Machine Learning for Software Analysis (MLSA)

Fabio Pinelli

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Outline for today

- Myself introduction
- Course presentation
- Introduction on software analysis
- Introduction to Machine learning
- Motivations of Machine Learning for Software analysis
- Research activities on MLSA

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Who I am

I am Associate professor in Computer Science at IMT School for advanced studies Lucca

Machine learning/Data mining on spatio-temporal data

Machine learning applied on Blockchain and Binary code analysis

Federated Learning on spatio-temporal data

https://scholar.google.it/citations?user=rfqxMS0AAAAJ&hl=it

Who I am

Phd held at University of Pisa

IBM Research in Dublin

IBM Research

Vodafone Italia

IMT SCUOLA ALTI STUDI LUCCA

School for advanced studies (PhD)

One of the 6 school of Excellence in Italy

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

My Research Unit

Faculty Members

Mirco Tribastone

Full Professor
SySMA Head
Modeling and Simulation, Software Performance Engineering, Computational Methods

Alessandro Betti

Assistant Professor

Machine Learning, Computer Vision, Lifelong Learning

Lorenzo Ceragioli

Assistant Professor

Formal Methods, Software Security, Quantum Communication and Computing

Gabriele Costa

Associate Professor

Cybersecurity, Penetration Testing, Formal Methods, Software Verification, Vulnerability Assessment

Rocco De Nicola

Full Professor
IMT Rector

Distributed Systems, Formal Verification, Concurrency Theory, Cybersecurity, Fake news detection

Letterio Galletta

Assistant Professor

Software Security, Software Verification, Formal Methods, Programming Languages

Emilio Incerto

Assistant Professor

Software Performance Modeling and Control, Layered Queueing Networks, Autoscaling, Cloud Computing

Cosimo Perini Brogi

Assistant Professor

Formal Methods, Mathematical Foundations of CS, Proof Theory, Certified Programming, Type Theory, Non-classical Logics

Fabio Pinelli

Associate Professor

Data Science, Machine Learning, Spatio-temporal Machine Learning

Simone Soderi

Assistant Professor

Physical Layer Security, 6G Security: Optical communications, Covert channels, Security in critical infrastructure systems

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Different computer science topics from Formal methods to Machine Learning and CyberSecurity, performance, etc.

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… and so why here at UNIFI?

Some question for you

1. What do you know about Machine Learning?
2. What do you know about Software Analysis?
3. What do you expect to learn in these class?

This course

The course contains some **theoretical** and **practical** aspects

- Understand fundamental machine learning concepts and algorithms
- Explore the application of machine learning techniques to software analysis tasks
- Develop practical skills in collecting, preprocessing, and analyzing software data
- Apply machine learning models to detect bugs, assess code quality, and make recommendations for software improvement
- Evaluate the strengths and limitations of using machine learning in software analysis

We will **read** some papers related to this topic

We will **test** some practical examples on real use cases

Moodle: MLSA2425 (please let me know if you have problems)

Exam: Seminar presenting a (set of) agreed paper(s).

Some details

Lessons:

Tuesday: 10:30 - 13:30

Thursday: 11:30 - 13:30

You can contact me anytime at: fabio.pinelli@imtlucca.it

https://sysma.imtlucca.it/people/fabio-pinelli

So… Let’s start

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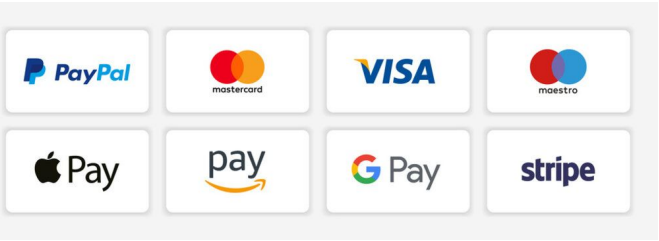
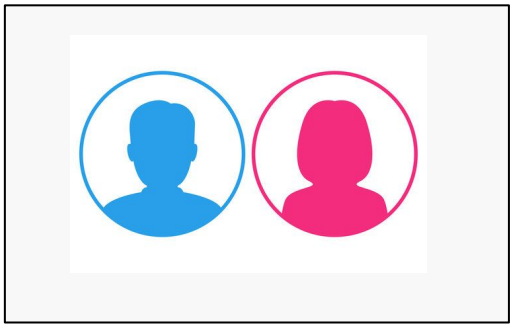
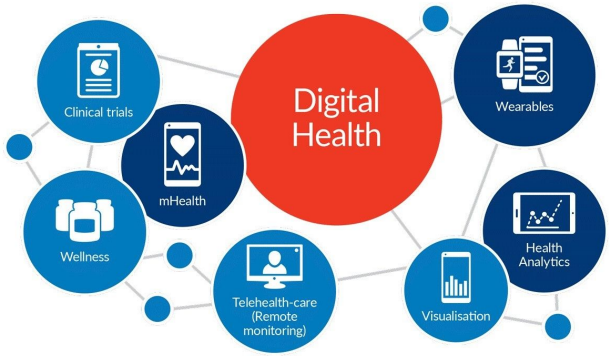
All around us







You want the code to be…

Thus the software should be?

Good software should be ...

Correct

Correctness is important for good software. There shouldn't be faults with specification, design or implementation.

Usable

Users should be able to learn and use a system easily.

Efficient

The less resource a piece of software uses, the better. Processor, battery, bandwidth, memory and disk space usage should be minimized.

Reliable

A system that can perform the required functions stably is important. Failures should be as rare as possible.

Secure

Security should be taken into account. Our software shouldn't let attackers access unauthorized resources.

Adaptability

A system that can be used without modification for different situations it's good.

Accuracy

The accuracy of its outputs is good. This measures if the software outputs the right results for users.

Robustness

If a system is still working after getting invalid inputs and stressful environmental conditions, then it's good for our system.

Maintainability

The ease in which an existing system can be changed is important. The easier that we can make changes, the better.

Portability

A system that operates in different environments from which it's originally designed makes it good.

Reusability

The more reusable parts that a piece of software has, the better.

Using reusable parts means that we don't have to reuse them from scratch.

Readability

Easy to read code is easy to change code. If we understand them faster, then we can make changes faster and in a less error-prone way.

Testability

Making our software system testable is critical. If our code is easy to write unit tests for, then that's good.

Understandability

The ability for us to understand our system in a global view or at the detailed code level is important.

Easier to understand systems are more coherent.

With good software, it's harder for us to create defects, and it's faster to make changes.

Software development

Today, the cost of **software development is less than 50% programming** with testing, debugging, security assessments, and similar tasks taking more resources than developing the software itself.

As a result, there is an increasing focus in the software industry **on using tools to write better software**.

These tools can take the form of **testing tools that help find bugs**

They can also take the **form of analysis techniques** that have the goal of building a **stronger code foundation** with fewer areas where defects can emerge

The end result being **less risk in the software development lifecycle**.

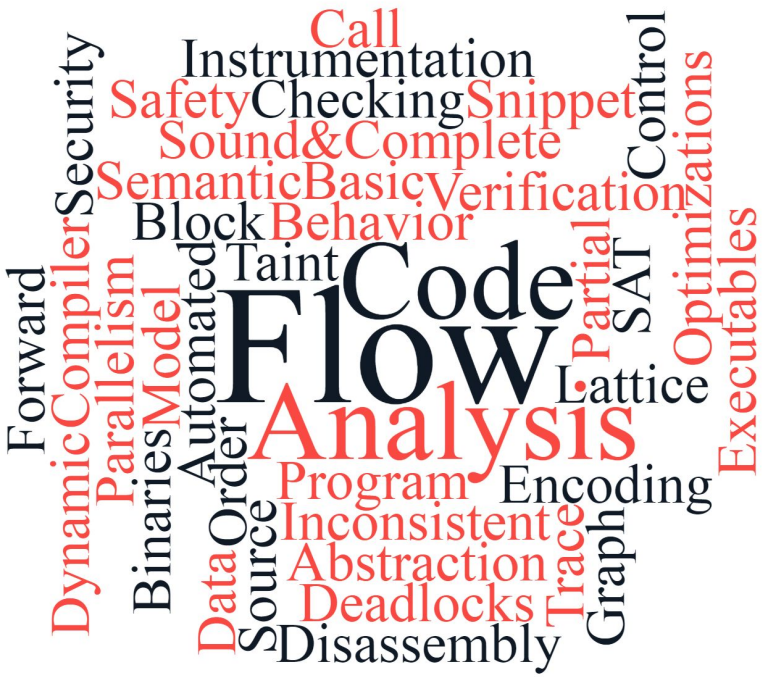
Software analysis

Software or Program analysis refers to the process of examining and evaluating software artifacts:

- source code,
- executables, and
- documentation

to gain insights into various aspects of software quality, performance, security, and maintainability.

