TreeNodes on both sides at each recursive step.
- To make the Decision tree class compatible with Adaboost we used weights for measuring impurity:
  - we initially tried to implement an "adaboost" loss function (Weighted error - as used in the stumps example in class). When comparing the performance vs. the sklearn adaboost model, we obtained inferior results, and seeked further guidance on how to correctly implement the tree class which considers the adaboost weights.
  - We tried to solve the issue by resampling the input data, using the adaboost weights as the underlying distribution, but this didn't improve the results.
  - In class, it was mentioned that we need to use the original model's loss function, but to adapt it to consider the weights. Looking through relevant sources in the internet, we realized we need to produce a weighted impurity function, and also to consider the weights in the split gain calculation, and in the majority vote in the leaves level.

In [150…

```
# An object that represents a node (junction) in the decision tree.
# If it's a leaf, it holds a value – the predicted classification (e.g., 1 or -1).
class TreeNode:
    def __init__(
        self,
        feature: str,                     # The feature to ask the question about
        threshold: float,                 # The threshold to split the data
        left: "TreeNode",      # The left child node (or class label if it's a leaf
        right: "TreeNode",     # The right child node (or class label if it's a lea
        value: int = None        # The class label if this node is a leaf
    ):

        self.feature = feature
        self.threshold = threshold
        self.left = left
        self.right = right
        self.value = value
```

In [151…

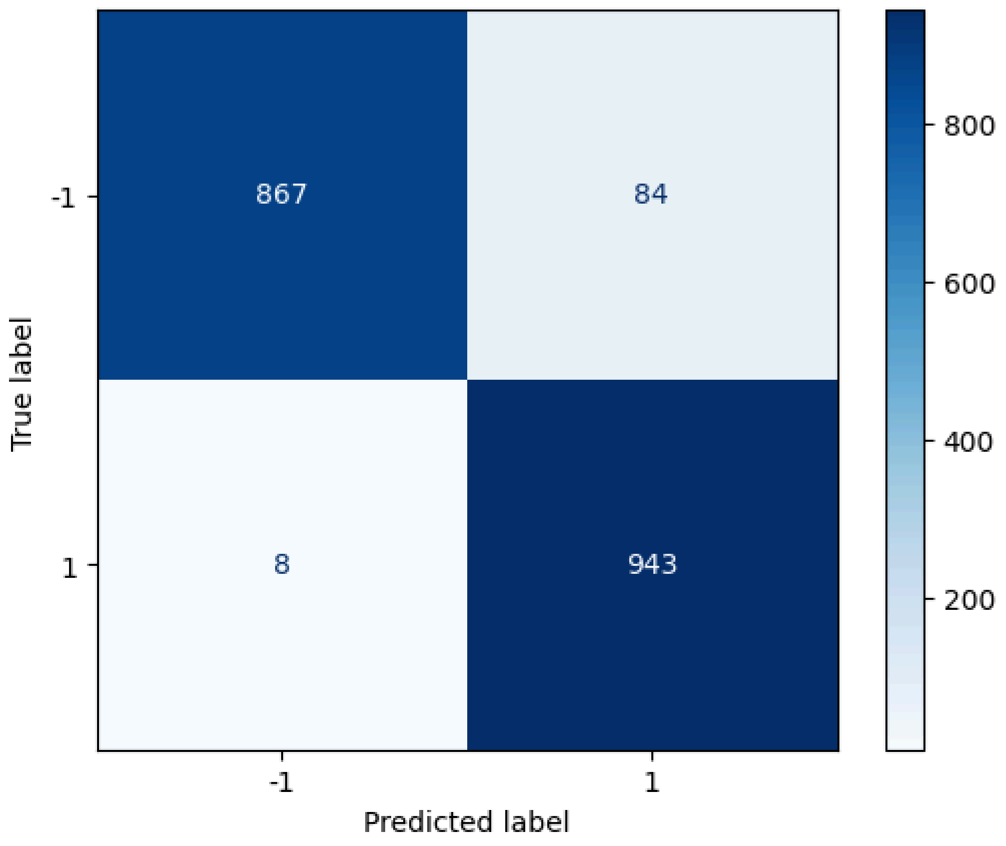
```

class DecisionTreeClassifier:

    #initialize decision tree and its params:
    def __init__(self, max_depth=None, min_samples_split=2, criterion='gini', max_n
        self.tree = None                                    #initializing empty tree.
        self.max_depth = max_depth                          #the max depth of the tre
        self.max_num_features = max_num_features            #limits the number of fea
        self.min_samples_split = min_samples_split          #minimum number of data p
        self.criterion = criterion                          #user's choice of loss fu

        #setting the calc_loss according to user's choice
        if criterion == "entropy":
            self.calc_loss = self.entropy
        elif criterion == "gini":
            self.calc_loss = self.gini



    #function to calculate entropy  - W are weights for adaboost later use
    def entropy(self, y, W=None):
        classes = np.unique(y)                                      # get the labels (-1
        entropy = 0                                                 # initialize entropy
        if W is None:                                               # simple entropy
            for cls in classes:                                     # for each class (-1
                p_cls = np.sum(y == cls) / len(y)                   # calculate percenta
                if p_cls > 0:                                       # if class is presen
                    entropy -= p_cls * np.log2(p_cls)               # this calcs - How l

        else:                                                       # Weighted entropy -
            W = np.array(W)                                         # Set weights as a N
            total_weight = np.sum(W)                                # Total weight of al

            if total_weight == 0:                                   # Edge case: all wei
                return 0
            for cls in classes:                                     # for each class (-1
                # Calculate weighted proportion for this class
                class_mask = (y == cls)                             #boolean mask - to g
                weighted_class_count = np.sum(W[class_mask])        #sums the weights on
                p_cls = weighted_class_count / total_weight         #devide that in tota

                if p_cls > 0:                                       # if class is presen
                    entropy -= p_cls * np.log2(p_cls)               #same calc as in sim
        return entropy



    #function to calculate gini  - W are weights for adaboost later use
    def gini(self, y, W=None):
        classes = np.unique(y)                                     # get the labels (-1,
        gini  = 1                                                  # initialize gini to
        if W is None:                                              # simple gini
            for cls in classes:                                    # for each class
                p_cls = np.sum(y == cls) / len(y)                  # Count of this class
                gini -= p_cls ** 2                                 # subtracts the squar

        else:                                                      # Weighted gini - for
            W = np.array(W)                                        # Set weights as a Nu
            total_weight = np.sum(W)                               # total weights

            if total_weight == 0:                                  # that means that All
                return 0

            for cls in classes:                                     # for each class (-1
                # Calculate weighted proportion for this class
                class_mask = (y == cls)                             #boolean mask - to g
                weighted_class_count = np.sum(W[class_mask])        # add their weights
                p_cls = weighted_class_count / total_weight         # divided by the tot
            gini -= p_cls ** 2                               # subtracts the squa
        return gini



    #function to find the best split of all possible splits (using the chosen loss
    def best_split(self, X, y, W=None):
        best_gain = 0                    #initilize gain to 0 - How much "better" (pur
        best_feature = None              #initilize what is the best feature to split
        best_threshold = None            #initilize what is the best threshold (for th
        loss = self.calc_loss(y, W)      #define the loss function according to the co

        n_samples = X.shape[0]            #get number of samples

        #this is fo\r random forest case - if we defined max num of features to cho
        all_features = X.columns if self.max_num_features is None else np.random.ch

        for feature in all_features:                             # iterate each fea
            thresholds = np.unique(X[feature])
            for threshold in thresholds:                         # iterate each pos
                #devide the samples by <= or > then thresh
                lower_than_thresh = X[feature] <= threshold
                higher_than_thresh = X[feature] > threshold
                n_lower, n_higher = lower_than_thresh.sum(), higher_than_thresh.sum
                if n_lower == 0 or n_higher == 0:                # if we didn't cre
                    continue
                loss_lower = self.calc_loss(y[lower_than_thresh], None if W is None
                loss_higher = self.calc_loss(y[higher_than_thresh], None if W is No

                #if adaboost - calculate total loss by wighted sum of both sides (m
                if W is not None:
                    total_weight = np.sum(W)
                    weight_lower = np.sum(W[lower_than_thresh])
                    weight_higher = np.sum(W[higher_than_thresh])
                    split_loss = (weight_lower / total_weight) * loss_lower + (weig
                #if not adaboost - calculate total loss by simple sum of both sides
                else:
                    split_loss = (n_lower / n_samples) * loss_lower + (n_higher / n

                info_gain = loss - split_loss      # the improvement in loss functi

                if info_gain > best_gain:          # if best improvement - this is
                    best_gain = info_gain
                    best_feature = feature
                    best_threshold = threshold

        return best_feature, best_threshold, best_gain



    #recrusive function that build the tree top to bottom - using previous function
    def build_tree(self, X, y, cur_depth=0, W=None):
        n_samples = X.shape[0]
        n_labels = len(np.unique(y))

        # stop building - if:
```

```
                    #we reached max depth or
                    #pure class division (only 1 label in split) or
                    #number of samples is less the minimum defined to continue
    if (self.max_depth is not None and cur_depth >= self.max_depth) or n_labels
        value = self.majority_class(y)   #this will return a value (1,-1) meani
        return TreeNode(feature=None, threshold=None, left=None, right=None, va

    #get the best split for the current sample
    feature, threshold, gain = self.best_split(X, y, W)

    #if there is no improvement - then stop building that branch... return the
    if gain == 0:
        value = self.majority_class(y)  #this will return a value (1,-1) meanin
        return TreeNode(feature=None, threshold=None, left=None, right=None, va

    #else - we continue to build... we split the data by the selected feature a
    lower_idx = X[feature] <= threshold
    higher_idx = X[feature] > threshold

    #in case of adaboost - we also send the relevant weights data
    if W is not None:
        W_lower = W[lower_idx]
        W_higher = W[higher_idx]
    else:
        W_lower = W_higher = None

    #we recursively continue to chose best splits for our two new samples - the
    lower = self.build_tree(X[lower_idx], y[lower_idx], cur_depth + 1, W_lower)
    higher = self.build_tree(X[higher_idx], y[higher_idx], cur_depth + 1, W_hig

    #this returns the current tree built up to this point
    return TreeNode(feature, threshold, lower, higher)


#function to return majority class in sample
def majority_class(self, y, W=None):
    # if not adaboost - simple count and return label of max
    if W is None:
        labels, counts = np.unique(y, return_counts=True)
        return labels[np.argmax(counts)]
    else:
        #if adaboost - the "votes" should be counted taking the sample's weight
        labels = np.unique(y)
        weighted_counts = []
        for label in labels:                                 #for each class
            weighted_counts.append(np.sum(W[y == label]))    # we calculate
        return labels[np.argmax(weighted_counts)]            #we return clas


#function to preform fit (build the tree)
def fit(self, X, y, W=None):
    if self.max_num_features:                             #in case of random fo
        assert self.max_num_features<=X.shape[1]
    self.tree = self.build_tree(X, y, W=W)
#function to predict one sample of unseen data (test) - Advancing along the tre
def predict_sample(self, inputs, node):
    if node.value is not None:
        return node.value

    feature = node.feature
    threshold = node.threshold

    if inputs[feature] <= threshold:
        return self.predict_sample(inputs, node.left)
    else:
        return self.predict_sample(inputs, node.right)


#function to predict X matrix - number of samples - each predicted using  predi
def predict(self, X):
    return np.array([self.predict_sample(inputs[1], self.tree) for inputs in X.
```

