# MACHINE LEARNING FOR SOFTWARE MAINTAINABILITY

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"A software system must be continuously adapted during its overall life cycle or it progressively becomes less satisfactory" (cit. Lehman's Law of Software Evolution)



 Software Maintenance is one of the most expensive and time consuming phase of the whole life cycle

Code the program

Analyse user

requirements

Design the

program

Operate and

maintain the system

Document and

test the system

- Anticipating the Maintenance operations reduces the cost
- 85%-90% of the total cost are related to the effort necessary to comprehend the system and its source code [Erlikh, 2000]

### SOFTWARE ARCHITECTURE

- Provide *models* and *views* representing the relationships
   among different **software artifacts**
  - Clustering of Software Artifacts
    - Advantages:
  - To aid the comprehension
  - To reduce maintenance effort

Software Artifacts				
Application Facade	Service Interfaces Messages Interfaces			
UI Components Operational Ma	nagement Business Components			
UI Process Components Components	Data Helpers / Buisiness Utilities Workflows			
Communications	Security			

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#### Clusters of Software Artifacts



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### SOFTWARE ARTIFACTS

Software Artifacts may be analyzed at different

levels of abstractions



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### SOFTWARE ARTIFACTS

Software Artifacts may be analyzed at **different levels of abstractions** 

The different levels of abstractions lead to different **analysis tasks:** 

 Identification of functional modules and their hierarchical arrangement

• i.e., Clustering of Software classes

• Identification of Code Clones

• i.e., Clustering of Duplicated code fragments (blocks,

```
class WrappedClassLoader extends ClassLoader {
    private Bundle bundle;
    public WrappedClassLoader(Bundle bundle) {
        super();
       this.bundle = bundle;
    3
    /* (non-Javadoc)
     * @see java.lang.ClassLoader#findClass(java.lang.String)
   public Class findClass(String name) throws ClassNotFoundException {
        return bundle.loadClass(name);
    /* (non-Javadoc)
     * @see java.lang.ClassLoader#findResource(java.lang.String)
    public URL findResource(String name) {
        return bundle.getResource(name);
    3
    /* (non-Javadoc)
     * @see java.lang.ClassLoader#findResources(java.lang.String)
    protected Enumeration findResources(String name) throws IOException {
        return bundle.getResources(name);
    3
```

### SOFTWARE ARTIFACTS CLUSTERING

**Problem**: Definition of a proper similarity measure to apply in the clustering analysis, which is able to exploit the considered representation of software artifacts

- Mine information directly from the source code:
  - Exploit the syntactic/lexical information provided in the source code text
  - Exploit the relational information between artifacts
    - e.g., Program Dependencies

```
class WrappedClassLoader extends ClassLoader {
   private Bundle bundle;
    public WrappedClassLoader(Bundle bundle) {
        super();
       this.bundle = bundle;
    }
    /* (non-Javadoc)
     * @see java.lang.ClassLoader#findClass(java.lang.String)
     */
    public Class findClass(String name) throws ClassNotFoundException {
        return bundle.loadClass(name);
    /* (non-Javadoc)
      @see java.lang.ClassLoader#findResource(java.lang.String)
    public URL findResource(String name) {
        return bundle.getResource(name);
    }
    /* (non-Javadoc)
      @see java.lang.ClassLoader#findResources(java.lang.String)
    protected Enumeration findResources(String name) throws IOException {
        return bundle.getResources(name);
```

### MINING LARGE REPOSITORIES



- Analysis of large and complex systems
- Solutions and algorithms must be able to **scale** efficiently (*in the large* and *in the many*)

### ADVANCED MACHINE LEARNING FOR SOFTWARE MAINTENANCE

**Idea**: Definition of Machine Learning techniques to mine information from the source code

- Combine different kind of information (lexical and structural)
  - Application of **Kernel Methods** to software artifacts
- Provide flexible and computational effective solutions to analyze large data sets

### ADVANCED MACHINE LEARNING FOR SOFTWARE MAINTENANCE

**Idea**: Definition of Machine Learning techniques to mine information from the source code

- Combine different kind of information (lexical and structural)
  - Application of **Kernel Methods** to software artifacts
- Provide flexible and computational effective solutions to analyze large data sets

#### **Advanced Machine Learning**

- Learning with syntactic/semantic information (Natural Language Processing)
- Learning in relational domains (Structured-output learning, Logic Learning, Statistical Relational Learning)

### KERNEL METHODS FOR STRUCTURED DATA

- A **Kernel** is a function between (arbitrary) pairs of entities
  - It can be seen as a kind of **similarity measure**
- Based on the idea that structured objects can be described in terms of their constituent parts
- Generalize the computation of the dot product to arbitrary domains
- Can be easily tailored to specific domains
  - Tree Kernels
  - Graph Kernels

![](_page_12_Figure_8.jpeg)

....