The primary goal of program analysis is to improve software reliability, efficiency, and maintainability while reducing the risk of errors, vulnerabilities, and defects.



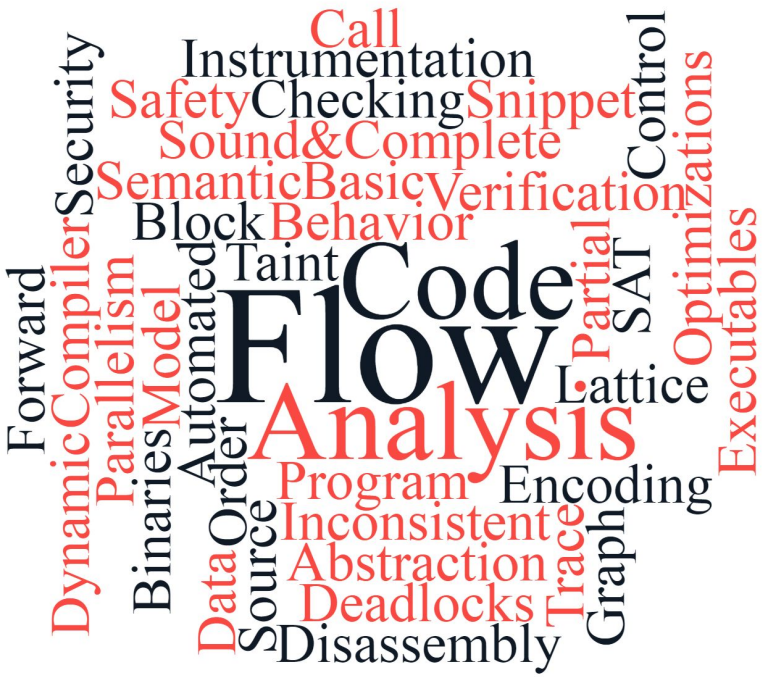
Software analysis

Software analysis encompasses a range of techniques, methods, and tools aimed at

- understanding,
- evaluating, and
- improving

software artifacts throughout the software development lifecycle.

It involves **static** and **dynamic** analysis approaches to identify software **defects**, **security vulnerabilities**, **performance bottlenecks**, and **compliance issues**.



Static analysis

- Static analysis involves examining software artifacts **without executing the code**. It analyzes source code, configuration files, and documentation to identify potential defects, coding standards violations, and security vulnerabilities.

- **Techniques** include syntax checking, data flow analysis, control flow analysis, and abstract interpretation.

- **Tools**: Static analysis tools such as linters, static code analyzers, and code review platforms automate the process of identifying code issues and enforcing coding standards. Reverse engineering techniques are also used.

Dynamic analysis

- Dynamic analysis involves analyzing software behavior **during execution**. It focuses on runtime properties, memory usage, performance characteristics, and error handling.

- **Techniques** include profiling, memory analysis, code coverage analysis, and runtime monitoring.

- **Tools**: Dynamic analysis tools such as profilers, debuggers, memory analyzers, and dynamic testing frameworks capture runtime information and diagnose performance issues, memory leaks, and runtime errors.
-

Model checking

- Model checking is a **formal verification** technique used to systematically verify whether a software model **satisfies a set of desired properties or specifications**.

- It involves exhaustively exploring all possible states of a finite-state model to identify potential violations of safety and liveness properties.

- Tools: Model checking tools such as SPIN, NuSMV, and Alloy provide automated verification capabilities for concurrent and distributed systems.
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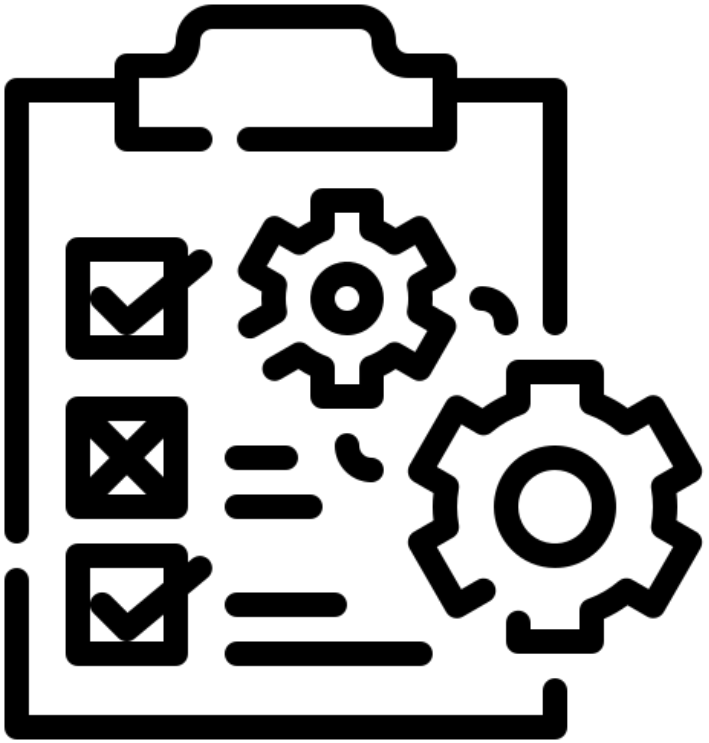

Fuzz testing

- Fuzz testing, also known as fuzzing, involves providing invalid, unexpected, or random inputs to a software system to uncover vulnerabilities, crashes, and unexpected behaviors.

- It helps identify security vulnerabilities, memory corruption issues, and boundary condition errors in software applications.

- Tools: Fuzz testing frameworks such as AFL, Peach, and Radamsa automate the process of generating and executing diverse input data to stress-test software systems.
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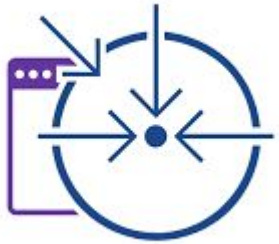
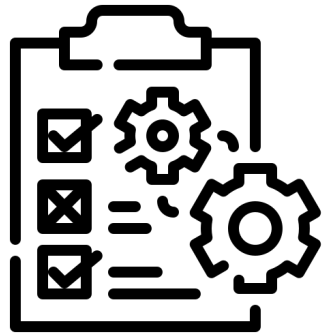
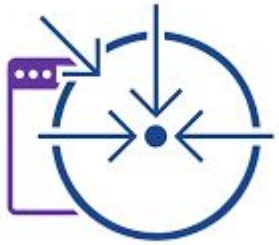


Software analysis

Overall, program or software analysis plays a crucial role in ensuring software quality, reliability, and security throughout the software development lifecycle.

By employing a combination of static analysis, dynamic analysis, formal verification, and testing techniques, organizations can identify and mitigate software defects, vulnerabilities, and performance issues early in the development process.





Machine learning

Machine Learning enables systems to learn from data and make predictions or decisions

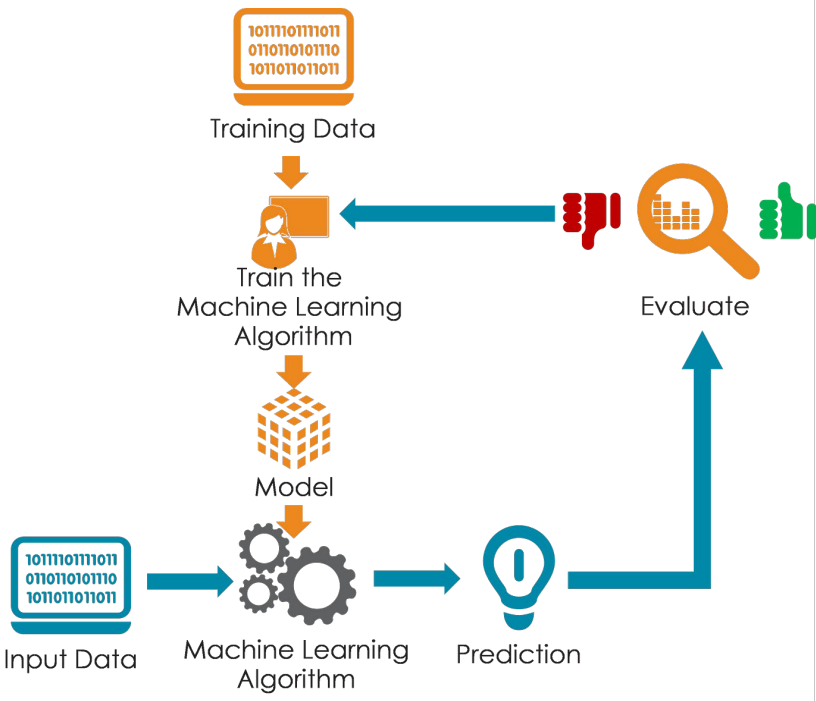
Basic Components of Machine Learning:

- **Data**: Machine learning algorithms require data to learn patterns, relationships, and trends. Data can be structured or unstructured and may include **features** or **attributes** relevant to the problem.

