Deep Learning Similarities from Different Representations of Source Code

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Source Code

Source Code

Source Code

- Plain Text
- Abstract Syntax Tree
- Control Flow Graph
- Bytecode

Source Code

- Plain Text (domain)
- Abstract Syntax Tree
- Control Flow Graph
- Bytecode

Source Code

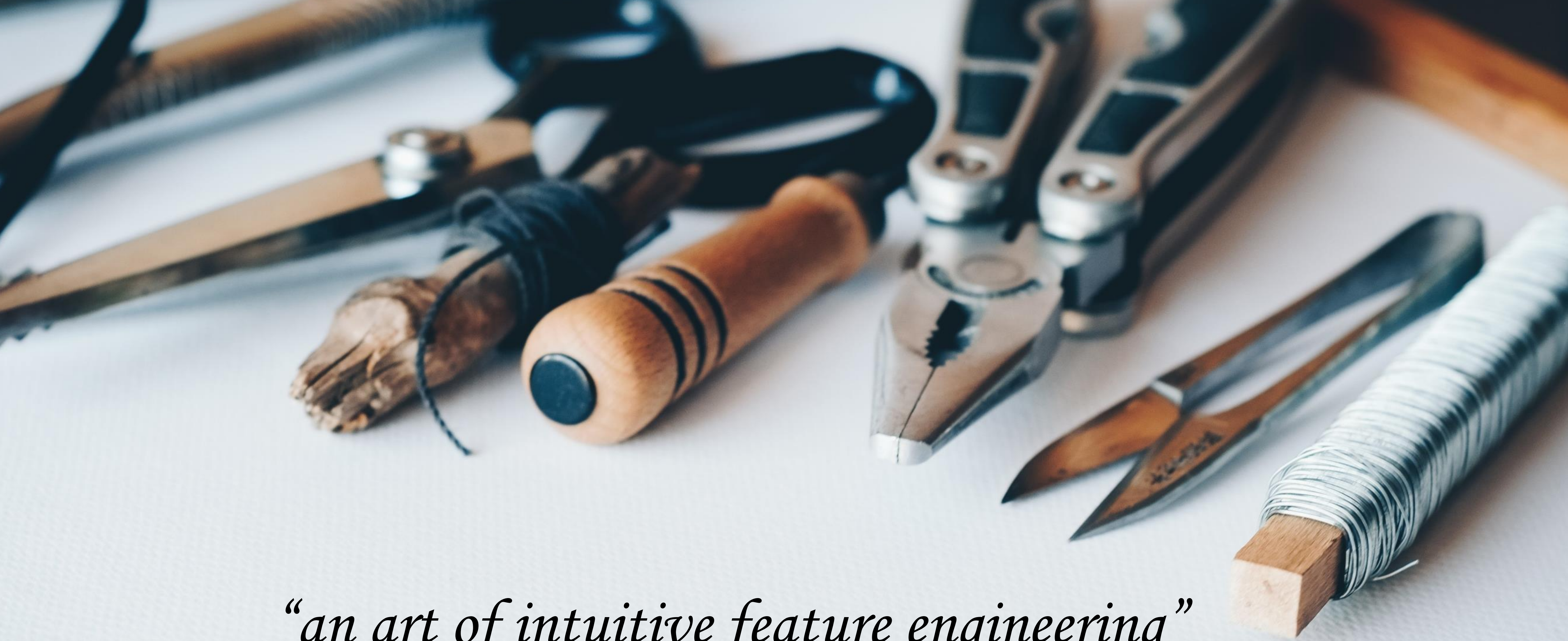
- Plain Text (domain)
- Abstract Syntax Tree (structure)
- Control Flow Graph
- Bytecode

Source Code

- Plain Text (domain)
- Abstract Syntax Tree (structure)
- Control Flow Graph (execution)
- Bytecode

Source Code

- Plain Text (domain)
- Abstract Syntax Tree (structure)
- Control Flow Graph (execution)
- Bytecode (instruction)



“an art of intuitive feature engineering”

REPRESENTATION (or FEATURE) LEARNING

Learn vector representation of Source Code

Different Representations + Feature Learning

🤔

APPROACH

1. Extract multiple representation from code

2. Learn embeddings for each representation

3. Compute similarities

4. Assemble a combined model

5. Reusability and Transfer Learning

1. Extract multiple representation from code

Identifiers

Abstract Syntax Tree

Control Flow Graph

Bytecode

1. Extract multiple representation from code

Identifiers

Abstract Syntax Tree

Control Flow Graph

Bytecode

Extraction

Leaf nodes of the AST

Stream of identifiers and constants in code

Normalization

Replace constant values with their type

- < int >
- < float >
- < char >
- < string >

1. Extract multiple representation from code

Identifiers

Abstract Syntax Tree

Control Flow Graph

Bytecode

Extraction
Pre-order visit of the AST
Stream of AST Node Types

Normalization
Remove AST node types:

- SimpleName
- QualifiedName

1. Extract multiple representation from code

Identifiers

Abstract Syntax Tree

Control Flow Graph

Bytecode

Extraction

Use Soot to extract CFG

Graph:

- Nodes (statements)
- Directed edges (control flow)

1. Extract multiple representation from code

Identifiers

Abstract Syntax Tree

Control Flow Graph

Bytecode

Extraction

`javap -c -private <classname>`

Stream of bytecode mnemonic opcodes (e.g., `iload`, `invokevirtual`)

Normalization

Remove references to constants

`putfield #2 -> putfield`

Embedding Learning

AutoenCODE NN Language Model + Recursive AutoEncoder (RvNN)

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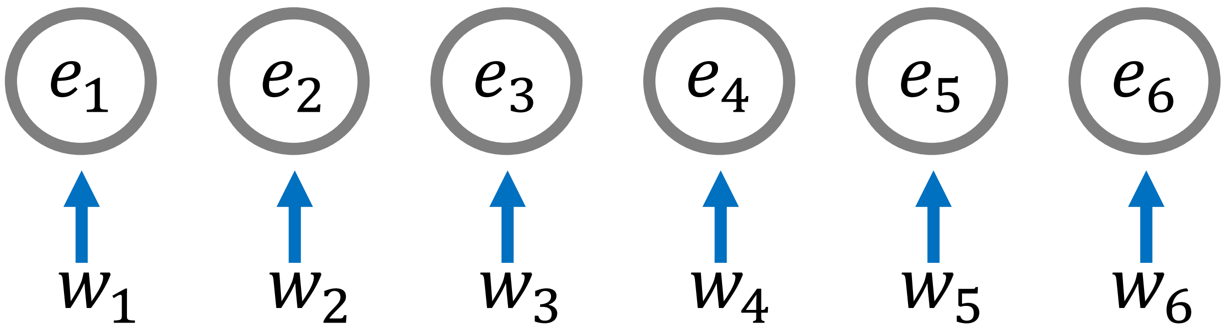
w_1 w_2 w_3 w_4 w_5 w_6 Representation

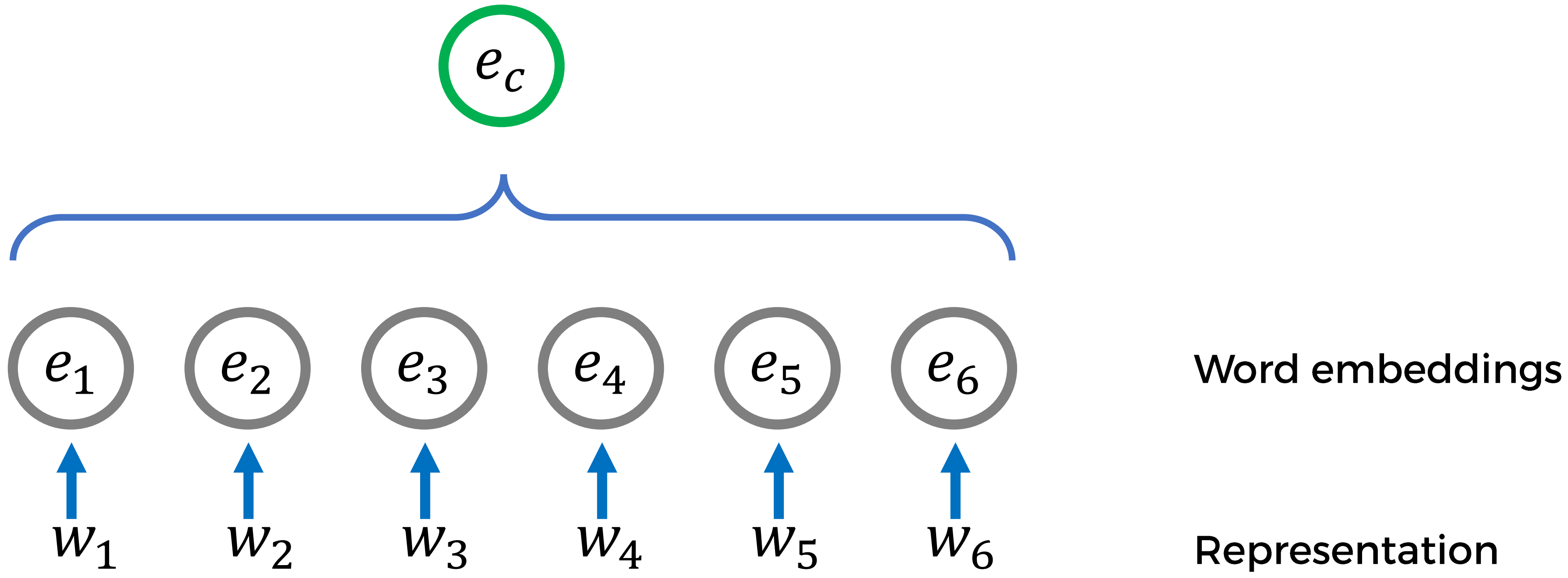
AutoenCODE NN Language Model + Recursive AutoEncoder (RvNN)