In [152…

```
def decisionTree(X_train, y_train, max_depth=30, criterion='gini'):
    model = DecisionTreeClassifier(criterion=criterion, max_depth=max_depth)
    model.fit(X_train, y_train)
    return model

dt_model = decisionTree(X_train, y_train, best_depth)
#Make Predictions
y_pred = dt_model.predict(X_test)
#Evaluate
evaluate_model(y_test,y_pred,"dt_model")
```

```
Accuracy: 0.9516298633017876
Precision: 0.9545327583808596
Recall: 0.9516298633017877
F1 Score: 0.9515525102524263
Confusion Matrix:
 [[867  84]
 [  8 943]]
```



Interpretation

- **Accuracy** - Of all the predictions, 95% were correct.
- **Precision** – Of all predictions labeled as LLM-generated, 95% were correct. → The model rarely mislabels human-written code as LLM-generated.
- **Recall** – Of all actual LLM-generated samples, 95% were correctly identified by the model. → The model correctly identifies most of the LLM-generated samples.
- **F1 Score** – A balanced measure of precision and recall: 95%, which shows the model is both accurate and consistent.
- Only 92 mis-classifications in total (8 + 84)
- The model is very good at catching LLM code (only 8 misses out of 951)
- It sometimes mistakes Human-written code as LLM-generated (84 false positives)
- Overall, the model is well-balanced and highly accurate —yet the previous model performs slightly better across all metrics

---

Scikit-learn Random Forest

- Random Forest is an ensemble learning method that builds many decision trees and combines their outputs to make better predictions.
- Each tree is trained on a random subset of the data and a random subset of features.

- Random Forest reduces overfitting and improves accuracy by averaging the predictions of many decision trees.
- Random Forest = Many Decision Trees + Randomness + Voting/Averaging = Better Generalization

In [153…

```
from sklearn.ensemble import RandomForestClassifier as RandomForestClassifier_sklea

def sk_randomforest(X_train, y_train, n_estimators=30, max_depth=30, max_num_featur
    sk_rf_model = RandomForestClassifier_sklearn(
        n_estimators=n_estimators,
        max_depth=max_depth,
        max_features=max_num_features,
        n_jobs=-1
    )
    sk_rf_model.fit(X_train, y_train)
    return sk_rf_model
```

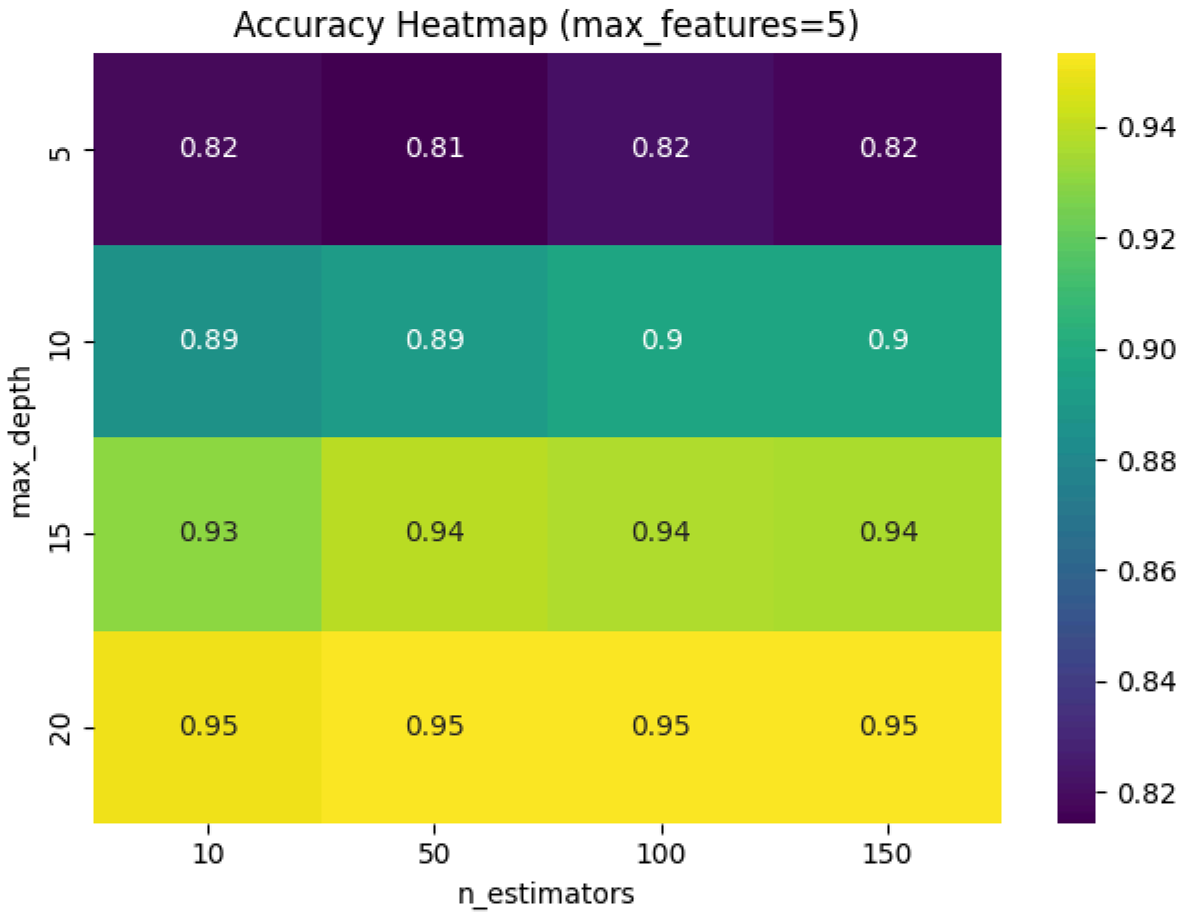
- Run the function systematically to find best depth , number of trees, and number of max featuers:

In [154…

```
from sklearn.model_selection import GridSearchCV

param_grid = {
    'n_estimators': [10, 50, 100, 150],
    'max_depth': [5, 10, 15, 20, None],
    'max_features': [3, 5, 10],
}

grid_search = GridSearchCV(
    estimator=RandomForestClassifier_sklearn(n_jobs=-1),
    param_grid=param_grid,
    cv=3,
    scoring='accuracy',
    verbose=1,
    n_jobs=-1
)

grid_search_result = grid_search.fit(X_train, y_train)

print("Best Parameters:", grid_search_result.best_params_)
print("Best Accuracy:", grid_search_result.best_score_)

best_max_features = grid_search_result.best_params_["max_features"]
best_max_depth=grid_search_result.best_params_["max_depth"]
best_n_estimators=grid_search_result.best_params_["n_estimators"]

print(f"results visualiztion for best max_features {best_max_features}")
# Convert CV results to DataFrame
results_df = pd.DataFrame(grid_search_result.cv_results_)

# Filter for fixed max_features
filtered = results_df[results_df['param_max_features'] == best_max_features]
```

