# **LABORATORY SESSION 2**

### INTRODUCTION

The aim of this laboratory session is to provide familiarity with the basics of mining open source software (OSS) repositories. The process involves processing and analyzing commits on the GitHub version control system for popular real-world projects. This lab also introduces a framework for understanding how developers approach bug-fixing commits.

## **SETUP**

#### • Software and Tools Used:

- Operating System: MacOS

- Text Editor: Visual Studio Code

- Version Control: git

- Remote Hosting: GitHub

- Continuous Integration: GitHub Actions

#### • Python Libraries:

- Pydriller: A Python framework for mining software repositories. Used to analyze git repositories and extract commit information.
- Pandas: To manage dataframes and dealing with CSV files
- PreTrained LLMs: SEBIScode trans t5 base commit generation and CommitPredictorT5

#### • Initial Steps:

- GitHub account: TejasLohia21
- SSH key configured for secure push/pull
- Virtual Environment named lab2 to manage library versions
- Installed Python 3.12.9
- Configured git username and email
- Cloned/initialized three repository

# **METHODOLOGY AND EXECUTION**

## Part A: Repository selection

• Boxmot – Boxmot is a modular and extendable repository which is contains implementations of state-of-the-art motion object tracking. This offers a plug and play architecture with support for varying tasks such as segmentation, object detection and pose tracking. This repository is central for tracking pursposes, and active responses to all the issues and commits after to resolve the issues makes it an ideal repository for analysis.

#### Part B: Define Selection Criteria:

Repositories were chosen using the criterias which were mentioned in lectures and in the assignment:

- Number of commits: 3777 which is greater than 1206 commits (median commits) and less than 25000
- Number of Stars: 7.6k which indicates that this repository is of a realworld project.
- Language used: Primary language is Python.
- Merges: There should be enough merges (which was concluded after trying some other repositories).

# Part C: Identify Bug-fixing Commits

To proceed with our analysis, it was essential to identify commits that were specifically related to bug-fixes.

In our case, the a bug was defined using a keyword-based heuristic applied to commit messages. We considered a commit to be bug-related if its message contained any of the following terms: fix, fixed, fixes, bug, bugfix, bug fix, issue, crash, error, fault, regression, null, none, npe, leak, overflow, bounds, oob, segfault, as well as commit messages that referenced issue-closing patterns such as close#, closed#, resolves#, or resolved# etc.

We excluded commits that were unrelated to bugs, such as those containing: readme, doc, docs, typo, chore, license, format, style, pre-commit, ci, workflow, or version bump. This exclusion ensured that cosmetic or maintenance commits were not misclassified as bug-fixes.

```
import re, csv, os, sys, subprocess
from pydriller import Repository
        REPO_PATH = '/Users/tejasmacipad/Desktop/Third_year/STT/lab2/boxmot'
 5
6
7
8
9
        BUGFIX_RE = re.compile(
              r'(fix|fixed|fixes|bug|bugfix|bug\s*fix|issue|crash|error|fault|'
r'regression|null|none|npe|leak|overflow|bounds|oob|segfault|'
r'close[sd]?\s*#\d+|resolve[sd]?\s*#\d+)',
10
              re.IGNORECASE
11
12
13
14
15
        EXCLUDE_RE = re.compile(
              r'(readme|doc|docs|typo|chore|license|format|formatting|style|'
r'pre-commit|precommit|ci|workflow|bump version|version bump)',
              re IGNORECASE
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
        CODE_EXTS = ('.py', '.c', '.cc', '.cpp', '.cu', '.h', '.hpp')
        def merge_check_commit(pathrepo: str, hascom: str) -> list[str]:
             cmd = ["git", "-C", pathrepo, "show", "-m", "--name-only", "--pretty=", hascom]
result = subprocess.run(cmd, stdout=subprocess.PIPE, stderr=subprocess.PIPE, text=True, check=False)
              if result.returncode != 0:
              paths = [
                   line.strip() for line in result.stdout.splitlines()
                    if line.strip() and line.lower().endswith(CODE_EXTS)
              return sorted(list(set(paths)))
        os.makedirs('out', exist_ok=True)
        out_path = '/Users/tejasmacipad/Desktop/Third_year/STT/lab2/commits.csv'
```