Word embeddings

Representation

AutoenCODE NN Language Model + Recursive AutoEncoder (RvNN)



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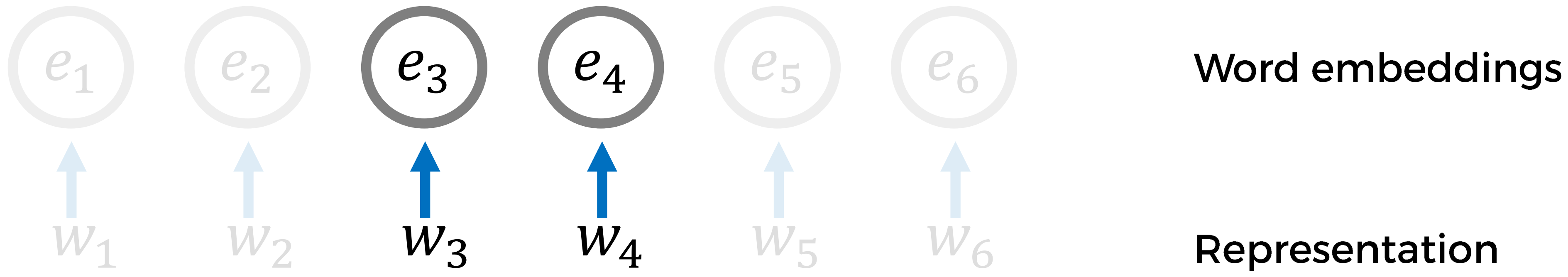

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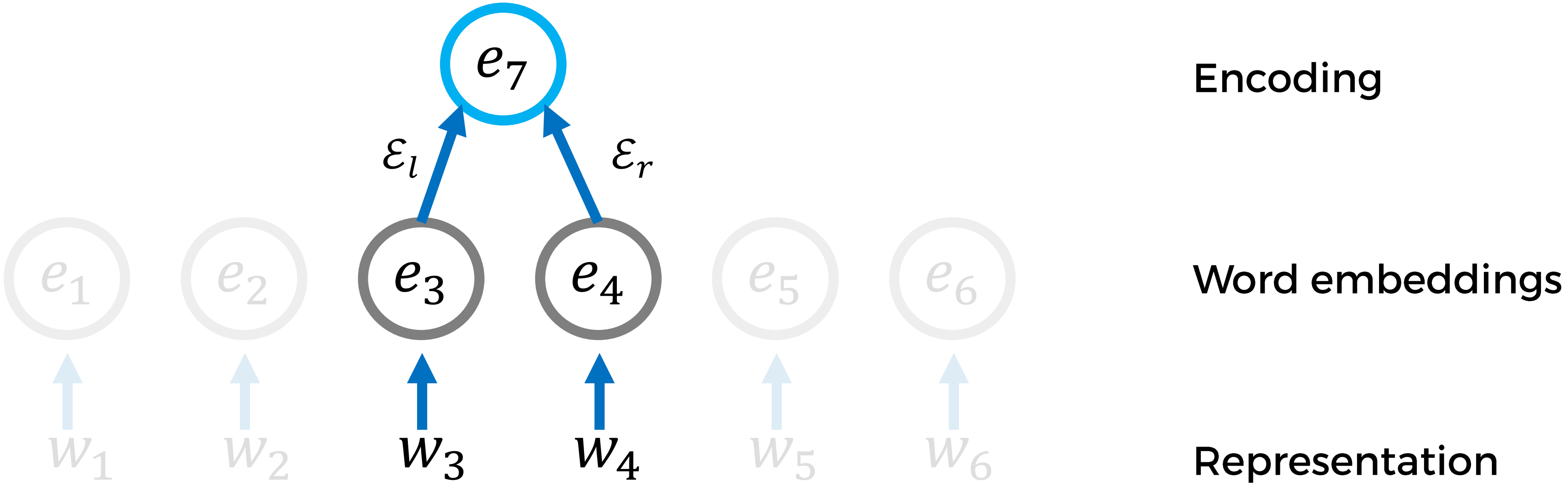