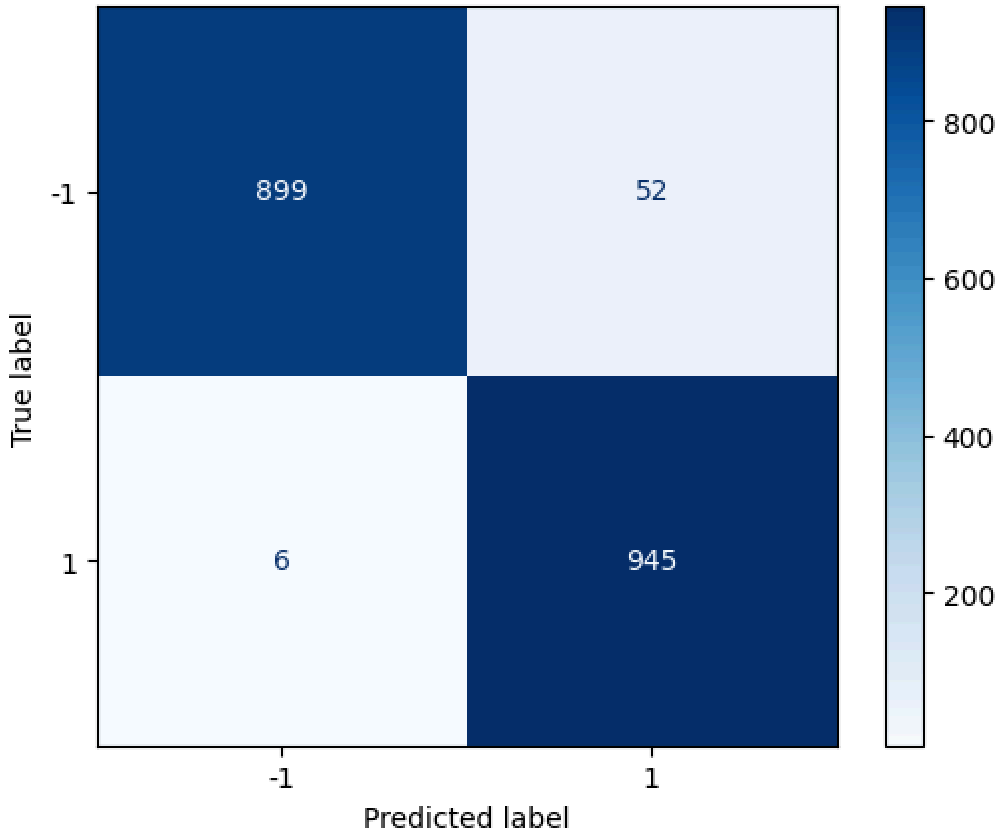
```
# Pivot table for heatmap
pivot_table = filtered.pivot_table(values='mean_test_score',
                                    index='param_max_depth',
                                    columns='param_n_estimators')

sns.heatmap(pivot_table, annot=True, cmap='viridis')
plt.title(f"Accuracy Heatmap (max_features={best_max_features})")
plt.xlabel("n_estimators")
plt.ylabel("max_depth")
plt.tight_layout()
plt.show()
```

```
Fitting 3 folds for each of 60 candidates, totalling 180 fits
Best Parameters: {'max_depth': None, 'max_features': 5, 'n_estimators': 50}
Best Accuracy: 0.9606992639327023
results visualiztion for best max_features 5
```



In [155…
```
sk_rf_model = sk_randomforest(X_train,y_train, best_n_estimators, best_max_depth, b
#Make Predictions
y_pred = sk_rf_model.predict(X_test)
#Evaluate
evaluate_model(y_test,y_pred,"sk_rf_model")
```

```
Accuracy: 0.9695057833859095
Precision: 0.9706068481688158
Recall: 0.9695057833859095
F1 Score: 0.9694879363449692
Confusion Matrix:
 [[899  52]
 [  6 945]]
```



Interpretation

- **Accuracy** - Of all the predictions, 97% were correct.
- **Precision** – — When the model predicts a positive class (LLM), it's correct 97% of the time.
- **Recall** – 97% — The model successfully detects 97.27% of the actual positive cases.
- **F1 Score** – 97% Balanced combination of precision and recall; excellent performance.
- False Positives (52) slightly higher than False Negatives (6) – the model tends to predict positive more easily, which could be good or bad depending on the domain.
- The overall performance is excellent and very balanced. All four metrics (accuracy, precision, recall, F1) are almost identical and very high.
- Compared to previous result: This new model improved significantly in all metrics.

Random forest - custom implementation

- Our random forest implementation, is utilizing the basic decision tree class. To allow random trees generation, we implemented

1. Random feature sampling
2. Folding the data, each time sending different samples using sampling with repetitions

- Final decision is based on a majority vote, using only integer tree results, and not probabilities like the sklearn implementation

In [156…

```
from scipy.stats import mode
class RandomForestClassifier:

    def __init__(self,n_estimators, max_depth=30, criterion='gini',  max_num_featur
        #initialize list of trees (n_estimators)
        self.trees=[]
        #insert n trees to that list - each is a DecisionTreeClassifier object from
        for i in range(n_estimators):
            self.trees.append(DecisionTreeClassifier(max_depth, min_samples_split,


    #fit the model - train the model and build the n trees (the forest)
    def fit(self, X_train, y_train):
        #for each tree(DecisionTreeClassifier object)  in our n trees - make bootst
        for i,tree in enumerate(self.trees):
            n_samples = X_train.shape[0]
            sampled_X, sampled_y = resample(X_train, y_train, n_samples=n_samples,
            tree.fit(sampled_X, sampled_y)

    #predict using majority vote of n trees
    def predict(self, X):
        all_preds = np.array([tree.predict(X) for tree in self.trees])
        majority_vote = mode(all_preds, axis=0)[0]  # scipy.stats returns a special
        return majority_vote
```

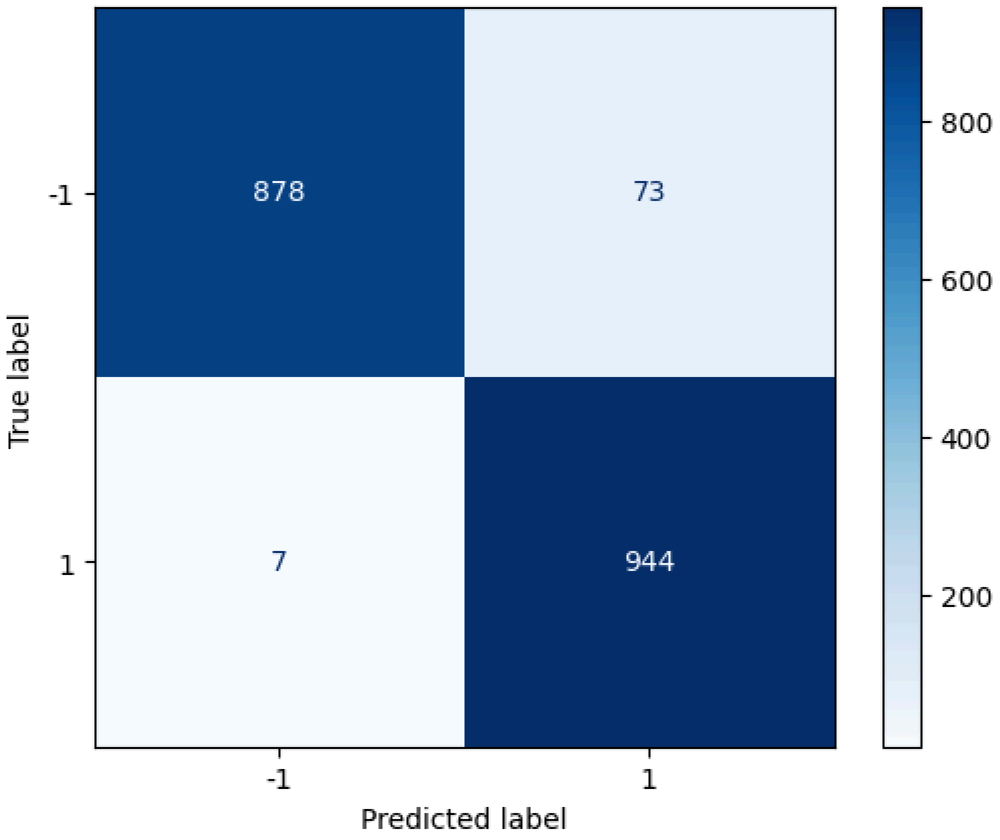
In [157…

```
def randomforest(X_train,y_train, n_estimators=30, max_depth=30, max_num_features=5
    rf_model = RandomForestClassifier(n_estimators=n_estimators, max_depth=max_dept
    rf_model.fit(X_train, y_train)
    return rf_model
```