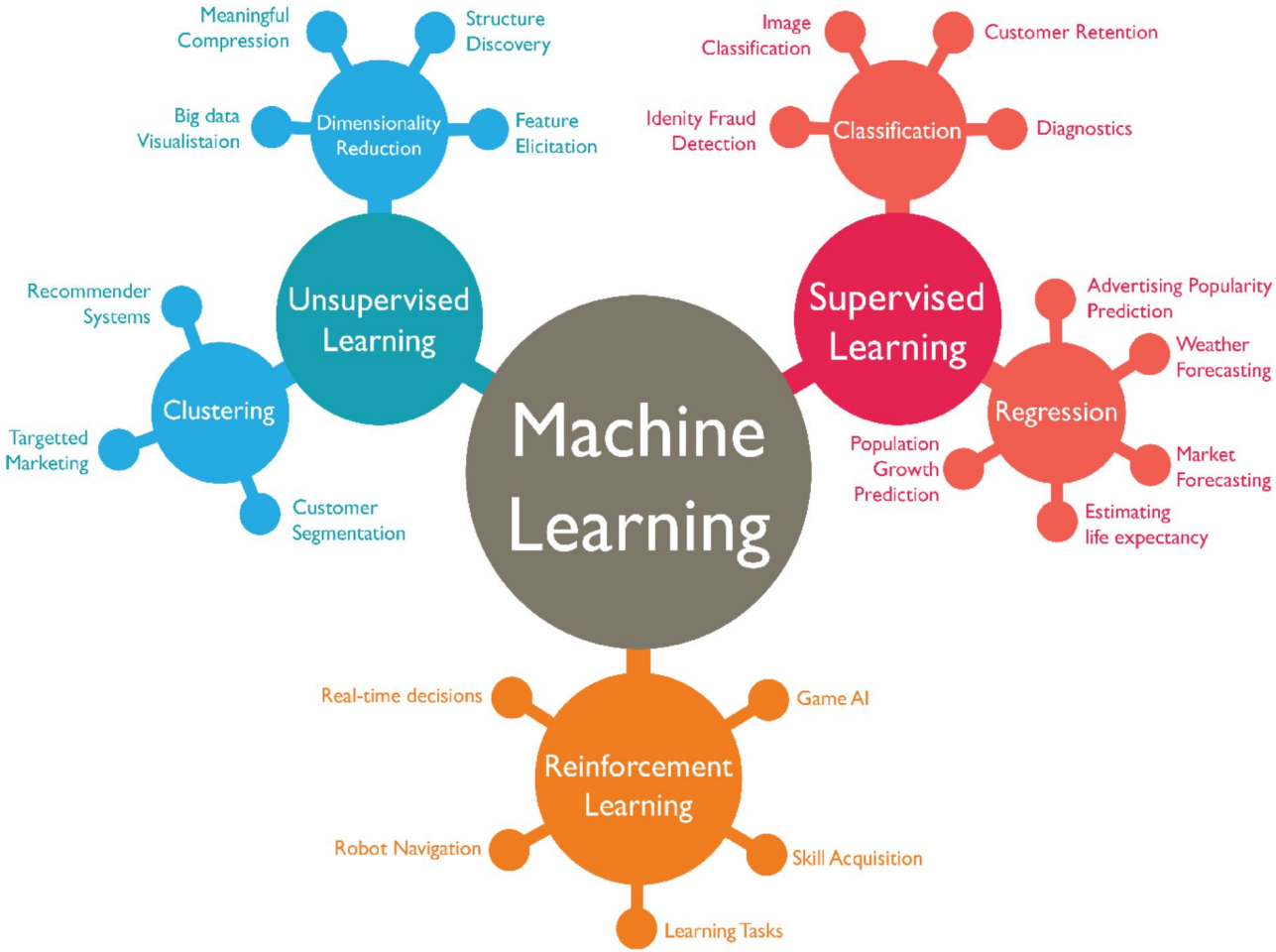
- **Model**: A machine learning model is **a mathematical representation** of the patterns and relationships in the data. Models can be trained using various algorithms to make **predictions** or **classifications**.

- **Training**: The process of training a machine learning model involves feeding it with labeled data (supervised learning) or unlabeled data (unsupervised learning) and adjusting its parameters to minimize errors or maximize accuracy.

- **Inference**: Once trained, the machine learning model can make predictions or classifications on new, unseen data based on the patterns learned during training.



Machine learning tasks



from amazonaws.com

Machine learning tasks

Classification: Classifying data points into predefined categories or classes based on their features.

Features: Input variables or attributes that describe the characteristics of the data points.

Classes: Categories or labels that the data points belong to.

Classifier: Machine learning algorithm used to learn the relationship between input features and classes and make predictions on new data.

Applications of Classification:

Email Spam Detection: Classify incoming emails as spam or non-spam based on their content and features.

Medical Diagnosis: Predict the presence or absence of a disease based on patient symptoms, medical history, and diagnostic tests.

Sentiment Analysis: Determine the sentiment of text documents, such as reviews or social media posts, as positive, negative, or neutral.

Credit Risk Assessment: Classify loan applicants as low, medium, or high risk based on their credit history, income, and financial data.

Machine learning tasks

Regression: Predicting continuous values or numerical outcomes based on input features.

Features: Independent variables or attributes that influence the target variable.

Target Variable: Dependent variable or outcome that we want to predict.

Regression Model: Mathematical function that maps input features to the target variable.

Application fields:

Stock Price Prediction: Forecast future stock prices based on historical market data, economic indicators, and company performance metrics.

Demand Forecasting: Predict consumer demand for products or services based on historical sales data, marketing efforts, and external factors.

House Price Estimation: Estimate the market value of residential properties based on features such as location, size, and amenities.

Weather Forecasting: Predict future weather conditions such as temperature, precipitation, and wind speed based on historical climate data and atmospheric variables.

Machine learning tasks

Clustering: Grouping similar data points together into clusters based on their inherent characteristics or patterns.

Data Points: Observations or instances in the dataset that are grouped based on similarity measures.

Centroids: Representative points within each cluster that summarize the characteristics of the cluster.

Distance Metric: Measure of similarity or dissimilarity between data points, often computed using Euclidean distance, Manhattan distance, or cosine similarity.

Applications of Clustering:

Customer Segmentation: Group customers with similar behaviors, preferences, or demographics for targeted marketing strategies.

Image Segmentation: Divide images into meaningful regions or segments for object recognition, image compression, and computer vision tasks.

Anomaly Detection: Identify outliers or unusual patterns in data that deviate from normal behavior.

Document Clustering: Organize text documents into clusters based on topics, themes, or content similarity for information retrieval and categorization.

Market Basket Analysis: Discover associations and patterns in transaction data to understand purchasing behavior and recommend related products.

Machine learning tasks

Anomaly Detection: Identifying outliers or unusual patterns in data that deviate from normal behavior.

Normal Behavior: Baseline or typical patterns of behavior observed in the data under normal operating conditions.

Anomalies: Data points or events that deviate from normal behavior and may indicate potential errors, fraud, or unusual activity.

Detection Methods: Algorithms and techniques used to identify anomalies based on statistical analysis, machine learning, or domain-specific rules.

Applications of Anomaly Detection:

Fraud Detection: Identify fraudulent transactions, activities, or behavior in financial transactions, cybersecurity, insurance claims, and healthcare billing.

Network Intrusion Detection: Detect unauthorized access, malicious attacks, or suspicious activity in computer networks and systems.

Equipment Failure Prediction: Predict potential failures or malfunctions in machinery, equipment, or infrastructure based on abnormal sensor readings or operational parameters.

Health Monitoring: Monitor physiological data, patient vital signs, or medical imaging to detect anomalies indicative of disease, infection, or health risks.

Machine learning tasks

Dimensionality Reduction: Reducing the number of input features while retaining relevant information to improve model efficiency and interpretability.