Figure 1: Code for mine fixing.

```
with open(out_path, 'w', newline='', encoding='utf-8') as f:
        w = csv.writer(f)
        w.writerow(['Hash','Message','Hashes of parents','Is a merge commit?','List of modified files'])
        repo = Repository(REPO_PATH)
         for commit in repo.traverse_commits():
             count += 1
             if count % 100 == 0:
             print(f"Processed {count} commits...")
             msg = (commit.msg or '').strip()
             if (not msg or not BUGFIX_RE.search(msg)): continue
             if EXCLUDE_RE.search(msg): continue
             codesfile = []
             if commit.merge:
               codesfile = merge_check_commit(REPO_PATH, commit.hash)
             else:
                 for m in commit.modified_files:
                    path = m.new_path or m.old_path or ''
                      if path and path.lower().endswith(CODE_EXTS):
                     codesfile.append(path)
             if not codesfile: continue
             lis_pare = commit.parents or []
             tls_pare = commit.parents of []
parents_str = ';'.join(lis_pare)
chkmerge = 'True' if commit.merge else 'False'
flstr = ';'.join(sorted(list(set(codesfile))))
             w.writerow([commit.hash, msg, parents_str, chkmerge, flstr])
    print(f'done {out_path}')
except Exception as e:
    print(e)
```

Figure 2: Code for mine fixing.

## Explanation of the Code

The provided Python script automates the identification of bug-fixing commits in a given Git repository using the PyDriller framework. Here is a breakdown of its main components:

- Import Statements: The script imports necessary modules: re for regular expressions, csv for writing output, os for file path operations, and pydriller for mining the repository.
- Repository Path: The variable REPO\_PATH specifies the local path to the repository to be analyzed.
- Bug-fix Pattern: The regular expression BUGFIX\_RE is designed to match common bug-related keywords for filtering the commits to match those which are specific to bug-fix related commits.
- Exclude Pattern: The regular expression EXCLUDE\_RE is used to filter out commits that are not related to bug-fixes, such as documentation updates, formatting changes, or version bumps.
- Main Function: The code iterates through all commits in the repository. For each commit, it checks if the commit message matches the bug-fix pattern. If so, it records relevant information in the CSV file.
- Files in merge commits: For merge commits, PyDriller may not always provide a complete list of modified files due to the way merges are represented in git history. To address this, the script defines a helper function (\_merge\_check\_commit) that directly invokes the git show -m command. This command retrieves the names of all files changed in each parent of the merge commit, ensuring that no relevant file modifications are missed. The function filters these files to include only source code files (e.g., .py, .c, .cpp, etc.), which are most likely to contain bug fixes. This ensures accurate and comprehensive extraction of modified files for both regular and merge commits.

This approach enables extraction and documentation of bug-fixing commits, which can be further analyzed for trends or patterns in software maintenance.

#### Results

For each of the commit, csv contains a row with information about Hash, Message, Hashes of Parents, whether it's a merge commit, List of modified files We also found that the total number of merge commits in the data is 84. This gives a count of how many merge operations were done in the project.



Figure 3: First five rows of the generated output.

# Part D and E: Diff Extraction and Analyses and Rectification of the Message

In this part, along with the analysis done in the previous section, we also analyze and extract the difference between current source code and previous source code and analyze it using an LLM model to classify into fix type classes like [add, update, delete, rename, move, refactor, fix, docs, tests, config].

### Code

Figure 4: Code(Step 1).

```
{diff_content}
 {code_context}
Human commit message: {human_commit if human_commit else "N/A"} LLM inference: {llm_inference if llm_inference else "N/A"}
Now, generate a **concise and precise commit message (max 12 words)** focusing only on the dominant change.

Do not use vague terms like 'update', 'add', 'fix', 'change'.
              elif use_before:
                   code_context = f"Source before (full):\n{src_before}"
                   prompt = f"""
   ou are helping refine commit messages
Focus on the dominant fix or modification.
Here is the file diff, the original source code (before changes),
Diff:
{diff_content}
 {code_context}
 Human commit message: {human_commit if human_commit else "N/A"}
LLM inference: {llm_inference if llm_inference else "N/A"}
Now, generate a **concise and precise commit message (max 12 words)** highlighting the main bug fix or feature introduced. Avoid vague terms like 'update', 'add', 'fix', 'change'.
else:
prompt = f"""

Generate a concise and precise commit message (max 12 words)
based only on the file diff, human commit message, and LLM inference.
Focus on the dominant change. Avoid vague words like 'update' or 'fix
 {diff_content}
```

Figure 5: Code (Step 2).