In [158…

```
rf_model = randomforest(X_train,y_train, 30,30,6)  #Manual testing revealed the bes
#Make Predictions
y_pred = rf_model.predict(X_test)
#Evaluate
evaluate_model(y_test,y_pred,"rf_model")
```

```
Accuracy: 0.9579390115667719
Precision: 0.960155325567055
Recall: 0.9579390115667719
F1 Score: 0.9578883043732398
Confusion Matrix:
 [[878  73]
 [  7 944]]
```



Interpretation

- **Precision** – 96% — When the model predicts a positive class (LLM), it is correct 95.1% of the time.
- **Recall** – 96% — The model successfully detects 96% of all actual LLM-generated samples.
- **Accuracy** – 96% — Very high overall classification correctness.
- **F1 Score** – 96% — A strong balance between precision and recall, indicating consistent and reliable performance.
- False Positives (73) are more frequent than False Negatives (7) — the model tends to slightly over-predict the positive class.
- Overall, the model performs excellently, with all core metrics (accuracy, precision, recall, F1) tightly grouped and very high.
- Compared to previous results: This model maintains high and balanced performance, though slightly below the previous model’s near-perfect metrics — still a strong and reliable classifier.

Scikit-learn AdaBoost

- AdaBoost is a method for combining many weak models (like shallow decision trees) into a single strong model that makes more accurate predictions.

- Think of it as using a team of experts, where each new expert is recruited to focus on the areas where the team is currently weak.
- Each expert (or model) is given a different weight (or voting power) — experts who perform better get more influence on the final decision.
- The result is a powerful model that learns to handle difficult cases more effectively than any single weak learner.
- AdaBoost has two algorithm modes:
  - SAMME.R (default): Uses predicted probabilities (not just labels); converges faster and usually gives better results.
  - SAMME: Uses only predicted class labels; useful when the base model doesn't support probabilities (predict_proba).

In [159…

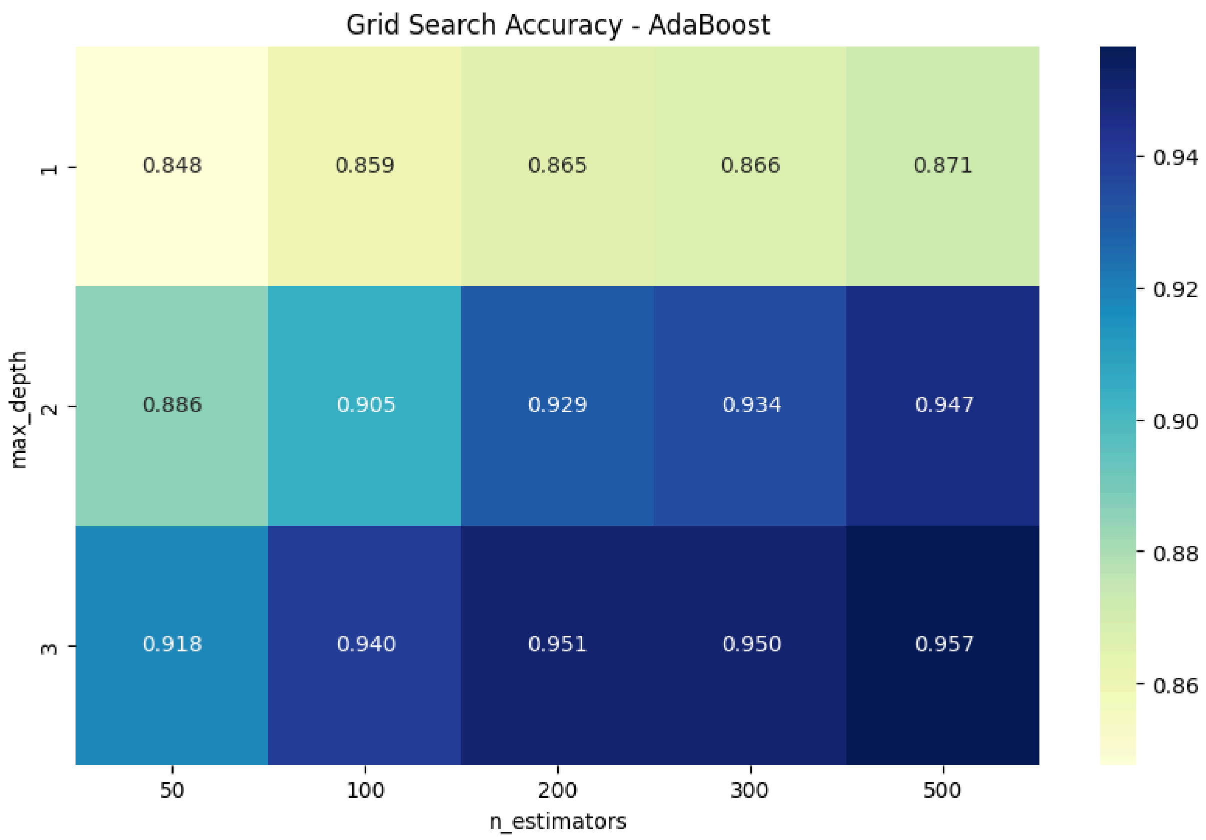
```
from sklearn.ensemble import AdaBoostClassifier as AdaBoostClassifier_sklearn
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

def sk_adabbost(X_train,y_train, n_estimators=500, tree_depth=1, random_state=0):
    base_tree = DecisionTreeClassifier_sklearn(max_depth=tree_depth)
    sk_ab_model = AdaBoostClassifier_sklearn(algorithm='SAMME.R',estimator=base_tre
    sk_ab_model.fit(X_train, y_train)
    return sk_ab_model
```

- Run the function systematically to find best model depth and number of models

In [160…

```
param_grid = {
    'n_estimators': [50,100, 200, 300, 500],
    'estimator__max_depth': [1, 2, 3]
}

model = AdaBoostClassifier_sklearn(estimator=DecisionTreeClassifier_sklearn(), algo
grid_search = GridSearchCV(model, param_grid, cv=5, scoring='accuracy', n_jobs=-1,
grid_search.fit(X_train, y_train)

print("Best Parameters:", grid_search.best_params_)
print("Best Accuracy:", grid_search.best_score_)

best_max_depth = grid_search.best_params_["estimator__max_depth"]
best_n_estimators = grid_search.best_params_["n_estimators"]

results = grid_search.cv_results_
df_results = pd.DataFrame(results)
df_results = df_results[['param_n_estimators', 'param_estimator__max_depth', 'mean_
df_results.columns = ['n_estimators', 'max_depth', 'accuracy']
pivot_table = df_results.pivot(index='max_depth', columns='n_estimators', values='a

plt.figure(figsize=(10, 6))
sns.heatmap(pivot_table, annot=True, fmt=".3f", cmap="YlGnBu")
plt.title("Grid Search Accuracy - AdaBoost")
plt.xlabel("n_estimators")
plt.ylabel("max_depth")
plt.show()
```

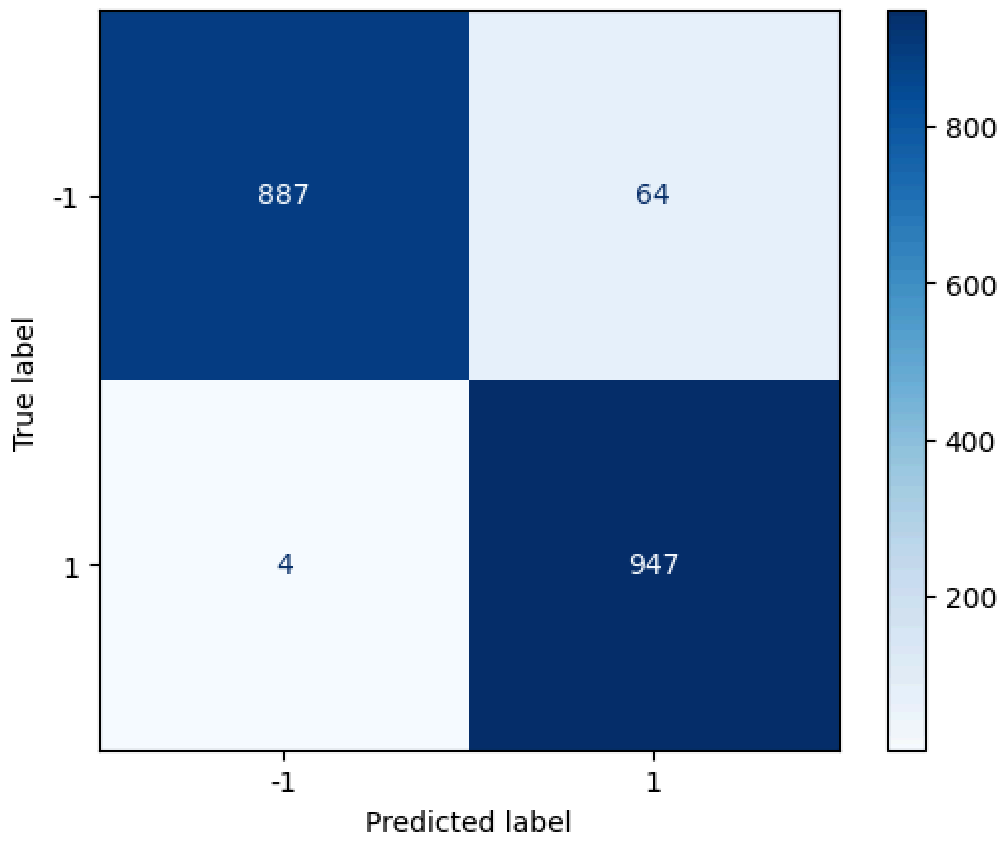
```
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Best Parameters: {'estimator__max_depth': 3, 'n_estimators': 500}
Best Accuracy: 0.9566247739703719
```