High-dimensional datasets often suffer from the **curse of dimensionality**, leading to increased computational complexity, overfitting, and reduced interpretability.

Dimensionality reduction helps alleviate these issues by extracting the **most relevant features** and reducing **noise** and **redundancy** in the data.

Feature Selection: Selecting a subset of the original features based on their relevance to the target variable or predictive power.

Feature Extraction: Creating new, lower-dimensional features that capture the most important information in the data.

Applications of Dimensionality Reduction:

Data Visualization: Visualize high-dimensional data in two or three dimensions for exploratory analysis and interpretation.

Feature Engineering: Create informative and concise features for downstream machine learning tasks, such as classification, regression, and clustering.

Image and Signal Processing: Reduce the dimensionality of image and signal data for compression, denoising, and feature extraction.

Text Mining and Natural Language Processing (NLP): Extract semantic meaning and structure from text documents by reducing the dimensionality of word embeddings and document representations.

Why machine learning for software analysis

Handling Complexity

Modern software systems are highly complex, often consisting of **millions of lines of code** with intricate **dependencies** and **interactions**.

Machine learning algorithms excel at processing **large volumes** of data and identifying **complex patterns**, making them well-suited for **analyzing software systems of varying scales and complexities**.

Why machine learning for software analysis

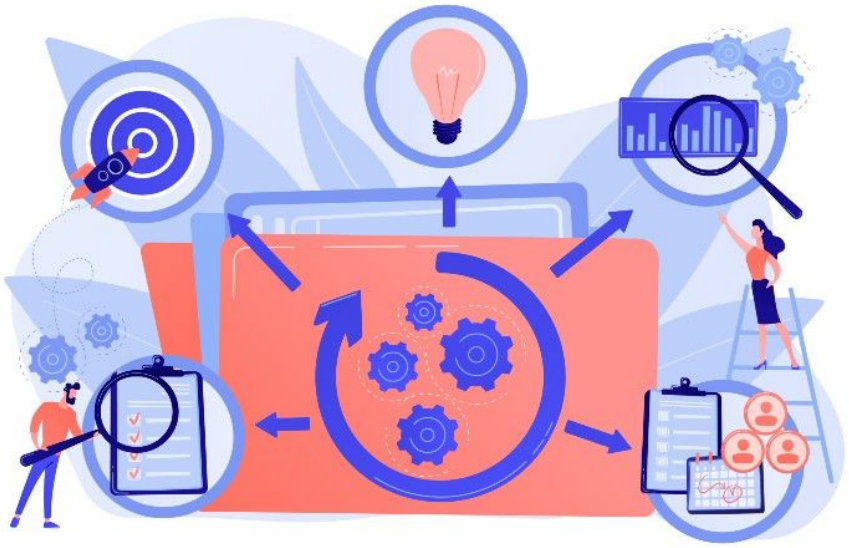
Automating Analysis Tasks

Traditional program analysis techniques often involve **manual inspection**, which can be **time-consuming** and **error-prone**, especially for large codebases.

Machine learning enables the **automation** of various program analysis tasks:

- bug detection,
- code optimization, and
- software testing,

allowing developers to focus on higher-level design and problem-solving.

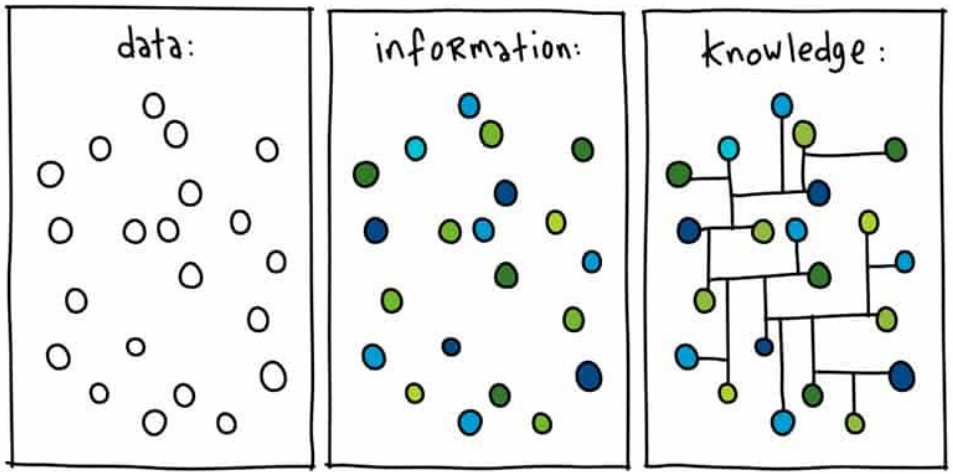


Why machine learning for software analysis

Learning from Data

Machine learning algorithms **learn from data**, which is abundant in software development projects.

By training on historical **code repositories**, **bug reports**, **version control histories**, and **user feedback**, machine learning models can capture valuable insights and patterns that **may not be apparent** through **manual analysis** alone.

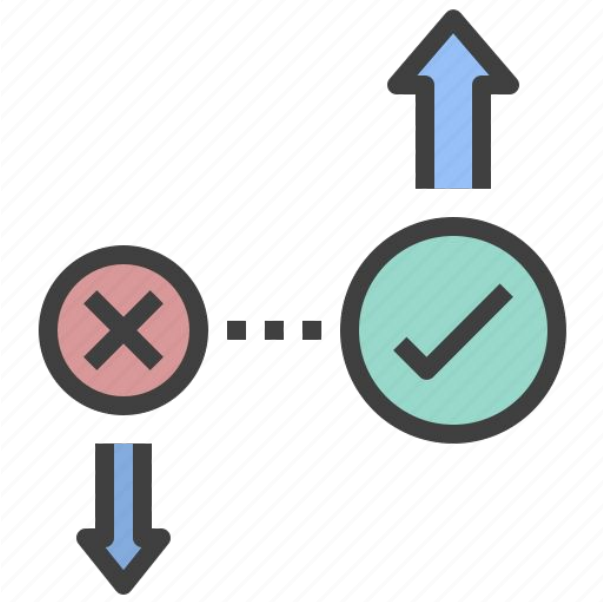


Why machine learning for software analysis

Improving Accuracy and Efficiency

Machine learning techniques can enhance the accuracy and efficiency of program analysis by identifying **subtle patterns** and **anomalies** in software behavior that may **be difficult for humans to detect**.

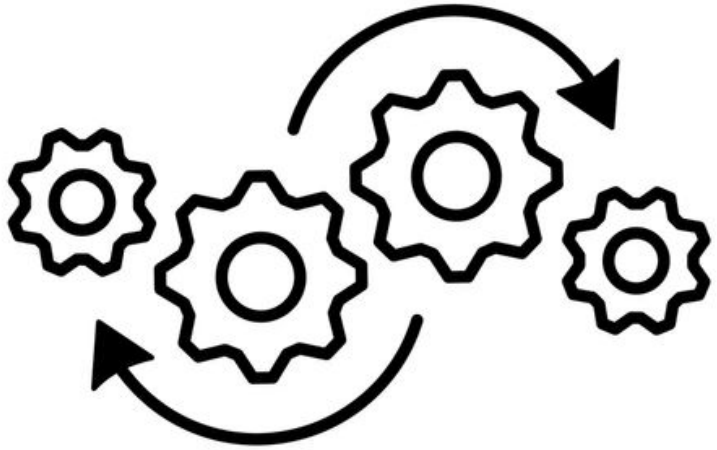
Additionally, machine learning models can **prioritize analysis efforts** by focusing on the most critical areas of the codebase, thereby improving overall development productivity.



Why machine learning for software analysis

Adapting to Change

Software systems evolve over time in response to changing requirements, technologies, and user needs. Machine learning models can adapt and evolve alongside software systems, continuously learning from new data and feedback to improve their performance and relevance in dynamic environments.



Why machine learning for software analysis

Predictive Capabilities

Machine learning enables predictive analytics in program analysis, allowing developers to anticipate and mitigate potential issues before they arise. For example, machine learning models can forecast software defects, identify performance bottlenecks, and predict code maintainability based on historical data and patterns.