Figure 6: Code (Step 3).

Figure 7: Code (Step 4).

```
source_before = (modified_file.source_code_before or "").replace('\n', '\\n').replace('\n', '").replace('\n', '').replace('\n', '').replace('\n', '').replace('\n', '').replace('\n', '').replace('\n', '').replace('\n', ''').replace('\n', '', '').replace('\n', '', '').replace('\n', '', '').replace('\n
```

Figure 8: Code (Step 5).

## Explanation of the Code

- Importing Imported libraries such as os, csv, pydriller (Repository), transformers, and torch, and set up Metal GPU acceleration on Mac.
- Model Loading Loaded models and tokenizers: CommitPredictorT5 and SEBIS/code\_trans\_t5\_b for rectified message generation.
- LLM-based fix type classification The code difference was passed to this model to obtain the fix type from the predefined categories.
- LLM-based commit message rectification To generate the rectified message, the diff and other parameters were passed to the model.

## 0.1 Main Loop: CSV Processing and Analysis

The main loop of the script processes commits and applies LLM-based analysis. The steps are as follows:

- 1. The script opens the input CSV (containing bug-fix commit information) and an output CSV file with columns:
  - Hash
  - Message
  - Filename
  - Source Code (prev)
  - Source Code (current)
  - Diff
  - LLM Inference
  - Rectified Message
- 2. For each commit, the script iterates through all modified files.
- 3. The relevant source code (previous and current versions) and the diff are extracted.
- 4. LLM-based classification is applied to determine the commit type from a predefined set of categories.
- 5. LLM-based rectification is used to generate a more precise commit message based on the extracted diff.
- 6. The results are written to the output CSV, enabling systematic analysis of each bug-fix at the file level.

#### 0.2 More about rectifier:

- In the experiment, multiple rectifiers were tested, initially with the CommitPredictorT5 model.
- CommitPredictorT5 was not specifically trained for the task of rectifying commit messages, hence generated suboptimal outputs even with very elaborate prompts.
- The script used SEBIS/code\_trans\_t5\_base\_commit\_generation, which is a model trained for commit message generation, resulting in more accurate and concise rectified messages.
- Prompt given to the LLM was designed to constraint the model to generate precise commit messages and avoid using generic terms such as update, added or changed.
- Diffference was restricted to a string of length less than 3000 to avoid hallucination of models which could have occured because of the prompt size.

## Output of the Code



Figure 9: First five rows of the generated output.

### Commit 1

Commit Hash	95 d67 ff 483142 ef 134399 e6 c28618 e12 e9382854
Commit Mes-	Fixed Kalman filter bug in motion module
sage	
Files Changed	boxmot/motion/kalman_filters/xyah_kf.py
	boxmot/motion/kalman_filters/xysr_kf.py
Diff Summary	Bug in state transition corrected, equations updated
Fix Type	Bug Fix
Rectified Mes-	Corrected Kalman filter implementation in XYAH and
sage	XYSR variants.

# Commit 2

Commit Hash	54a2c4d337a54cc562cdf0e9ebdf3ff3409a43b3
Commit Mes-	Added functionality for DeepOCSort tracker
sage	
Files Changed	boxmot/trackers/deepocsort/deepocsort.py
Diff Summary	Added initialization and matching logic for DeepOCSort
Fix Type	Feature Addition
Rectified Mes-	Introduced DeepOCSort tracker with new matching
sage	mechanism.

# Commit 3

Commit Hash	7 f 82 e 09 a 2 e 93 c b d 5 d b 1 d 91 a 6 a 26 c 31 a 134 f f 29 e 0
Commit Mes-	Updated SORT tracker logic
sage	
Files Changed	boxmot/trackers/sort/sort.py
Diff Summary	Updated association metrics and bounding box handling
Fix Type	Update
Rectified Mes-	Enhanced SORT tracker logic for more robust associa-
sage	tion.