In [161…

```
sk_ab_model = sk_adabboost(X_train,y_train, best_n_estimators,best_max_depth)
#Make Predictions
y_pred = sk_ab_model.predict(X_test)
#Evaluate
evaluate_model(y_test,y_pred,"sk_ab_model")
```

```
Accuracy: 0.964248159831756
Precision: 0.96610350121725
Recall: 0.964248159831756
F1 Score: 0.9642125465273419
Confusion Matrix:
 [[887  64]
 [  4 947]]
```



Interpretation

- **Precision** – Of all predictions labeled as positive (e.g., LLM-generated), 97% were correct → The model rarely mislabels human-written code as LLM-generated.
- **Recall** – Of all actual positive samples, 96% were correctly identified → The model captures nearly all LLM-generated samples.
- **F1 Score** – A balanced measure of precision and recall: 96%, showing the model is both accurate and consistent.
- **Accuracy** - — 96% high overall classification correctness.
- Only 68 misclassifications in total (64 false positives + 4 false negatives).
- The model is excellent at detecting LLM code — only 4 real LLM samples were missed out of 951.
- Occasionally, the model confuses human-written code as LLM-generated (64 cases).
- Overall, the model is highly accurate, precise, and balanced — a strong performer with minimal error.
- This preformance is slightly less than sklearn random forest

Adaboost Classifier - custom implementation

- Based on simple decision trees as weak learners, which should have a max_depth of no more than 3 to prevent overfitting on the training data.
- The user can choose the number of weak learners, but if the loss doesn't decrease or the sample weights stop changing, the model will stop adding new learners.

- Additionally, if the loss for the best current learner is 0.5 or more, we stop adding learners, since such a model performs no better than random guessing.
- The final prediction is made based on the selected models and their individual contributions (α values) to the final decision:

$$\hat{y} = \operatorname{sign}(F(x)) = \operatorname{sign}\left(\sum_{t=1}^{T} \alpha^t h^t(x)\right)$$

- The model's loss function is the sum of weighted prediction errors:

AdaBoost Weighted Error:

$$\varepsilon^t = \sum_{i:h^t(x_i)\neq y_i} w_i^t$$

- Alpha (α), or the partial model's influence in the final decision, increases as the model's loss decreases. It is computed as:

$$\alpha^t = \frac{1}{2}\ln\left(\frac{1-\varepsilon^t}{\varepsilon^t}\right)$$

  Note that if the loss is 0.5, α becomes 0 — meaning the model contributes nothing to the final decision.
- Each sample's weight is updated based on the previous weights and the current model's performance — misclassified samples receive higher weights:

  1. For **correctly classified** samples (נכון):

  $$w_i^{(t+1)} = \frac{1}{2} w_i^{(t)} \cdot \frac{1}{1-\varepsilon^t}$$

  2. For **misclassified** samples (לא נכון):

  $$w_i^{(t+1)} = \frac{1}{2} w_i^{(t)} \cdot \frac{1}{\varepsilon^t}$$

- Finally, note that inside each weak model, the sample weights affect the loss function (e.g., Gini or Entropy) used to train the decision tree.

In [162…
```python
#loss function for model - sum of weights of bad predictions
def weighted_exponential_loss(y_pred,y,W):
        return (W*(y!=y_pred)).sum()


import math
```

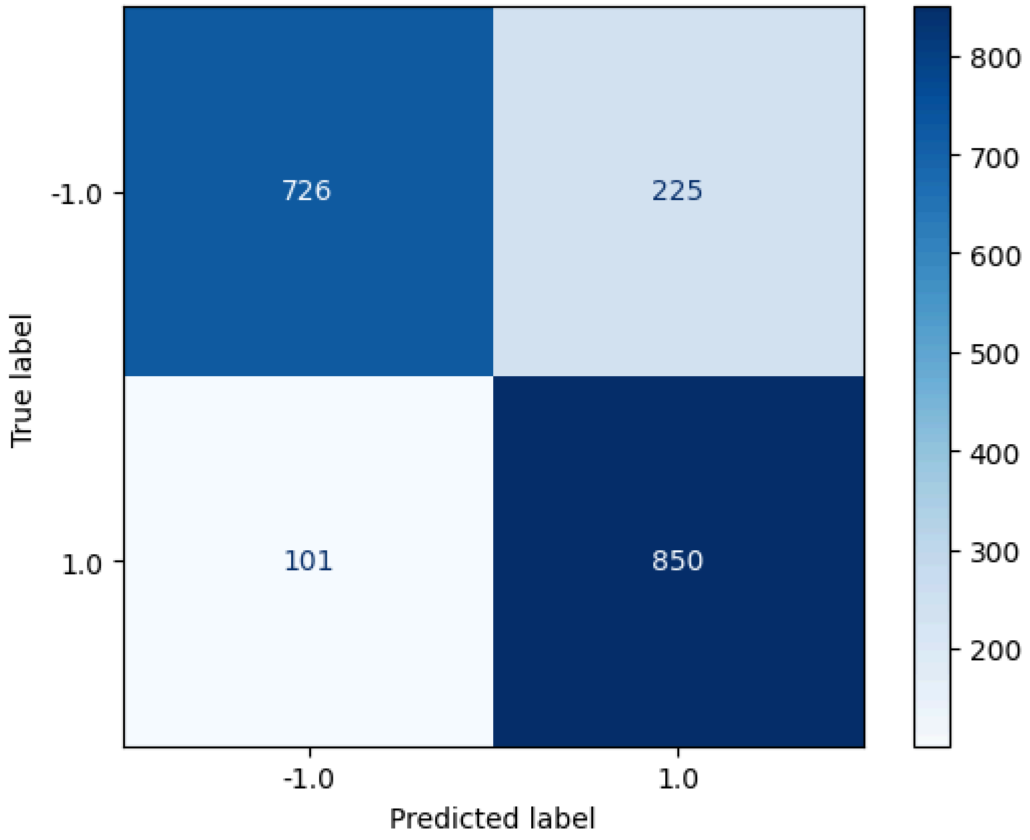
```
class AdaBoostClassifier:

    def __init__(self,n_estimators, criterion="gini", max_depth=2, min_samples_spli
        self.weak_learners=[]             # list of models - weak learners (experts
        self.W=None                      # initialize Weights vector
        self.alphas=[]                   # initialize alfa vector
        self.criterion=criterion         # user's chosen criterion for eak learner'

        #initializing n models - DecisionTreeClassifier objects
        for i in range(n_estimators):
            self.weak_learners.append(DecisionTreeClassifier(max_depth, min_samples

    #fit - train the model (build the team of experts)
    def fit(self, X_train, y_train):
        self.alphas=[]
        #equal weights initialize
        self.W = np.array([1/X_train.shape[0]]*X_train.shape[0])
        for counter,weak_learner in enumerate(self.weak_learners):
            weak_learner.fit(X_train, y_train, W=self.W)
            y_pred = weak_learner.predict(X_train)
            loss = weighted_exponential_loss(y_pred,y_train,self.W)
            if loss>=0.5:
                print(f"loss is >= 0.5, stopped after {counter} weak learners")
                break
            self.alphas.append(0.5*math.log((1-loss)/loss))
            if loss==0:
                print(f"loss=0, after {counter} weak learners")
                break

            W_correct = 0.5*(1/(1-loss))
            W_wrong = 0.5*(1/loss)
            prev_W = self.W
            self.W = self.W*(y_train==y_pred)*W_correct + self.W*(y_train!=y_pred)*
            if np.array_equal(prev_W, self.W):
                print(f"No change in weights, after {counter} weak learners")
                break


    #function to make predictions
    def predict(self, X):
        sum_predicts = np.zeros([X.shape[0], 1], dtype=np.float64)
        for i, alpha in enumerate(self.alphas):
            sum_predicts += alpha * self.weak_learners[i].predict(X)[:, None]
        return np.sign(sum_predicts)
```