### KERNELS FOR STRUCTURES

Computation of the dot product between (Graph) Structures

![](_page_13_Figure_2.jpeg)

![](_page_14_Picture_0.jpeg)

- Parse Trees represent the syntactic structure of a sentence
- Tree Kernels can be used to measure the similarity between parse trees

![](_page_14_Figure_3.jpeg)

### KERNELS FOR LANGUAGES

- Parse Trees represent the syntactic structure of a sentence
- Tree Kernels can be used to measure the similarity between parse trees

### KERNELS FOR SOURCE CODE

- Abstract Syntax Trees (AST) represent the syntactic structure of a piece of code
- Research on Tree Kernels for NLP carries over to AST (with adjustments)

![](_page_15_Figure_6.jpeg)

![](_page_15_Figure_7.jpeg)

### KERNELS FOR PARSE TREE

![](_page_16_Figure_1.jpeg)

![](_page_17_Figure_1.jpeg)

a 2 b

# KERNEL MACHINES

**Idea:** Any learning algorithm relying on similarity measure can be used

- Supervised Learning
  - Binary Classification
  - Multi-class Classification
  - Ranking

- Unsupervised Learning
  - Clustering
  - Anomaly Detection

### KERNEL MACHINES FOR CONE DETECTION

#### • Supervised Learning

• Pairwise classifier: predict if a pair of fragments is clone

#### • Unsupervised Learning

• Clustering: cluster together all candidate clones

## KERNEL FOR CLONES

![](_page_20_Figure_1.jpeg)

# EARNING SIMILARITIES

#### **KERNEL LEARNING**

- Construct a number of candidate kernels with different characteristics
  - e.g., Ignore variables names or not
- Employ kernel learning approaches which learn a weighted combination of candidate kernels
- Useless/harmful kernels will get zero weight and will be discarded in the final model

### STRUCTURED-OUTPUT LEARNING

#### **Supervised Clustering**

- Exploit information on already annotated pieces of software
- Training examples are software projects/portions with annotation on existing clones (clustering)
- A learning model uses training examples to refine the similarity measure for correctly clustering novel examples

# SUMMARY

- Software has a rich structure and heterogeneous information
- Advanced Machine learning approaches are promising for exploiting such information
- Kernel Methods are natural candidate
  - e.g., see the analogy between NLP parse trees and AST
- Many applications:
  - architecture recovery, code clone detection, vulnerability detection ....

# CASE STUDY; KERNELS FOR CLONES

## 

£

```
d_setitem(arrayobject *ap, Py_ssize_t i, PyObject *v)
£
       double x;
       if (!PyArg_Parse(v, "d;array item must be float", &x))
               return -1;
       if (i >= 0)
                     ((double *)ap->ob_item)[i] = x;
       return 0;
```

```
i_setitem(arrayobject *ap, Py_ssize_t i, PyObject *v)
        int x;
       /* 'i' == signed int, maps to PyArg_Parse's 'i' formatter */
        if (!PyArg_Parse(v, "i;array item must be integer", &x))
               return -1;
       if (i >= 0)
                    ((int *)ap->ob_item)[i] = x;
        return 0;
```

- **Goal:** "Identify and group all duplicated code fragments/functions"
- Copy&Paste programming
- Taxonomy of 4 different types of clones
- Program Text similarities and Functional similarities
- Clones affect the reliability and the maintainability of a software system

## CODE

### **Kernels for Structured Data:**

 The source code could be represented by many different data structures

Abstract Syntax Tree (AST)

STRUCTURES

- Tree structure representing the syntactic structure of the different instructions of a program (function)
- **Program Dependencies Graph** (PDG)
  - (Directed) Graph structure representing the relationship among the different statement of a program

![](_page_27_Picture_0.jpeg)

### ABSTRACT SYNTAX TREE (AST)

![](_page_27_Figure_2.jpeg)

![](_page_28_Picture_0.jpeg)

### ABSTRACT SYNTAX TREE (AST)

![](_page_28_Figure_2.jpeg)