Why machine learning for software analysis

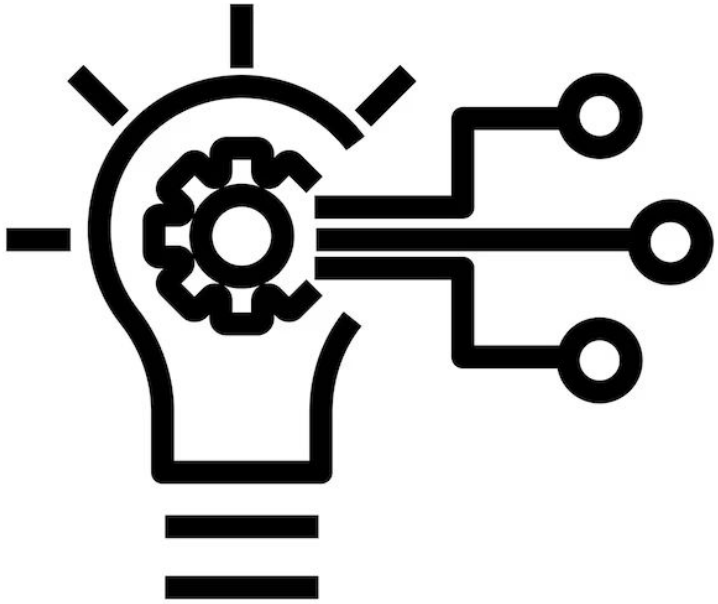
Supporting Decision-Making

Machine learning provides valuable insights and recommendations to support decision-making processes in software development. By analyzing software metrics, code patterns, and user behavior, machine learning models can inform decisions related to resource allocation, feature prioritization, and software architecture design.

Why machine learning for software analysis

Enabling Innovation

The application of machine learning in program analysis opens up new avenues for innovation in software development practices. From automated code generation to intelligent debugging tools, machine learning enables developers to explore novel approaches and solutions to complex software engineering challenges.



Is it really studied?

A survey on machine learning techniques applied to source code
Tushar Sharma, Maria Kechagia, Stefanos Georgiou, Rohit Tiwari, Indira Vats, Hadi Moazen, Federica Sarro
Journal of Systems and Software, 2024

Reports that:

- The use of ML techniques **is constantly increasing** for source code analysis.
- A wide range Software Engineering (SE) tasks involving source code analysis use ML.
- The study identifies challenges in the field and potential mitigations.
- They identify commonly used datasets and tools used in the field.

N. of papers per topic

Search terms and corresponding relevant studies found in the second round of phase 1.

Category	Search terms	#Studies
Vulnerability analysis	Feature learning in source code	9
	Vulnerability prediction in source code using machine learning	70
	Deep learning-based vulnerability detection	8
	Malicious code detection with machine learning	45
Testing	Word embedding in software testing	2
	Automated Software Testing with machine learning	12
	Optimal machine learning based random test generation	1
Refactoring	Source code refactoring prediction with machine learning	39
	Automatic clone recommendation with machine learning	14
	Machine learning based refactoring detection tools	16
	Search-based refactoring with machine learning	6
Quality assessment	Web service anti-pattern detection with machine learning	25
	Code smell prediction models	34
	Machine learning-based approach for code smells detection	17
	Software design flaw prediction	37
	Linguistic smell detection with machine learning	2
	Software defect prediction with machine learning	66
	Machine learning based software fault prediction	35
Program synthesis	Automated program repair methods with machine learning	45
	Program generation with machine learning	2
	Object-oriented program repair with machine learning	15
	Predicting patch correctness with machine learning	3
	Multihunk program repair with machine learning	9
Program comprehension	Autogenerated code with machine learning	6
	Commits analysis with machine learning	34
	Supplementary bug fixes with machine learning	9
Code summarization	Automatic source code summarization with machine learning	43
	Automatic commit message generation with machine learning	19
	Comments generation with machine learning	11
Code review	Security flaws detection in source code with machine learning	20
	Intelligent source code security review with machine learning	2
Code representation	Design pattern detection with machine learning	10
	Human-machine-comprehensible software representation	1
	Feature learning in source code	6
Code completion	Missing software architectural tactics prediction with machine learning	1
	Software system quality analysis with machine learning	6
	Package-level tactic recommendation generation in source code	3
	Identifier prediction in source code	13
	Token prediction in source code	29

...visually represented

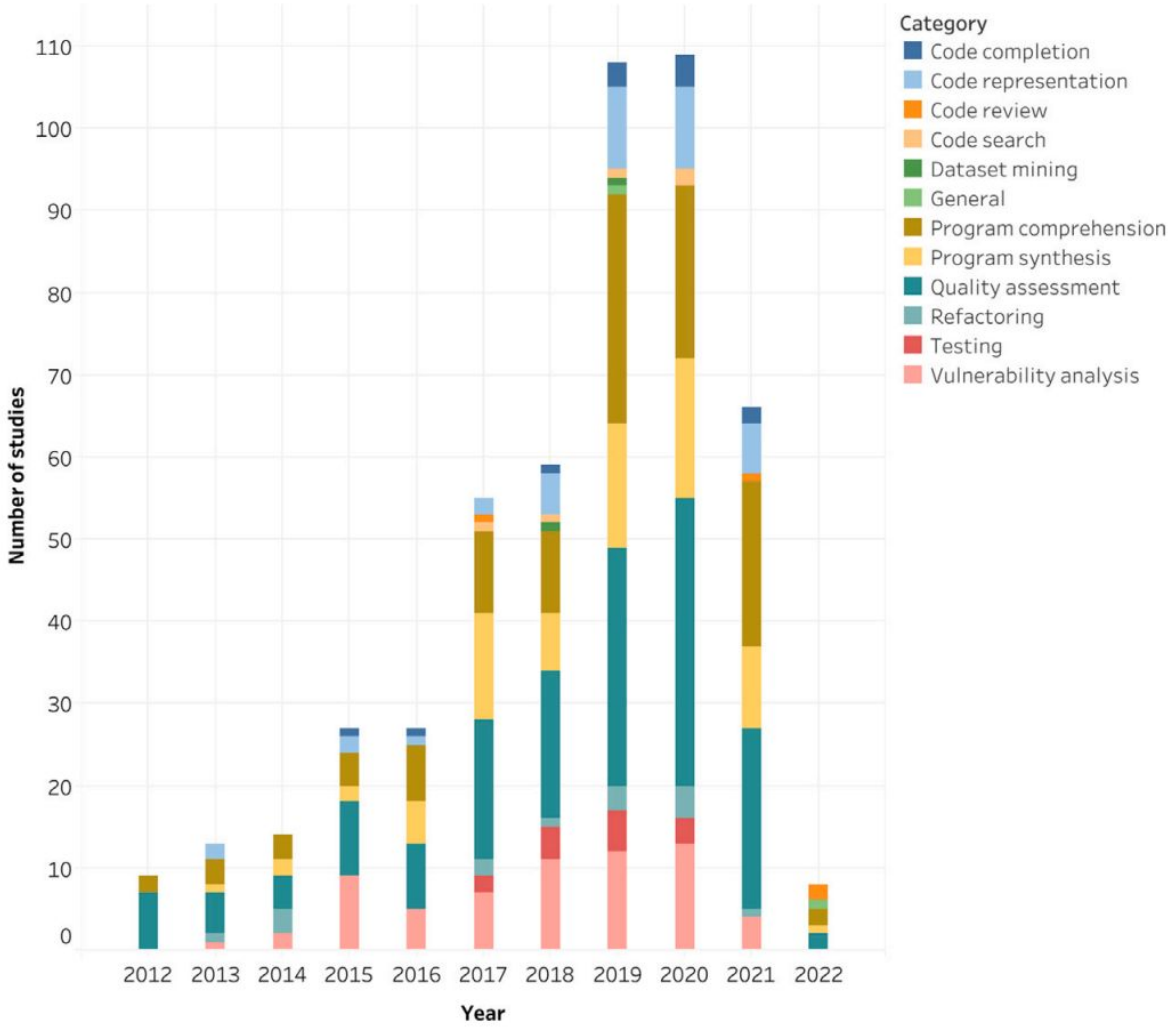


Fig. 2. Category-wise distribution of studies.