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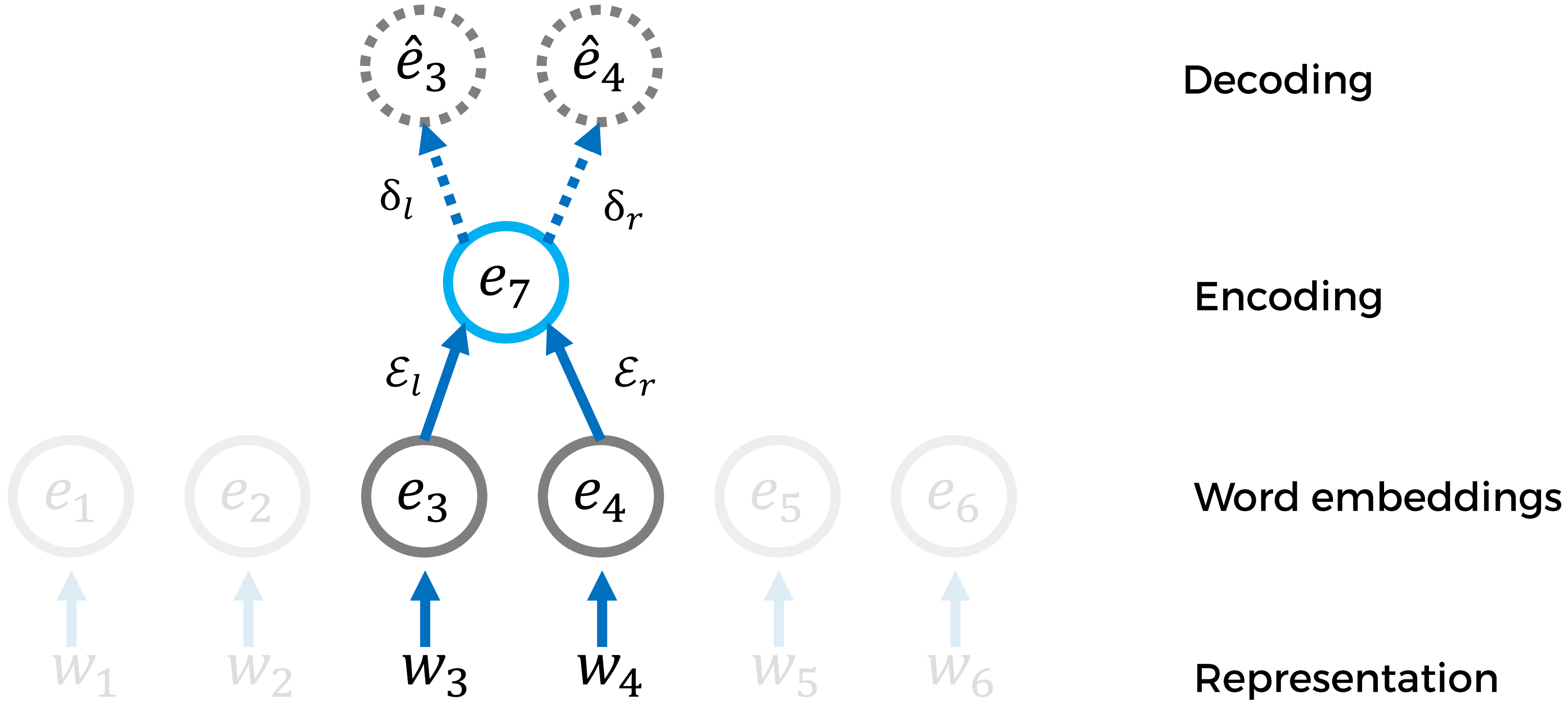

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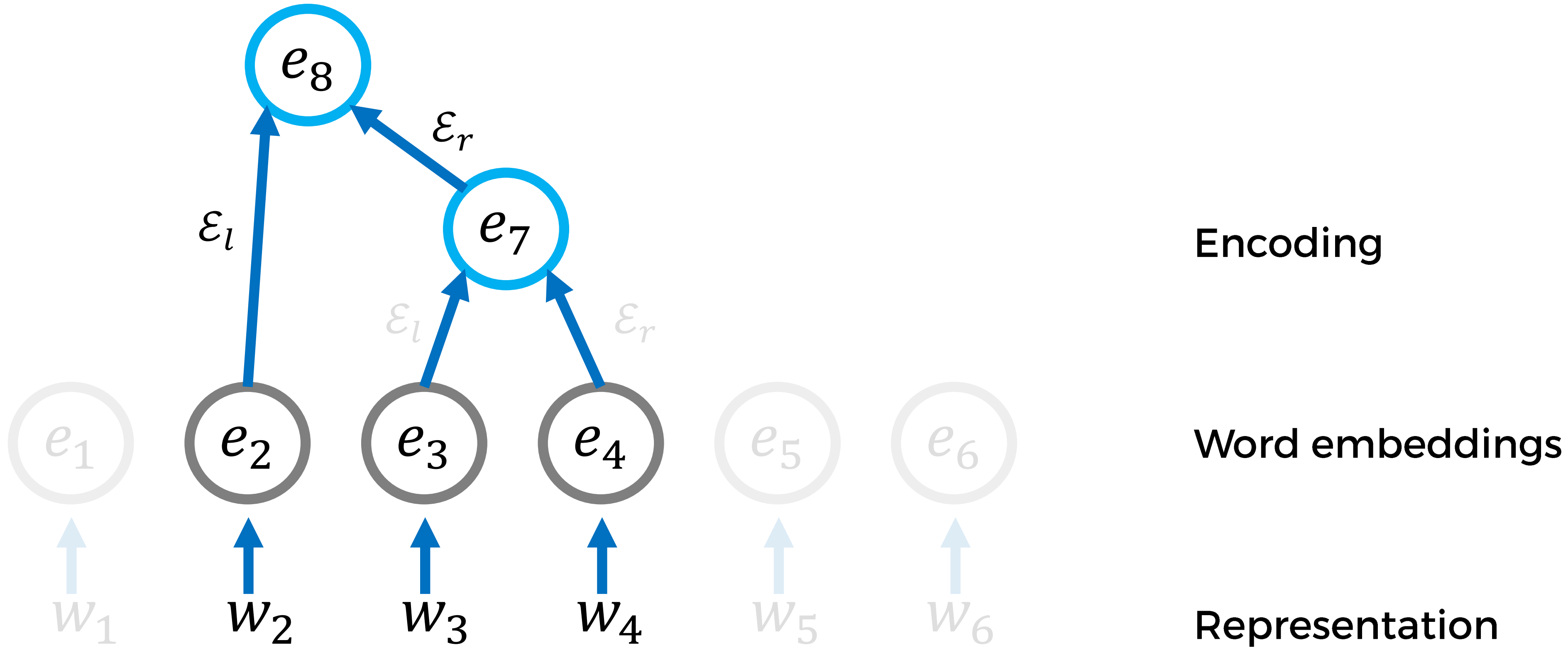