In [163…

```
def adabboost(X_train,y_train, n_estimators=500, max_depth=3):
    ab_model = AdaBoostClassifier(n_estimators=20,max_depth=max_depth, criterion="g
    ab_model.fit(X_train, y_train)
    return ab_model

ab_model = adabboost(X_train,y_train, best_n_estimators,best_max_depth)
#Make Predictions
y_pred = ab_model.predict(X_test)
```

```
#Evaluate
evaluate_model(y_test,y_pred,"ab_model")
```

```
loss is >= 0.5, stopped after 9 weak learners
Accuracy: 0.8286014721345951
Precision: 0.8342847501476336
Recall: 0.8286014721345951
F1 Score: 0.8278698627627123
Confusion Matrix:
 [[726 225]
 [101 850]]
```



Interpretation

- **Precision** – Of all predictions labeled as positive (e.g., LLM-generated), 83% were correct → The model still avoids many false alarms but has room for improvement.
- **Recall** – Of all actual positive samples, 83% were correctly identified → The model captures most LLM-generated samples, though some are missed.
- **F1 Score** – A balanced measure of precision and recall: 83%, indicating a solid but not perfect model.
- **Accuracy** – 83% overall classification correctness.
- 306 misclassifications in total (225 false positives + 101 false negatives).
- The model performs reasonably well at detecting LLM-generated code — 101 real LLM samples were missed out of 951.
- There are 225 cases where the model mislabels human-written code as LLM-generated.
- Overall, the model is fairly accurate and balanced, though there is noticeable room for improvement compared to previous performance.

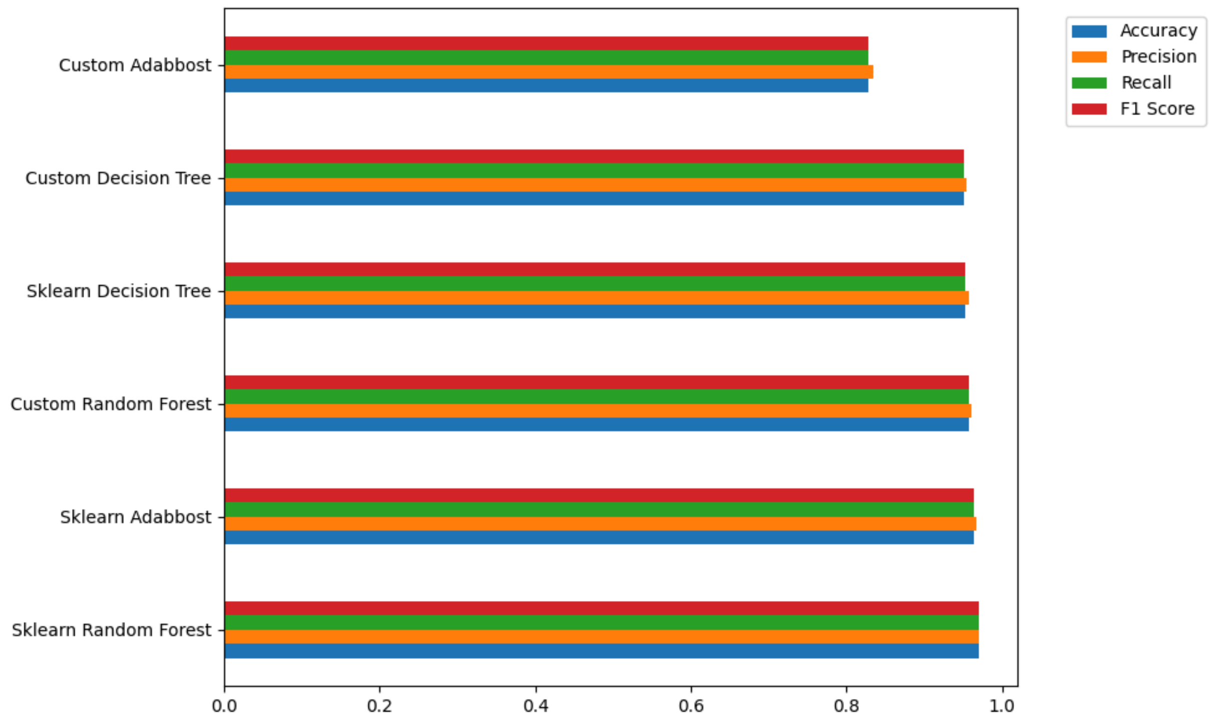
- When compared to sklearn's AdaBoost, we observe similar performance when SAMME is used, but noticeably lower scores in our custom model compared to sklearn's model when SAMME.R is used.
- This is because SAMME.R leverages the confidence (probabilities) of the weak learners rather than just their hard predictions, enabling more refined updates and often better performance.
- Our custom implementation only supports hard-label voting (as in SAMME), and cannot benefit from these probability-based refinements, explaining the performance gap.

Models - preformance overview ans summery

In [164…

```
# Create DataFrame for table display
df = pd.DataFrame(evaluations).T
df = df.round(4)  # Round to 2 decimal places for better readability

# Rename index for better display
model_names = {
    'sk_dt_model': 'Sklearn Decision Tree',
    'dt_model': 'Custom Decision Tree',
    'sk_rf_model': 'Sklearn Random Forest',
    'rf_model': 'Custom Random Forest',
    'sk_ab_model': 'Sklearn Adabbost',
    'ab_model': 'Custom Adabbost',
}

df.index = [model_names[idx] for idx in df.index]
df_sorted = df.sort_values('Accuracy', ascending=False)
print("="*70)
print("MODEL EVALUATION RESULTS")
print("="*70)
print(df_sorted)
print("="*70)

#plot
df_sorted.plot.barh(figsize=(10, 6))
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