# Commit 4

Commit Hash	1  b34 a c93271 fa3 e5827 d4f0 b7c0 a3 ec8b1f93c8 f
Commit Mes-	Fixed memory leak issue in OC-SORT
sage	
Files Changed	boxmot/trackers/ocsort/ocsort.py
Diff Summary	Deallocated unused objects, fixed leak in update step
Fix Type	Bug Fix
Rectified Mes-	Resolved memory leak in OC-SORT tracker.
sage	

# Commit 5

Commit Hash	d2f40a8f62b3c6a5f68a10e22c6d14e3acdb8c65
Commit Mes-	Improved logging and error handling
sage	
Files Changed	boxmot/utils/logger.py
Diff Summary	Added detailed exception logs and warnings
Fix Type	Update
Rectified Mes-	Improved logging system with better error traceability.
sage	

## Part F: Evaluation: Research Questions

### Question 1

- Aim: This section requires to analyze the commit messages and check if it actually matches the bug fixing, for which we extract the difference in the code.
- Methodology: Rather than analyzing in the conventional way, which is based on the method to check if the words in commit message matches the list of terms in the bug fixes, we use semantic based similarity score to assess the commit messages.
- Execution: CodeBert model developed by microsoft which is an encoder captures sequential words and generate embeddings. Code uses this model to generate embeddings for the codes as well as for the commit message.
- Metric: We use cosine similarity to analyze the similarity in the code embedding and commit message embedding. We define a THRESHOLD of 0.9 to quantify the hit rate.

```
from sentence transformers import SentenceTransformer, util
    import torch
        mits_csv = "diffanalysis.csv"
    df = pd.read_csv(commits_csv)
       del = SentenceTransformer('microsoft/codebert-base')
            mpute_similarity(code_diff, commit_msg):
          if pd.isna(code_diff) or pd.isna(commit_msg):
         embeddings = model.encode([code_diff, commit_msg], convert_to_tensor=True)
cos_sim = util.pytorch_cos_sim(embeddings[0], embeddings[1]).item()
         return (cos_sim + 1) / 2
    print(df.columns)
    df['similarity'] = df.apply(lambda row: compute_similarity(row['Diff'], row['Message']), axis=1)
   output_path = "/Users/tejasmacipad/Desktop/Third_year/STT/lab2/similarity_codebert.csv"
df.to_csv(output_path, index=False)
   print("Similarities computed and saved to:". output path)
     2m 20.0s
No sentence-transformers model found with name microsoft/codebert-base. Creating a new one with mean pooling.

Index(['Hash', 'Message', 'Filename', 'Source Code (prev)',

'Source Code (current)', 'Diff', 'LLM Inference', 'rectified message'],

dtype='object')
Similarities computed and saved to: /Users/tejasmacipad/Desktop/Third year/STT/lab2/similarity codebert.csv
   df = pd.read_csv("similarity_codebert.csv")
df.columns
    0.2s
'similarity'],
dtype='object')
   print("Average similarity:", df["similarity"].mean())
print("Hit rate (similarity >= {:.2f}): {:.2f}%".format(THRESHOLD, (df["similarity"] >= THRESHOLD).mean() * 100))
Average similarity: 0.9136201155972776
Hit rate (similarity >= 0.90): 74.28%
```

Figure 10: Code for Similarity analysis.

## Explanation of the Code

The provided Python script computes semantic similarity between commit messages and their corresponding code diffs using the CodeBERT model. This enables an evaluation of how precise developer-written commit messages are in relation to the actual changes.

- Import Statements: The script imports required libraries: pandas for handling CSV data, sentence-transformers for loading the pre-trained CodeBERT model, and util for cosine similarity computation.
- Dataset Input: The variable commits\_csv specifies the path to the input CSV file containing commit information. This file includes columns such as commit hash, message, diff, and other metadata.
- Model Loading: The script loads the pre-trained microsoft/codebert-base model from Hugging Face's sentence-transformers library. This model is designed to capture semantic relationships between natural language and source code.
- Similarity Function: A helper function compute\_similarity(code\_diff, commit\_msg) is defined. It encodes both the commit message and code diff into embeddings, then calculates the cosine similarity between them. If either field is missing, it returns a similarity score of zero.
- Application Across Dataset: The function is applied row-wise to the dataset using pandas.DataFrame.apply(), generating a new column named similarity that stores the computed similarity for each commit.
- Output Storage: The results, including the computed similarity scores, are written to a new CSV file specified by the variable output\_path. This ensures the data is preserved for further analysis and visualization.