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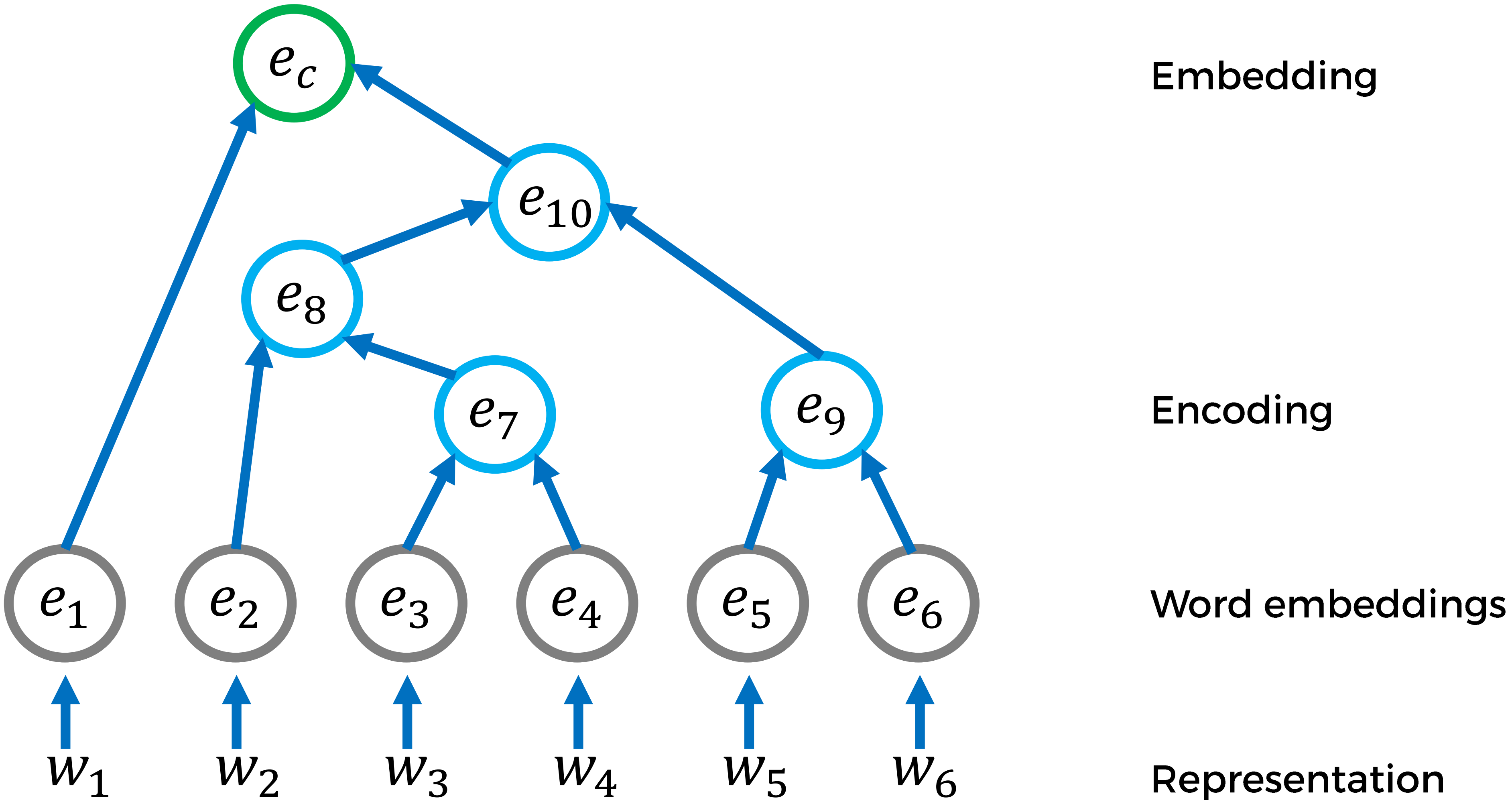