![](_page_29_Picture_0.jpeg)

![](_page_29_Figure_1.jpeg)

![](_page_30_Picture_0.jpeg)

![](_page_30_Figure_1.jpeg)

![](_page_31_Picture_0.jpeg)

}

### PROGRAM DEPENDENCIES GRAPH (PDG)

```
int function (int parameter) {
    int k = 10;
    printf("Hello, this is the function");
    int i = 0;
    while (i < 7) {
        i++;
        // do something cool
    }
</pre>
```

- Nodes correspond to instructions
- Edges represent relationships between couple of nodes

![](_page_31_Figure_5.jpeg)

![](_page_32_Figure_0.jpeg)

- Nodes correspond to instructions
- Edges represent relationships between couple of nodes

![](_page_32_Figure_3.jpeg)

![](_page_33_Figure_0.jpeg)

expr

arg

- Nodes correspond to instructions
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![](_page_34_Figure_0.jpeg)

expr

arg

- Nodes correspond to instructions
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![](_page_35_Figure_0.jpeg)

expr

arg

- Nodes correspond to instructions
- Edges represent relationships between couple of nodes

![](_page_36_Picture_0.jpeg)

## NODES AND EDGES

- Two Types of Nodes
  - Control Nodes (Dashed ones)
    - e.g., if for while function calls...
  - Data Nodes
    - e.g., expressions parameters...

![](_page_36_Picture_7.jpeg)

![](_page_36_Figure_8.jpeg)

![](_page_37_Picture_0.jpeg)

## NODES AND EDGES

- Two Types of Nodes
  - Control Nodes (Dashed ones)
    e.g., if for while function calls...
    Data Nodes
    e.g., expressions parameters...
- Two Types of Edges (i.e., *dependencies*)
  - Control edges (Dashed ones)
  - Data edges

![](_page_37_Figure_7.jpeg)

#### KERNELS FOR CODE STRUCTURES DEFINING KERNELS FOR STRUCTURED DATA

- The definition of a new Kernel for a Structured Object requires the definition of:
- Set of features to annotate each part of the object

- A Kernel function to measure the similarity on the smallest part of the object
  - e.g., Nodes of AST and Graphs

 A Kernel function to apply the computation on the different (sub)parts of the structured object

# TREE KERNELS FOR

FOR FOR-FOR-INIT BODY

**KERNELS** 

FOR CODE STRUCTURES:

AST

- Features: each node is characterized by a set of 4 features
  - Instruction Class
    - i.e., LOOP, CONDITIONAL\_STATEMENT, CALL
  - Instruction
    - i.e., FOR, IF, WHILE, RETURN
  - Context
    - i.e., Instruction Class of the closer statement node
  - Lexemes
  - Lexical information gathered (recursively) from leaves

# TRE KERNELS FOR

Instruction Class = LOOP **Instruction** = FOR FOR **Context** = (e.g., LOOP) **Lexemes** = (e.g, name of variables in FOR-INIT..) FOR-FOR-INIT BODY

**KERNELS** 

FOR CODE

**STRUCTURES:** 

AST

- Features: each node is characterized by a set of 4 features
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KERNELS FOR CODE STRUCTURES: AST

### TREE KERNELS FOR AST

- **Goal:** Identify the maximum isomorphic Tree/Subtree
- Comparison of blocks to each other
- Blocks: Atomic unit for (sub) tree considered

![](_page_41_Figure_5.jpeg)

KERNELS FOR CODE STRUCTURES: AST

### TREE KERNELS FOR AST

- **Goal:** Identify the maximum isomorphic Tree/Subtree
- Comparison of blocks to each other
- Blocks: Atomic unit for (sub) tree considered

![](_page_42_Figure_5.jpeg)

#### KERNELS FOR CODE STRUCTURES: PDG GRAPH KERNELS FOR PDG

![](_page_43_Figure_1.jpeg)

- Features of nodes:
  - Node Label
    - i.e., , WHILE, CALL-SITE, EXPR, ...
  - Node Type
    - i.e., Data Node or Control Node

- Features of edges:
  - Edge Type
    - i.e., Data Edge or Control Edge

#### KERNELS FOR CODE STRUCTURES: PDG GRAPH KERNELS FOR PDG

![](_page_44_Figure_1.jpeg)

- Features of nodes:
  - Node Label
    - i.e., , WHILE, CALL-SITE, EXPR, ...
  - Node Type
    - i.e., Data Node or Control Node