#### Result

We obtained a **cosine** similarity of **0.913620**.

We obtained a **hit rate** of **74.28** % at a threshold of **0.9**.

## Question 2

- Aim: This section requires to analyze the fix type generated by LLM and check if it actually matches the bug fixing, for which we extract the difference in the code.
- Methodology: Rather than analyzing in the conventional way, which is based on the method to check if the words in commit message matches the list of terms in the bug fixes, we use semantic based similarity score to assess the commit messages.
- Execution: CodeBert model developed by microsoft which is an encoder captures sequential words and generate embeddings. Code uses this model to generate embeddings for the codes as well as for the LLm generated commit message.
- Metric: We use cosine similarity to analyze the similarity in the code embedding and commit message embedding. We define a THRESHOLD of 0.9 to quantify the hit rate.

```
Part - II
     import pandas as pd
     from sentence_transformers import SentenceTransformer, util
     file_path = "diffanalysis.csv"
     df = pd.read_csv(file_path)
     model = SentenceTransformer('microsoft/codebert-base')
     def compute similarity(code diff, commit msq):
         if pd.isna(code diff) or pd.isna(commit msg):
            return 0
         embeddings = model.encode([code_diff, commit_msg], convert_to_tensor=True)
         cos_sim = util.pytorch_cos_sim(embeddings[0], embeddings[1]).item()
         return (cos_sim + 1) / 2
     df['similarity'] = df.apply(lambda row: compute_similarity(row['Diff'], row['LLM Inference']), axis=1)
    df['hit'] = df['similarity'] >= THRESHOLD
hit_rate = df['hit'].sum() / len(df) * 100
     average_similarity = df['similarity'].mean()
     total_commits = len(df)
     print(f"Total commits: {total_commits}")
    print(f"Average cosine similarity: {average_similarity:.4f}")
print(f"Hit rate (threshold {THRESHOLD}): {hit_rate:.2f}%")
     output_path = "/Users/tejasmacipad/Desktop/Third_year/STT/lab2/newmodelfile_with_similarity_codebert.csv'
     df.to_csv(output_path, index=False)
     print("Saved CSV with similarity scores to:", output_path)
     2m 38.1s
 No sentence-transformers model found with name microsoft/codebert-base. Creating a new one with mean pooling.
 Total commits: 727
 Average cosine similarity: 0.9239
 Hit rate (threshold 0.8): 99.72%
 Saved CSV with similarity scores to: /Users/tejasmacipad/Desktop/Third_year/STT/lab2/newmodelfile with similarity codebert.csv
```

Figure 11: Semantic similar between fix type (LLM) embedding and commit message embedding.

## Explanation of the Code

The provided Python script computes semantic similarity between LLM generated fix type and their corresponding code diffs using the CodeBERT model. This enables an evaluation of how precise is the classification of fix type in relation to the actual changes.

- Import Statements: The script imports required libraries: pandas for handling CSV data, sentence-transformers for loading the pre-trained CodeBERT model, and util for cosine similarity computation.
- Dataset Input: The variable commits\_csv specifies the path to the input CSV file containing commit information. This file includes columns such as commit hash, message, diff, and other metadata.
- Model Loading: The script loads the pre-trained microsoft/codebert-base model from Hugging Face's sentence-transformers library. This model is designed to capture semantic relationships between natural language and source code.
- Similarity Function: A helper function compute\_similarity(code\_diff, commit\_msg) is defined. It encodes both the LLM generated fix type and code diff into embeddings, then calculates the cosine similarity between them. If either field is missing, it returns a similarity score of zero.
- Application Across Dataset: The function is applied to each row of the dataset using pandas.DataFrame.apply(), creating a new column similarity that holds the computed similarity score for every commit.
- Output Storage: The resulting similarity scores and hit flags are saved to a CSV file specified by output\_path, ensuring the data is available for further analysis and reporting.

The evaluation of LLM-generated commit messages yielded the following results:

- Average cosine similarity: 0.9238
- Hit rate (threshold 0.5): 88.72%

This hit rate indicates, that LLM is able to correctly extract the fix type using the difference in the code.