```
======================================================================
MODEL EVALUATION RESULTS
======================================================================
                       Accuracy  Precision  Recall  F1 Score
Sklearn Random Forest    0.9695     0.9706  0.9695    0.9695
Sklearn Adabbost         0.9642     0.9661  0.9642    0.9642
Custom Random Forest     0.9579     0.9602  0.9579    0.9579
Sklearn Decision Tree    0.9532     0.9565  0.9532    0.9531
Custom Decision Tree     0.9516     0.9545  0.9516    0.9516
Custom Adabbost          0.8286     0.8343  0.8286    0.8279
======================================================================
```



Model Evaluation Summary

Top Performer

- **Sklearn Random Forest** is the top-performing model across all metrics:
  - **Accuracy**: 96.95%
  - **Precision**: 97.06%
  - **Recall**: 96.95%
  - **F1 Score**: 96.95%
  - It provides highly accurate and consistent classification, with excellent balance between precision and recall.

Strong Contenders

- **Sklearn AdaBoost** and **Sklearn Decision Tree** follow closely:
  - **Sklearn AdaBoost**:
    - Accuracy: 96.42%
    - F1 Score: 96.42%
    - Shows the benefit of boosting over a single decision tree.
  - **Sklearn Decision Tree**:
    - Accuracy: 95.32%
    - F1 Score: 95.31%
    - A strong standalone model with competitive performance.

Custom Models vs. Sklearn

- **Custom Random Forest** and **Custom Decision Tree** perform well but slightly under sklearn counterparts:
  - **Custom Random Forest**:
    - Accuracy: 95.79%
    - F1 Score: 95.79%
  - **Custom Decision Tree**:
    - Accuracy: 95.16%
    - F1 Score: 95.16%
  - The ~1% gap suggests effective implementation but room for further optimization (e.g., better feature splits, randomness handling).
- **Custom AdaBoost** shows **significantly weaker results**:
  - **Accuracy**: 82.86%
  - **F1 Score**: 82.79%
  - Likely due to limitations in the boosting strategy (e.g., using `SAMME` instead of `SAMME.R`, lack of probabilistic weighting, or instability in weak learners).

Overall Insights

- **Sklearn ensemble models** (Random Forest and AdaBoost) clearly outperform all others in consistency and effectiveness.
- **Custom models** offer good results, with trees and forests close to sklearn, vali

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Feature importance

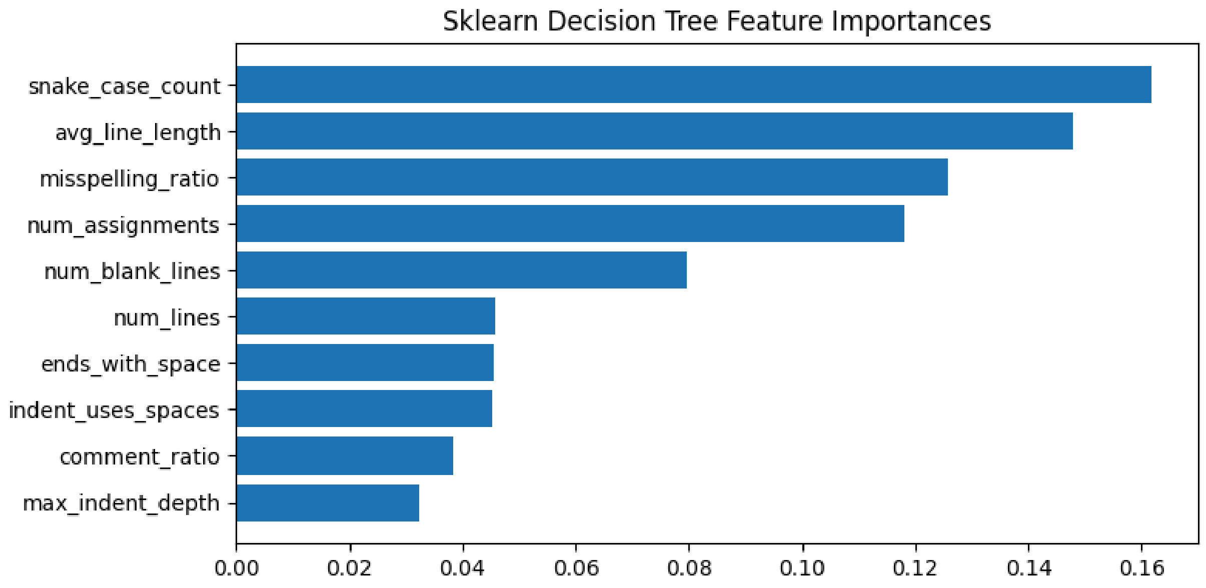
- This was done with sklearn's built-in functions in order to further understand the subject
- we did not implement custom function since it was not project's and course academic material focuse

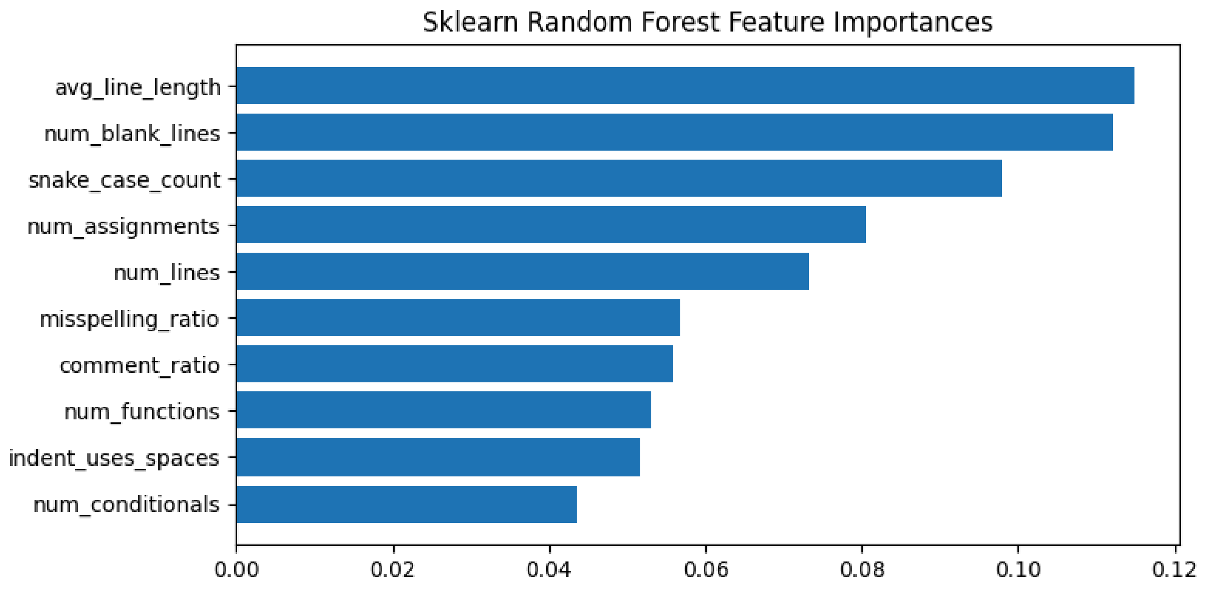
In [227…
```
feature_names = X_train.columns

for name, model in [('sk_dt_model', sk_dt_model), ('sk_rf_model', sk_rf_model), ('s
    importances = model.feature_importances_
    sorted_indices = np.argsort(importances)[::-1]
    print(f"\n{name} Top Features:")
    for idx in sorted_indices[:10]:  # top 10
        print(f"{feature_names[idx]}: {importances[idx]:.4f}")
```

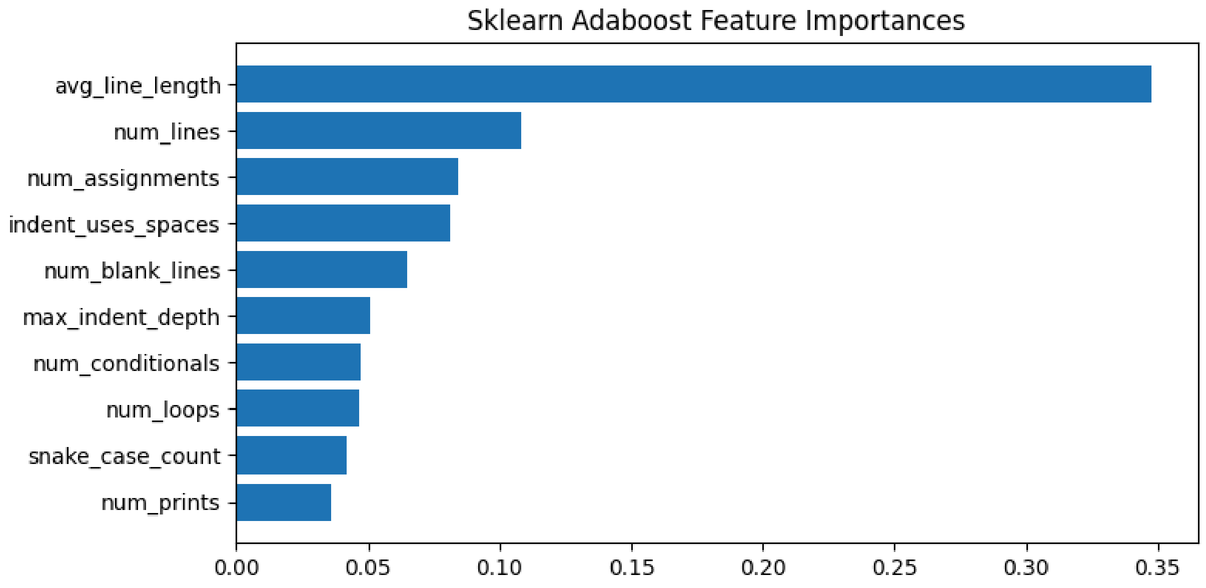
```
sk_dt_model Top Features:
snake_case_count: 0.1619
avg_line_length: 0.1478
misspelling_ratio: 0.1258
num_assignments: 0.1180
num_blank_lines: 0.0797
num_lines: 0.0457
ends_with_space: 0.0456
indent_uses_spaces: 0.0453
comment_ratio: 0.0385
max_indent_depth: 0.0324

sk_rf_model Top Features:
avg_line_length: 0.1150
num_blank_lines: 0.1121
snake_case_count: 0.0979
num_assignments: 0.0806
num_lines: 0.0732
misspelling_ratio: 0.0569
comment_ratio: 0.0558
num_functions: 0.0532
indent_uses_spaces: 0.0518
num_conditionals: 0.0436

sk_ab_model Top Features:
avg_line_length: 0.3479
num_lines: 0.1081
num_assignments: 0.0842
indent_uses_spaces: 0.0812
num_blank_lines: 0.0649
max_indent_depth: 0.0508
num_conditionals: 0.0473
num_loops: 0.0466
snake_case_count: 0.0421
num_prints: 0.0361
```

In [230…