HOPE

Graph Embedding

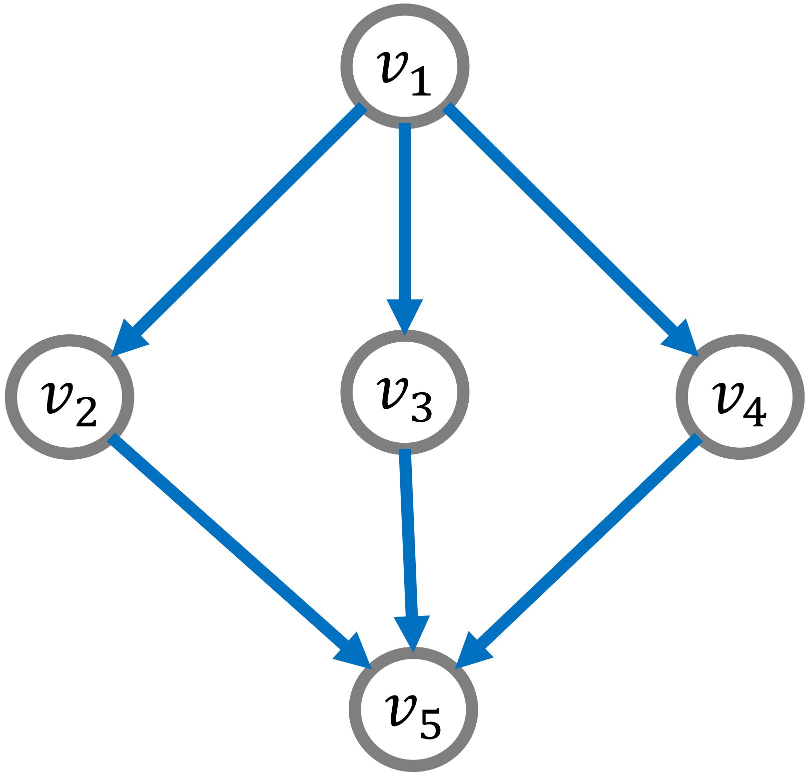
High-Order Proximity preserved Embedding

HOPE

Graph Embedding

High-Order Proximity preserved Embedding

- Embeds directed graphs
- Graph reconstruction from embedding
- Asymmetric transitivity
- Katz proximity metric



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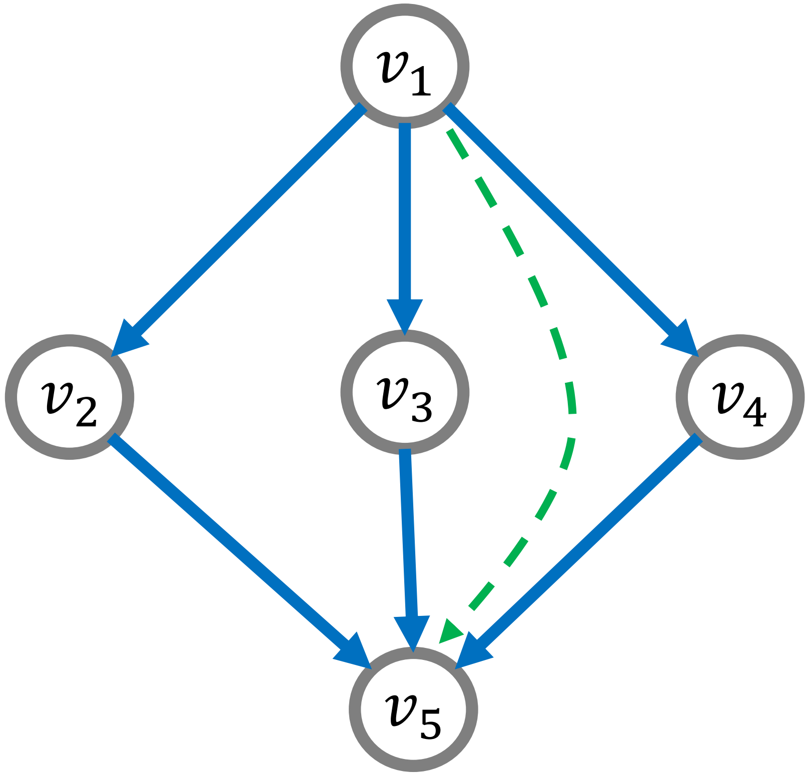