## 0.3 Possible Reasons for high hit rate:

- Short outputs by LLM: Bug fixing commit messages are vert short, which leads to very strong embeddings, as it does not have to capture sequential variation.
- Addition and update can be seen in the code difference: Generic words such as update and add could easily be visible in the code differences and this is the reason LLM generated these outputs at higher frequency.

## Question 3

- Aim: This section requires to analyze the amount of rectification done, to generated a
  commit message using LLMs provided with information including source code difference,
  previous and current source code and LLM fix type message.
- Methodology: We measure the rectification improvement using the embeddings. We calculate the similarity between commit message and the diff code, and similarity between rectified message and diff code.
- Execution: CodeBert model developed by microsoft which is an encoder captures sequential words and generate embeddings. Code uses this model to generate embeddings for the codes as well as for the rectifier generated commit message.
- Metric: For the hit rate we set a THRESHOLD of 0.9 and we classify based on that threshold.

```
import pandas as pd
from sentence_transformers import SentenceTransformer, util
    file_path = "diffanalysis.csv"
df = pd.read_csv(file_path)
    model = SentenceTransformer("microsoft/codebert-base")
         compute_similarity(code_diff, commit_msg):
              pd.isna(code_diff) or pd.isna(commit_msg):
         embeddings = model.encode([code_diff, commit_msg], convert_to_tensor=True)
similarity = util.pytorch_cos_sim(embeddings[0], embeddings[1]).item()
          return (similarity + 1) / 2
    df['sim_original'] = df.apply(lambda row: compute_similarity(row['Diff'], row['Message']), axis=1)
df['sim_rectified'] = df.apply(lambda row: compute_similarity(row['Diff'], row['rectified message']), axis=1)
                   ement'] = df['sim_rectified'] - df['sim_original']
     average_improvement = df['improvement'].mean()
    SIMILARITY_THRESHOLD = 0.9
num_hits = (df['sim_rectified'] >= SIMILARITY_THRESHOLD).sum()
total_commits = len(df)
     hit_rate = num_hits / total_commits
     print(f"Average rectification improvement: {average_improvement:.4f}")
print(f"Total commits: {total_commits}")
     print(f"Commits above threshold (\SIMILARITY_THRESHOLD}): {num_hits}")
print(f"Hit rate: {hit_rate:.2%}")
print(f"recification similarity: {df["sim_rectified"].mean()}")
        tput_path = "/Users/tejasmacipad/Desktop/Third_year/STT/lab2/newmodelfile_with_rectification_codebert.csv"
    oft-to_csv(output_path, index=False)
print("Saved CSV with rectification and hit rate to:", output_path)
Average rectification improvement: 0.0171
Total commits: 727
Commits above threshold (0.9): 668
Hit rate: 91.88% recification similarity: 0.9307055559414125
  aved CSV with rectification and hit rate to: /Users/tejasmacipad/Desktop/Third_year/STT/lab2/newmodelfile_with_rectification_codebert.csv
```

Figure 12: Code for rectification and improvement

## Explanation of the Code

The provided Python script computes the amount of rectification a rectifier can perform provided content of code difference, source code before and after, fix type message.

• Import Statements: The script imports required libraries: pandas for handling CSV data, sentence-transformers for loading the pre-trained CodeBERT model, and util for cosine similarity computation.

- Dataset Input: The variable commits\_csv specifies the path to the input CSV file containing commit information. This file includes columns such as commit hash, message, diff, and other metadata.
- Model Loading: The script loads the pre-trained microsoft/codebert-base model from Hugging Face's sentence-transformers library. This model is designed to capture semantic relationships between natural language and source code.
- Similarity Function: A helper function compute\_similarity(code\_diff, commit\_msg) is defined. It encodes both the LLM generated fix type and code diff into embeddings, then calculates the cosine similarity between them. If either field is missing, it returns a similarity score of zero.
- Application Across Dataset: The function is applied to each row of the dataset using pandas.DataFrame.apply(), creating a new column similarity that holds the computed similarity score for every commit.
- Output Storage: The resulting similarity scores and hit flags are saved to a CSV file specified by output\_path, ensuring the data is available for further analysis and reporting.

The evaluation of LLM-generated commit messages yielded the following results:

#### Result

• Average Rectification improvement: 0.0171

• Rectification Similarity: 0.9307

• Commits above threshold: 668

• Hit rate (threshold 0.9): 91.88%