... another visualization

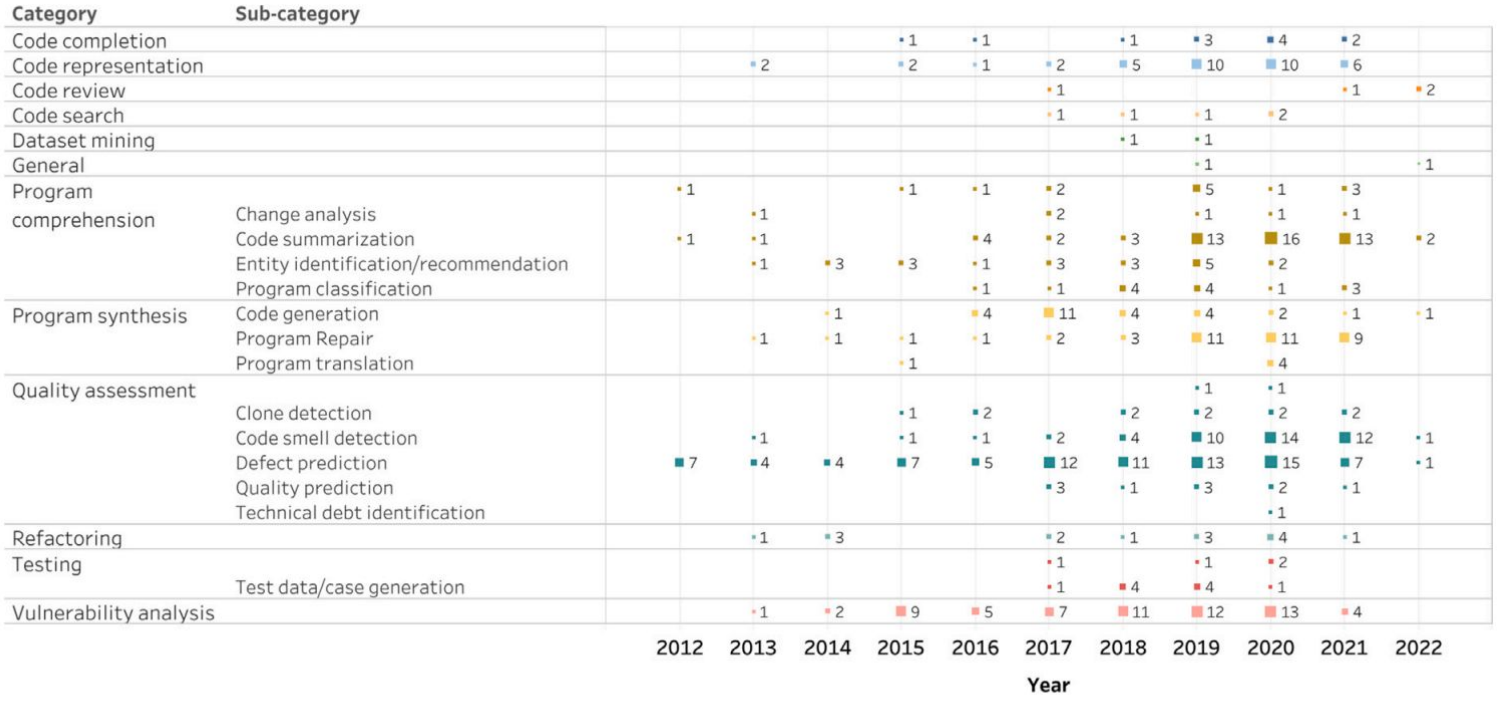


Fig. 3. Category- and sub-categories-wise distribution of studies.

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ML Methods

Table 3
Usage of ML techniques in the selected studies (Part-1).

				Code representation	Code completion	Code review	Code search	Dataset mining	Program comprehension	Program synthesis	Quality assessment	Refactoring	Testing	Vulnerability analysis	Total
Traditional Machine Learning	Model-based	Support Vector Regression	TML-SUP-MOD-SVR	0	0	0	0	0	0	0	1	0	1	0	2
		Support Vector Machine	TML-SUP-MOD-SVM	0	0	0	0	0	8	2	41	4	3	31	89
		Polynomial Regression	TML-SUP-MOD-POLY	0	0	0	0	0	0	0	1	0	0	0	1
		Logistic Regression	TML-SUP-MOD-LOG	0	1	0	0	1	2	2	22	4	1	8	41
		Locally Deep Support Vector Machines	TML-SUP-MOD-LDSVM	0	0	0	0	0	0	0	0	0	0	1	1
		Linear Regression	TML-SUP-MOD-LR	0	0	0	0	0	2	0	10	1	1	7	21
		Linear Discriminant Analysis	TML-SUP-MOD-LDA	1	1	0	0	0	0	0	0	0	0	2	4
		Least Median Square Regression	TML-SUP-MOD-LMSR	0	0	0	0	0	0	0	1	0	0	0	1
		LASSO	TML-SUP-MOD-LSS	0	0	0	0	0	0	0	0	0	0	1	1
	Tree-based	Boosted Decision Trees	TML-SUP-TR-BDT	0	0	0	0	0	0	0	0	0	0	1	1
		Classification And Regression Tree	TML-SUP-TR-CART	0	0	0	0	0	0	1	1	0	0	0	2
		Co-forest Random Forest	TML-SUP-TR-CRF	0	0	0	0	0	0	0	1	0	0	1	2
		Decision Forest	TML-SUP-TR-DF	0	0	0	0	0	0	0	0	0	0	1	1
		Decision Jungle	TML-SUP-TR-DJ	0	0	0	0	0	0	0	0	0	0	1	1
		Decision Stump	TML-SUP-TR-DS	0	0	0	0	0	0	0	0	0	0	2	2
		Decision Tree	TML-SUP-TR-DT	0	1	1	0	0	8	3	52	2	1	19	87
		Extra Trees	TML-SUP-TR-ET	0	0	0	0	0	0	0	3	0	0	0	3
		Gradient Boosted Trees	TML-SUP-TR-GBT	0	0	0	0	0	0	1	1	0	0	0	2
		Gradient Boosted Decision Tree	TML-SUP-TR-GBDT	0	0	0	0	0	0	0	0	0	0	2	2
		ID3	TML-SUP-TR-ID3	0	0	0	0	0	0	0	0	0	0	1	1
		Random Tree	TML-SUP-TR-RT	0	0	0	0	0	0	0	2	0	0	2	4
		Random Forest	TML-SUP-TR-RF	1	1	1	0	0	12	3	45	3	1	21	88
	Instance-based	COBWEB	TML-SUP-IN-CWEB	0	0	0	0	0	0	0	1	0	0	0	1
		KStar	TML-SUP-IN-KS	0	0	0	0	0	0	0	5	0	0	0	5
		K-Nearest Neighbours	TML-SUP-IN-KNN	0	0	0	0	0	3	0	13	0	1	9	26
	Probabilistic-based	Bayes Net	TML-SUP-PRO-BN	0	1	1	0	0	1	0	8	1	0	6	18
		Bayes Point Machine	TML-SUP-PRO-BPM	0	0	0	0	0	0	0	0	0	0	1	1
		Bernoulli Naives Bayes	TML-SUP-PRO-BNB	0	0	0	0	0	0	0	3	0	0	2	5
		Gaussian Naive Bayes	TML-SUP-PRO-GNB	0	0	0	0	0	0	0	5	0	0	1	6
		Graph random-walk with absorbing states	TML-SUP-PRO-GRASSHOPER	0	0	0	0	0	1	0	0	0	0	0	1
		Transfer Naive Bayes	TML-SUP-PRO-TNB	0	0	0	0	0	0	0	1	0	0	0	1
		Naive Bayes	TML-SUP-PRO-NB	0	0	0	0	0	7	1	40	2	2	16	68
		Multinomial Naive Bayes	TML-SUP-PRO-MNB	0	0	0	0	0	0	0	3	1	0	1	5
	Rule-based	Decision Table	TML-SUP-RUL-DTB	0	0	0	0	0	0	0	1	0	0	0	1
		Ripper	TML-SUP-RUL-Ripper	0	0	0	0	0	1	0	10	0	0	4	15
	Learn-to-Rank	Diverse Rank	TML-SUP-LR-DR	0	0	0	0	0	1	0	0	0	0	0	1
	Clustering	Hierarchical Clustering	TML-UNSUP-CLS-HC	0	0	0	0	0	0	1	0	0	0	0	1
		KMeans	TML-UNSUP-CLS-KM	0	0	0	0	0	0	0	1	0	0	1	2
	Other	Fuzzy Logic	TML-UNSUP-OTH-FL	0	0	0	0	0	0	0	1	0	0	0	1
		Maximal Marginal Relevance	TML-UNSUP-OTH-MMR	0	0	0	0	0	1	0	0	0	0	0	1
		Latent Dirichlet Allocation	TML-UNSUP-OTH-LDAA	0	0	0	1	0	9	0	3	1	0	0	14
	Evolutionary	Gene Expression Programming	TML-EVO-GEP	0	0	0	0	0	0	0	2	0	0	0	2
		Genetic Programming	TML-EVO-GP	0	0	0	0	0	0	0	3	0	0	0	3
	Meta-algorithms / General Approaches	AdaBoost	TML-GEN-AB	0	0	0	0	0	0	0	13	2	2	4	21
		Binary Relevance	TML-GEN-BR	0	0	0	0	0	0	0	1	0	0	0	1
		Classifier Chain	TML-GEN-CC	0	0	0	0	0	0	0	1	0	0	0	1
		Cost-Sensitive Classifer	TML-GEN-CSC	0	0	0	0	0	0	0	2	0	0	0	2
		Ensemble Learning	TML-GEN-EL	0	0	0	0	0	1	0	3	0	0	0	4
		Ensemble Learning Machine	TML-GEN-ELM	0	0	0	0	0	0	0	1	0	0	0	1
		Gradient Boosting	TML-GEN-GB	0	0	0	0	0	2	1	8	0	0	3	14
		Gradient Boosting Machine	TML-GEN-GBM	0	0	0	0	0	1	0	1	0	0	1	3
		Statiscal Machine Translation	TML-GEN-SMT	0	0	0	0	0	0	1	0	0	0	0	1
		Neural Machine Translation	TML-GEN-NMT	1	1	0	0	0	0	5	1	0	0	0	8
		Multiple Kernel Ensemble Learning	TML-GEN-MKEL	0	0	0	0	0	0	0	1	0	0	0	1
		Neural Machine Model	TML-GEN-NLM	0	0	0	0	0	1	0	0	0	0	0	1
		Majority Voting Ensemble	TML-GEN-MVE	0	0	0	0	0	0	0	1	0	0	0	1
		Bagging	TML-GEN-B	0	0	0	0	0	0	0	11	0	0	1	12
		LogitBoost	TML-GEN-LB	0	0	0	0	0	0	0	4	1	0	1	6
		Kernel Based Learning	TML-GEN-KBL	0	0	0	0	0	0	0	1	0	0	0	1