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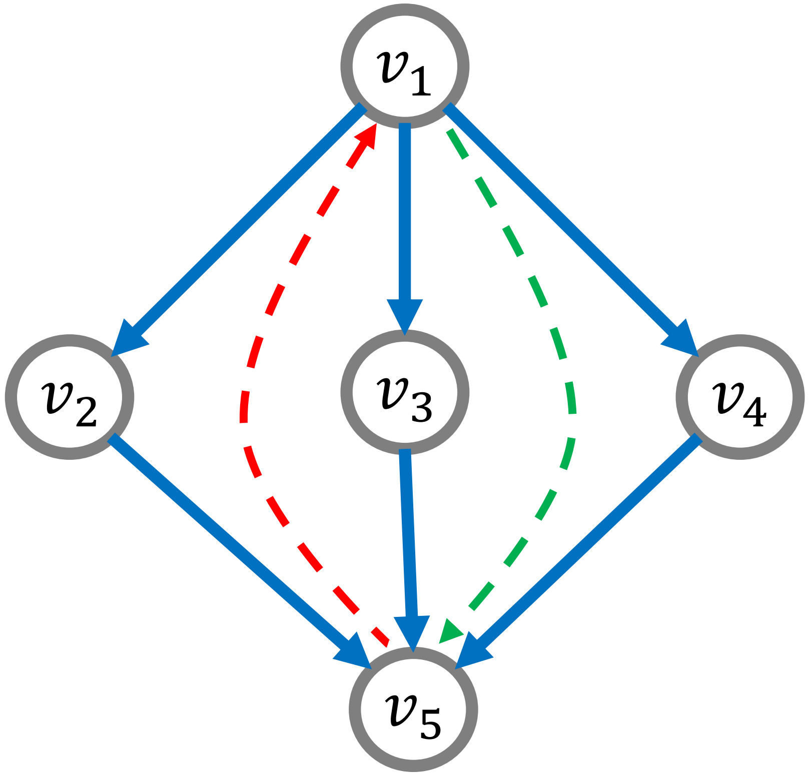


Combined Model

Combined Model

Ensemble Learning (Random Forest)

- Clone Detector
- Clone Classifier

Experimental Design & Results

RQ1 How effective are different representations in detecting similar code fragments?

Dataset: 10 Java projects from *Qualitas.class Corpus*

Granularity: Methods and Classes

1. Extract code representations
2. Train representation-specific models
3. Generate embeddings
4. Compute similarities
5. Analyze candidates

RQ1 How effective are different representations in detecting similar code fragments?

IDENT	AST	CFG	BYTECODE
F	F	F	T
F	F	T	F
F	F	T	T
F	T	F	F
F	T	F	T
F	T	T	F
F	T	T	T
T	F	F	F
T	F	F	T
T	F	T	F
T	F	T	T
T	T	F	F
T	T	F	T
T	T	T	F
T	T	T	T

RQ1 How effective are different representations in detecting similar code fragments?

IDENT	AST	CFG	BYTECODE	Precision %	
				Methods	Classes
F	F	F	T	5	49
F	F	T	F	9	58
F	F	T	T	88	73
F	T	F	F	79	63
F	T	F	T	95	93
F	T	T	F	100	100
F	T	T	T	100	100
T	F	F	F	95	100
T	F	F	T	100	100
T	F	T	F	100	-
T	F	T	T	100	100
T	T	F	F	100	100
T	T	F	T	100	100
T	T	T	F	100	100
T	T	T	T	100	100

RQ1 How effective are different representations in detecting similar code fragments?

Methods

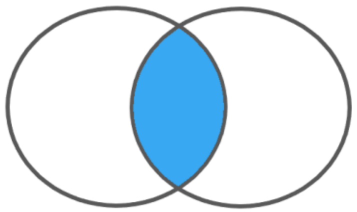
Representation	FP	TP	Type I	Type II	Type III	Type IV	Precision	Recall
IDENT	1	201	151	15	35	0	100	52
AST	11	292	138	132	19	3	96	75
CFG	43	178	69	81	19	9	81	46
BYTE	46	222	89	77	49	7	83	57

Classes

Representation	FP	TP	Type I	Type II	Type III	Type IV	Precision	Recall
IDENT	0	120	23	51	46	0	100	40
AST	18	188	18	121	44	5	91	63
CFG	24	120	7	65	41	7	83	40
BYTE	34	217	23	115	77	2	86	73

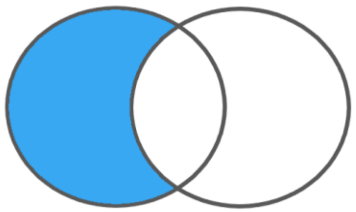
RQ2 What is the complementarity of different representations?

Intersection



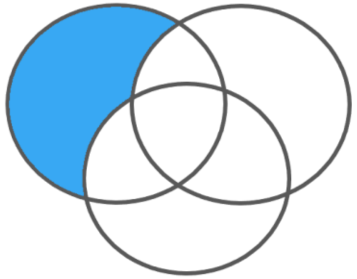
$$R_i \cap R_j = \frac{|TP_{R_i} \cap TP_{R_j}|}{|TP_{R_i} \cup TP_{R_j}|}\%$$

Difference



$$R_i \setminus R_j = \frac{|TP_{R_i} \setminus TP_{R_j}|}{|TP_{R_i} \cup TP_{R_j}|}\%$$

Exclusive



$$EXC(R_i) = \frac{|TP_{R_i} \setminus \bigcup_{j \neq i} TP_{R_j}|}{|\bigcup_j TP_{R_j}|}\%$$

RQ2 What is the complementarity of different representations?