- Features of edges:
  - Edge Type
    - i.e., Data Edge or Control Edge

### KERNELS FOR CODE STRUCTURES: PDG GRAPH KERNELS

- **Goal:** Identify common subgraphs
- **Selectors:** Compare nodes to each others and explore the subgraphs of only "compatible" nodes (i.e., Nodes of the same type)
- **Context:** The subgraph of a node (with paths whose lengths are at most L to avoid loops)

![](_page_45_Figure_4.jpeg)

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![](_page_46_Figure_4.jpeg)

### KERNELS FOR CODE STRUCTURES: PDG

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![](_page_47_Figure_4.jpeg)

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![](_page_48_Figure_4.jpeg)

![](_page_49_Picture_0.jpeg)

- Comparison of results with other two clone detector tools:
  - AST-based Clone detector
  - PDG-based Clone Detector

![](_page_50_Picture_0.jpeg)

- Comparison of results with other two clone detector tools:
  - AST-based Clone detector
  - PDG-based Clone Detector
- No publicly available clone detection dataset

![](_page_51_Picture_0.jpeg)

- Comparison of results with other two clone detector tools:
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  - PDG-based Clone Detector
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  - No unique set of analyzed open source systems

![](_page_52_Picture_0.jpeg)

- Comparison of results with other two clone detector tools:
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  - No unique set of analyzed open source systems
  - Usually clone results are not available

![](_page_53_Picture_0.jpeg)

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- Two possible strategies:

![](_page_54_Picture_0.jpeg)

- Comparison of results with other two clone detector tools:
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- No publicly available clone detection dataset
  - No unique set of analyzed open source systems
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- Two possible strategies:
  - To automatically modify an existing system with randomly generated clones

![](_page_55_Picture_0.jpeg)

- Comparison of results with other two clone detector tools:
  - AST-based Clone detector
  - PDG-based Clone Detector
- No publicly available clone detection dataset
  - No unique set of analyzed open source systems
  - Usually clone results are not available
- Two possible strategies:
  - To automatically modify an existing system with randomly generated clones
  - Manual classification of candidate results

![](_page_56_Picture_0.jpeg)

Project	Size (KLOC)	# PDGS
Apache-2.2.14	343	3017
Python-2.5.1	435	5091

- Comparison with another Graph-based clone detector
- MeCC (ICSE2011)
- **Baseline** Dataset
  - Results provided by MeCC
- Extended Dataset
  - Extension of Clones results by manual evaluation of candidate clones
    - Agreement rate calculation between the evaluators

#### EVALUATION TREE KERNELS FOR AST EMPIRICAL EVALUATION OF TREE KERNEL FOR AST

- Comparison with another (pure) AST-based clone detector
  - Clone Digger <a href="http://clonedigger.sourceforge.net/">http://clonedigger.sourceforge.net/</a>
- Comparison on a system with randomly seeded clones

![](_page_57_Figure_4.jpeg)

### PRECISION, RECALL AND F1 PLOT

EVALUATION TREE KERNELS FOR AST

()

Clone results with different similarity

thresholds

![](_page_58_Figure_4.jpeg)

0.6 0.62 0.64 0.66 0.68 0.7 0.72 0.74 0.76 0.78 0.8 0.82 0.84 0.86 0.88 0.9 0.92 0.94 0.96 0.98

Precision • Recall • F1

### RESULTS WITH APACHE 2.2.14

**EVALUATION** 

GRAPH KERNELS FOR PDG

Threshold	#Clones in the Baseline	#Clones in the Extended Dataset
1.00	874	1089
0.99	874	1514

![](_page_59_Figure_2.jpeg)

#### $\overline{}$ **EVALUATION** DN 2.5.2**GRAPH KERNELS**

Baseline

Extended

Threshold	#Clones in the Baseline	#Clones in the Extended Dataset
1.00	858	1066
0.99	858	2119

![](_page_60_Figure_2.jpeg)

FOR PDG

![](_page_60_Figure_3.jpeg)

## CHALLENGES AND OPPORTUNITIES

- Learning Kernel Functions from Data Set
  - Kernel Methods **advantages**:
    - flexible solution to be tailored to specific domain
    - efficient solution easy to parallelize
    - combinations of multiple kernels
  - Provide a publicly available data set

## THANK YOU FOR YOUR KIND ATTENTION