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ML methods

Table 4
Usage of ML techniques in the selected studies (Part-2).

				Code representation	Code completion	Code review	Code search	Dataset mining	Program comprehension	Program synthesis	Quality assessment	Refactoring	Testing	Vulnerability analysis	Total
Deep Learning	RNN	Bidirectional GRU	DL-RNN-Bi-GRU	1	0	0	0	0	0	0	0	0	0	1	2
		Bidirectional RNN	DL-RNN-Bi-RNN	0	0	0	0	0	1	0	0	0	0	0	1
		Bidirectional LSTM	DL-RNN-Bi-LSTM	0	0	0	0	0	5	2	2	0	0	3	12
		Gated Recurrent Unit	DL-RNN-GRU	1	1	0	0	0	9	0	1	0	0	3	15
		Hierarchical Attention Network	DL-RNN-HAN	1	0	0	0	0	1	0	0	0	0	0	2
		Recurrent Neural Network	DL-RNN-RNN	3	3	0	1	0	9	5	0	0	0	2	23
		Pointer Network	DL-RNN-PN	0	1	0	0	0	0	0	0	0	0	0	1
		Modular Tree Structured RNN	DL-RNN-MTN	1	1	0	0	0	0	0	0	0	0	0	2
		Long Short Term Memory	DL-RNN-LSTM	3	4	0	1	0	21	10	6	1	1	5	52
	Graph	Gated Graph Neural Network	DL-GRA-GGNN	0	0	0	1	0	0	2	0	0	0	0	3
		Graph Convolutional Networks	DL-GRA-GCN	0	0	0	0	0	0	0	0	0	0	1	1
		Graph Interval Neural Network	DL-GRA-GINN	1	0	0	0	0	0	0	0	0	0	0	1
		Graph Neural Network	DL-GRA-GNN	2	0	0	0	0	3	0	1	0	0	0	6
	CNN	Convolutional Neural Network	DL-CNN-CNN	3	0	0	1	0	4	2	8	0	0	5	23
		Faster R-CNN	DL-CNN-FR-CNN	0	0	0	0	0	0	0	0	0	1	0	1
		Text-CNN	DL-CNN-TCNN	0	0	0	0	0	0	0	0	0	0	1	1
	Vanilla	Artificial Neural Network	DL-ANN	0	1	0	0	0	2	1	21	3	1	3	32
		Autoencoder	DL-AE	1	0	0	0	0	0	0	2	0	0	1	4
		Deep Neural Network	DL-DNN	2	0	0	1	0	6	2	5	1	0	4	21
		Regression Neural Network	DL-RGNN	0	0	0	0	0	0	0	1	0	0	0	1
		Multi Level Perceptron	DL-MLP	0	0	0	0	0	2	3	14	1	1	5	26
	Transformers	Bidirectional Encoder Representation from T	DL-XR-BERT	0	0	0	0	0	1	1	0	0	0	0	2
		CodeBERT	DL-XR-CodeBERT	1	0	0	0	0	0	1	0	0	0	0	2
		Generative Pretraining Transformer for Code	DL-XR-GPT-C	0	0	0	0	0	0	1	0	0	0	0	1
		Transformer	DL-XR-TF	2	1	2	0	0	4	3	1	0	0	0	13
	Other	Bilateral Neural Network	DL-OTH-BiNN	0	0	0	0	0	0	0	1	0	0	0	1
		Cascade Correlation Network	DL-OTH-CCN	0	0	0	0	0	0	0	1	0	0	0	1
		Code2Vec	DL-OTH-Code2Vec	5	0	0	0	0	1	0	0	0	0	0	6
		Deep Belief Network	DL-OTH-DBN	0	0	0	0	0	0	0	2	0	0	2	4
		Doc2Vec	DL-OTH-Doc2Vec	0	0	0	0	0	0	0	0	0	0	2	2
		Encoder-Decoder	DL-OTH-EN-DE	3	1	0	0	0	17	10	0	0	0	0	31
		FastText	DL-OTH-FT	0	0	0	0	0	0	0	0	0	0	1	1
		Functional Link ANN	DL-OTH-FLANN	0	0	0	0	0	0	0	1	0	0	0	1
		Guassian Encoder-Decoder	DL-OTH-GED	0	0	0	0	0	0	1	0	0	0	0	1
		Global Vectors for Word Representation	DL-OTH-Glove	1	0	0	0	0	0	0	0	0	0	0	1
		Word2Vec	DL-OTH-Word2Vec	0	0	0	0	0	0	0	1	0	0	0	1
		Sequence-to-Sequence	DL-OTH-Seq2Seq	1	0	0	0	0	2	2	0	0	1	0	6
		Reverse NN	DL-OTH-ReNN	0	0	0	0	0	0	0	1	0	0	0	1
		Residual Neural Network	DL-OTH-ResNet	0	0	0	0	0	0	1	1	0	0	0	2
		Radial Basis Function Network	DL-OTH-RBFN	0	0	0	0	0	0	0	1	0	0	0	1
		Probabilistic Neural Network	DL-OTH-PNN	0	0	0	0	0	0	0	1	1	0	0	2
		Node2Vec	DL-OTH-Node2Vec	0	0	0	0	0	0	0	1	0	0	0	1
		Neural Network for Discrete Goal	DL-OTH-NND	0	0	0	0	0	0	0	2	0	0	0	2
Reinforcement Learning		Double Deep Q-Networks	RL-DDQN	0	0	0	0	0	0	0	0	0	1	0	1
		Reinforcement Learning	RL-RL	0	0	0	0	0	3	0	0	0	0	0	3
Others	Hybrid	Adaptive neuro fuzzy inference system	OTH-HYB-ANFIS	0	0	0	0	0	0	0	1	0	0	0	1
	Optimization Techniques	Expectation Minimization	OTH-OPT-EM	0	0	0	0	0	0	0	1	0	0	0	1
		Gradient Descent	OTH-OPT-GD	0	0	0	0	0	0	1	0	0	0	0	1
		Stochastic Gradient Descent	OTH-OPT-SGD	0	0	0	0	0	0	0	2	0	0	0	2
		Sequential Minimal Optimization	OTH-OPT-SMO	0	0	0	0	0	0	0	5	0	0	1	6
		Particle Swarm Optimization	OTH-OPT-PSO	0	0	0	0	0	0	0	1	0	0	0	1