Methods											
Intersection %					Difference %					Exclusive %	
$R_1 \cap R_2$	Iden	AST	CFG	Byte	$R_1 \setminus R_2$	Iden	AST	CFG	Byte	R_i	$EXC(R_i)$
Iden		40	21	36	Iden		17	43	29	Iden	5% (21)
AST			42	44	AST	43		46	38	AST	9% (33)
CFG				36	CFG	36	12		24	CFG	1% (4)
Byte					Byte	35	18	39		Byte	1% (2)

Classes											
Intersection %					Difference %					Exclusive %	
$R_1 \cap R_2$	Iden	AST	CFG	Byte	$R_1 \setminus R_2$	Iden	AST	CFG	Byte	R_i	$EXC(R_i)$
Iden		33	14	42	Iden		19	43	8	Iden	3% (8)
AST			31	51	AST	48		49	19	AST	9% (26)
CFG				34	CFG	43	20		14	CFG	7% (21)
Byte					Byte	49	30	52		Byte	7% (21)

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AST			31	51	AST	48		49	19	AST	9% (26)
CFG				34	CFG	43	20		14	CFG	7% (21)
Byte					Byte	49	30	52		Byte	7% (21)

RQ3 How effective are combined multi-representation models?

Ensemble Learning (Random Forest)

Clone Detector

Clone Classifier

RQ3 How effective are combined multi-representation models?

Clone Detector

	Methods			Classes		
	Precision	Recall	F-Measure	Precision	Recall	F-Measure
Clone	98	97	98	90	93	91
Not Clone	90	91	90	61	52	56

Clone Classifier

	Methods			Classes		
	Precision	Recall	F-Measure	Precision	Recall	F-Measure
Not Clone	89	94	91	59	61	60
Type I	89	88	88	86	78	82
Tye II	82	84	83	81	85	83
Type III	74	75	75	61	59	60
Type IV	67	18	29	0	0	0
Weighted Avg.	84	84	84	67	68	68

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RQ4 Are DL-based models applicable for detecting clones among different projects?

Scenarios:

- Software Maintainer has to analyze the amount of duplicated code across projects belonging to their organization
- Developer using a jar file (compiled library) needs to asses provenance and/or licensing issues before releasing the code

Dataset:

- 46 compiled Apache Commons libraries

RQ4 Are DL-based models applicable for detecting clones among different projects?

- Software Maintainer has to analyze the amount of duplicated code across projects belonging to their organization

```
▪ lang3-3.6      - text-1.1
▪ text-1.1       - collections4-4.1
▪ math3-3.6.1    - rng-1.0
▪ codec-1.9      - net-3.6
```

} Share Duplicated Code

- Developer using a jar file (compiled library) needs to asses provenance and/or licensing issues before releasing the code

```
weaver-1.3 imported and shaded:
▪ collections4-4.1 (373 classes)
▪ lang3-3.6 (79 classes)
▪ io-2.5 (13 classes)
```

RQ5 Can trained DL-based models be reused on different, previously unseen projects?

Model Reusability and Transfer Learning

Limited Vocabulary: AST, Bytecode, CFG

1. Train model on project A
2. Evaluate model on project B
3. Compare the candidates with original model

RQ5 Can trained DL-based models be reused on different, previously unseen projects?

AST model trained on `lucene`, evaluated on other 9 projects

Project	Methods %		Classes %	
	$L_R \in L_O$	$L_O \in L_R$	$L_R \in L_O$	$L_O \in L_R$
ant-1.8.2	99	88	73	31
antlr-3.4	100	100	33	100
argouml-0.34	99	96	97	73
hadoop-1.1.2	99	95	95	74
hibernate-4.2.0	89	82	30	84
jhotdraw-7.5.1	99	98	82	77
maven-3.0.5	97	84	50	100
pmd-4.2.5	97	99	99	99
tomcat-7.0.2	98	97	87	69
Overall	97	93	58	90

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maven-3.0.5	97	84	50	100
pmd-4.2.5	97	99	99	99
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Overall	97	93	58	90

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tomcat-7.0.2	98	97	87	69
Overall	97	93	58	90

Conclusions

Learn from available representations

Conclusions

- Learn from available representations

Combine multiple representations

Conclusions

- Learn from available representations
- Combine multiple representations

Reuse models on different projects

Open Science

Open Science

Data

https://sites.google.com/view/learningcodesimilarities

Open Science

Data

https://sites.google.com/view/learningcodesimilarities

Source Code

AutoenCODE

https://github.com/micheletufano/AutoenCODE

Open Science

Data

Source Code

GitHub

AutoenCODE

Michele Tufano

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http://www.cs.wm.edu/~mtufano/

https://sites.google.com/view/learningcodesimilarities

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