```python
import matplotlib.pyplot as plt

def plot_feature_importance(model, feature_names, model_name):
    importances = model.feature_importances_
    indices = np.argsort(importances)[::-1]
    plt.figure(figsize=(8, 4))
    plt.title(f"{model_name} Feature Importances")
    plt.barh(np.array(feature_names)[indices[:10]][::-1], importances[indices[:10]]
    plt.tight_layout()
    plt.show()

plot_feature_importance(sk_dt_model, X_train.columns, "Sklearn Decision Tree")
plot_feature_importance(sk_rf_model, X_train.columns, "Sklearn Random Forest")
plot_feature_importance(sk_ab_model, X_train.columns, "Sklearn Adaboost")
```





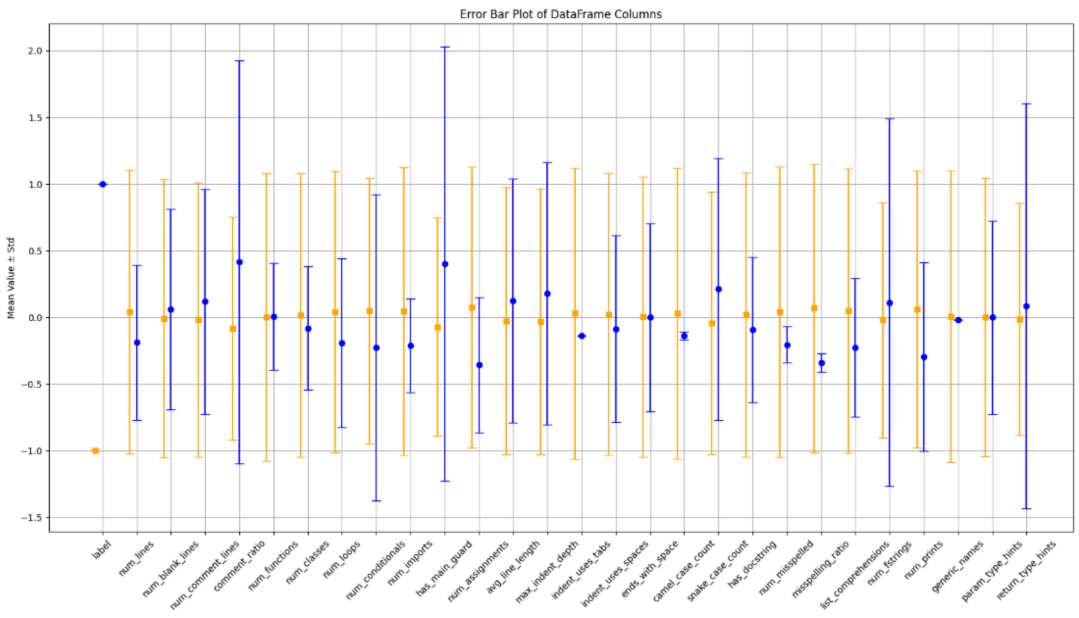


Feature Importance Summary (Top 10 Features per Model)

Feature	sk_dt_model	sk_rf_model	sk_ab_model
avg_line_length	0.1478	0.1150	0.3479
snake_case_count	0.1619	0.0979	0.0421
misspelling_ratio	0.1258	0.0569	-
num_assignments	0.1180	0.0806	0.0842
num_blank_lines	0.0797	0.1121	0.0649
num_lines	0.0457	0.0732	0.1081
ends_with_space	0.0456	-	-
indent_uses_spaces	0.0453	0.0518	0.0812
comment_ratio	0.0385	0.0558	-

| max_indent_depth | 0.0324 | - | 0.0508

recall correlations:



Key Takeaways

- `avg_line_length` is the most influential feature across all models, and **LLM-generated code tends to have longer lines** than human-written code.
- `snake_case_count` is higher in Human code, suggesting **Humans prefer more consistent naming styles**.
- `misspelling_ratio` is also higher in Human code, possibly due to the fact that humans aren't 100% consistent in their work.
- `num_assignments` and `num_blank_lines` are both higher in LLM code, hinting at **more verbosity** or **clearer spacing conventions**.

- Features like `max_indent_depth` , `num_loops` , and `num_conditionals` show mixed patterns but tend to have a slightlyhigher variance in Human code.

Testing our models with unseen data

- We used llama3_1_8b LLM (src: https://huggingface.co/spaces/ysharma/Chat_with_Meta_llama3_1_8b)
- to answer a python coding question from https://prepbytes.com/blog/top-20-coding-questions-for-basic-python-programming/
- the question - Write a python program to find a fibonacci of a number
- human answer was also obtain from that site

In [232…

```
def predict_code_src(path_to_code, dt_model, rf_model, ab_model, sk_dt_model, sk_rf
    # Read and clean code
    with open(path_to_code, "r", encoding='utf-8-sig') as f:
        code = f.read().lstrip('\ufeff')

    print(f"Analyzing code from: {path_to_code}:")
    print("-----------------------------------------------")
    print(code)
    print("-----------------------------------------------\n\n")

    # Extract features
    features = extract_features_from_code(code)
    X_new = pd.DataFrame([features])

    # Match training features
    training_features = [col for col in clean_df.columns if col != 'label']
    for col in training_features:
        if col not in X_new.columns:
            X_new[col] = 0
    X_new = X_new[training_features]

    # Normalize with training stats
    temp_df_features, _ = extract_features_df(human_vs_generated_df, 'code')
    original_mean = temp_df_features[training_features].mean()
    original_std = temp_df_features[training_features].std()
    X_new_normalized = ((X_new - original_mean) / original_std).fillna(0)

    # Mapping
    res_dict = {1: "LLM", -1: "Human"}
    predictions = {}

    # Get model predictions
    predictions['dt_model'] = dt_model.predict(X_new_normalized)[0]
    predictions['sk_dt_model'] = sk_dt_model.predict(X_new_normalized)[0]
    predictions['rf_model'] = rf_model.predict(X_new_normalized)[0]
    predictions['sk_rf_model'] = sk_rf_model.predict(X_new_normalized)[0]

    ab_pred_custom = ab_model.predict(X_new_normalized)
    predictions['ab_model'] = int(ab_pred_custom[0].item()) if hasattr(ab_pred_cust

    predictions['sk_ab_model'] = sk_ab_model.predict(X_new_normalized)[0]

    # Print individual model predictions
    print("Model Predictions:")
    for model_name, pred in predictions.items():
        print(f"{model_name}: {res_dict[pred]}")

    # Weighted vote
    total_accuracy = sum(model_eval['Accuracy'] for model_eval in evaluations.value
    weighted_sum = 0
    total_weight = 0
    for model_name, pred in predictions.items():
        weight = evaluations[model_name]['Accuracy']/total_accuracy
        weighted_sum += pred * weight
        total_weight += weight

    final_prediction = 1 if weighted_sum >= 0 else -1
    print(f"\nFinal Weighted Prediction: {res_dict[final_prediction]}")
```

In [222…

```
predict_code_src("./LLM_test.py", dt_model, rf_model, ab_model, sk_dt_model, sk_rf_
Analyzing code from: ./LLM_test.py:
----------------------------------------------
def fibonacci_recursive(n):
    """
    Calculate the nth Fibonacci number recursively.

    Args:
        n (int): The position of the Fibonacci number.

    Returns:
        int: The nth Fibonacci number.
    """
    if n <= 0:
        return 0
    elif n == 1:
        return 1
    else:
        return fibonacci_recursive(n-1) + fibonacci_recursive(n-2)

# Example usage
n = 10
print(f"The {n}th Fibonacci number is: {fibonacci_recursive(n)}")
----------------------------------------------



Model Predictions:
dt_model: LLM
sk_dt_model: LLM
rf_model: LLM
sk_rf_model: LLM
ab_model: LLM
sk_ab_model: Human

Final Weighted Prediction: LLM
```

In [223…

```
predict_code_src("./HUMAN_test.py", dt_model, rf_model, ab_model, sk_dt_model, sk_r
Analyzing code from: ./HUMAN_test.py:
-----------------------------------------------
nterms = int(input("How many terms? "))
n1, n2 = 0, 1
count = 0

if nterms <= 0:
   print("Please enter a positive integer")
elif nterms == 1:
   print("Fibonacci sequence upto",nterms,":")
   print(n1)
else:
   print("Fibonacci sequence:")
   while count < nterms:
       print(n1)
       nth = n1 + n2
       n1 = n2
       n2 = nth
       count += 1
-----------------------------------------------


Model Predictions:
dt_model: Human
sk_dt_model: Human
rf_model: Human
sk_rf_model: Human
ab_model: Human
sk_ab_model: Human

Final Weighted Prediction: Human
```

Conclusions

This project explored the feasibility of distinguishing between human-written and LLM-generated Python code using a variety of machine learning classifiers—both handcrafted and scikit-learn based—on the AIGCodeSet dataset. All models preformed nicely but SKlearn random forest was slightly better than the rest, reaching 97% accuracy.

Several important constraints impacted the scope of this work:

- The model was trained on code dated approximately 6–12 months prior.
- Outputs from recent LLMs like ChatGPT, Claude, and Cohere were not included in the dataset.
- The dataset focused only on short Python snippets, limiting generalizability.

- Non-English code and LLM-edited or post-processed code were not represented.

Despite these limitations, this work demonstrates meaningful progress toward identifying machine-generated code and offers useful insights for practical applications in academic integrity, technical hiring, and digital content verification.

Additionally, the model's insights into the key features indicative of LLM-generated code can be used to craft prompts that avoid stylistic patterns likely to reveal LLM generation. * Alternatively, these insights can guide manual post-generation edits that counteract the identified distinguishing features, making the code less detectable as machine-generated.

Future work should expand on this foundation by:

- Incorporating more recent and diverse model outputs.
- Exploring deeper code semantics and structural features.
- Addressing adversarial or obfuscated examples.

The insights derived here may also serve as a basis for crafting or editing code to either reveal or conceal signs of LLM involvement, depending on the use case.

Ultimately, as LLM capabilities continue to improve, so too must the methods for detecting their fingerprints—making this a dynamic and essential area for continued research.