Programming languages

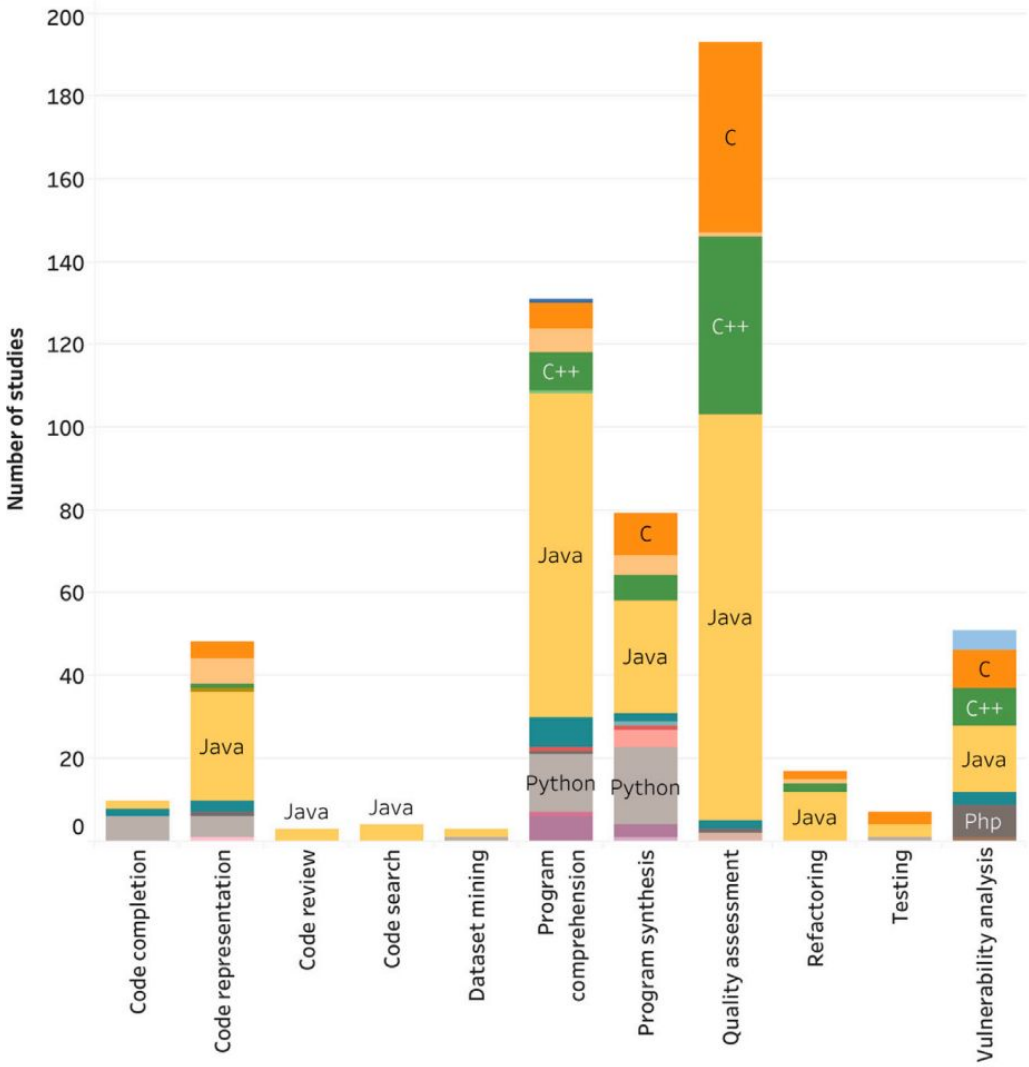

Fig. 6. Target programming languages for each considered category.

Conferences and journals

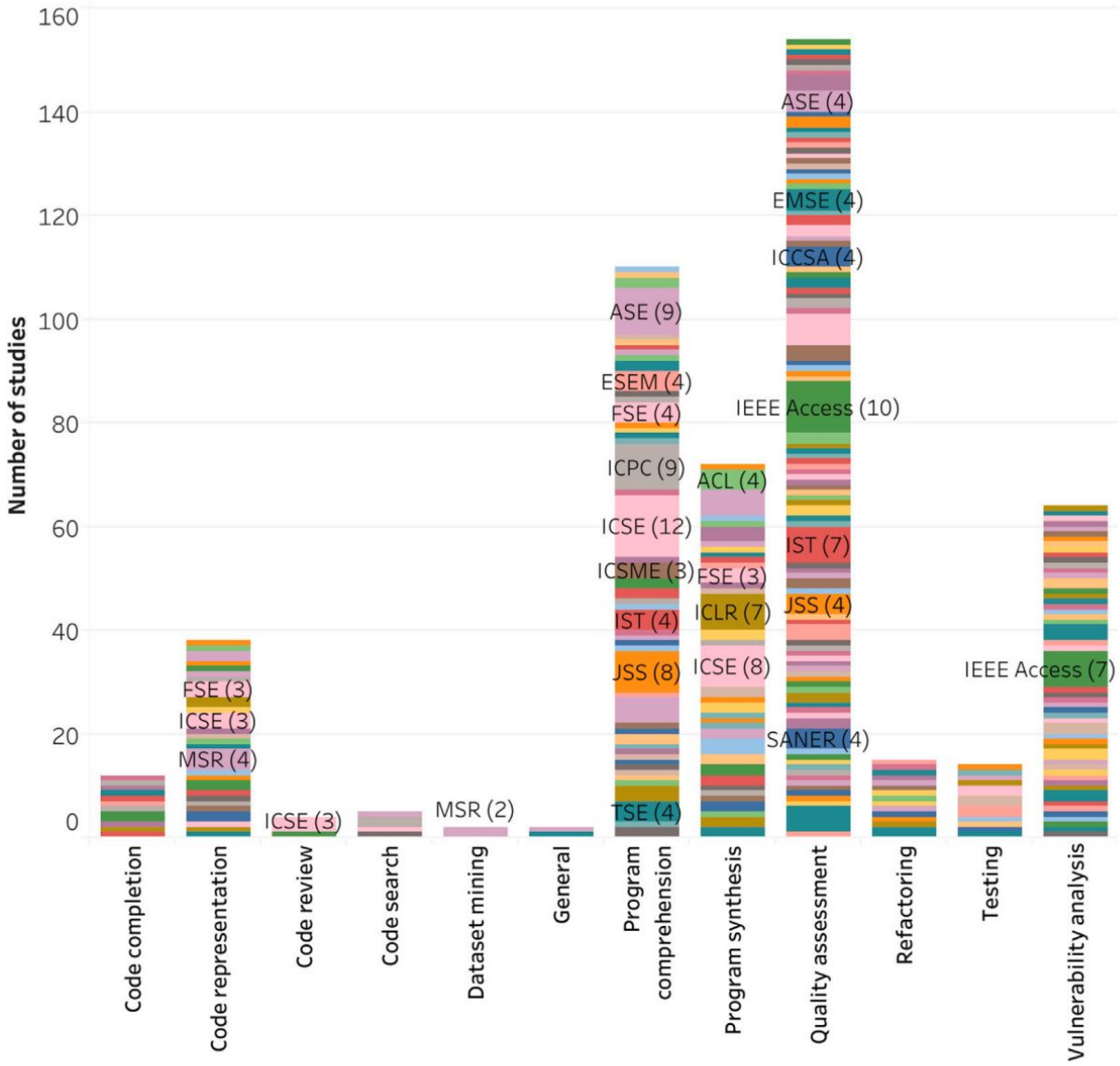

Fig. 5. Top venues for each considered category.

Paper citations

Table 5
Popular models proposed in the selected studies.

Model	#Citations	Model	#Citations
Transfer Naive Bayes (Ma et al., 2012)	513	Code Generation Model (Yin and Neubig, 2017)	651
Path-based code representation (Alon et al., 2018)	230	Multi-headed pointer network (Vasic et al., 2019)	128
Inst2Vec (Ben-Nun et al., 2018)	234	Code-NN (Iyer et al., 2016)	681
DeepCoder (Balog et al., 2016)	612	ASTNN (Zhang et al., 2019)	498
Code2Seq (Alon et al., 2019a)	643	Code2Vec (Alon et al., 2019b)	1093
TBCNN (Mou et al., 2016)	695	Program as graph model (Brockschmidt et al., 2019)	159
SLAMC (Nguyen et al., 2013)	130	Coding criterion (Peng et al., 2015)	128
TransCoder (Roziere et al., 2020)	115	TreeGen (Sun et al., 2020)	124
Codex (Chen et al., 2021b)	897	AlphaCode (Li et al., 2022)	317

To conclude

Software solutions are all around us, therefore we need good software.

Software analysis allows us to improve our software but with some limitations

Some of these limitations can be overcome adopting Machine Learning solutions since it allows handling complex data, in a more efficient way, with higher accuracy.

In addition, Machine Learning for Software Analysis is an active research stream where various techniques has been applied on different software analytics tasks, e.g., vulnerability and defect detection, code representation, etc.