

# Artificial Intelligence for the Automated Synthesis and Validation of Programs

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## **Abstract**

Programming errors, commonly known as *bugs*, cause undesired software behavior making a program crash or enabling malicious users to access private data. Just for 2017, the cumulative cost of software bugs is worldwide estimated in more than one trillion US dollars.

This research project aims to investigate a novel approach for software development, that leverages Artificial Intelligence, to reduce the chances of introducing programming errors. The project proposes to address **automatic program synthesis and validation starting from *input-output* tests cases, and using *AI planning* as a problem solving engine**. Our current work on this particular research topic is the recipient of the *2016 distinguished paper award* at IJCAI, the main international conference on Artificial Intelligence.

## 1 Historial científico-técnico del Equipo de Investigadores (Apartado 5.1, bases de la convocatoria)

The project will be developed within the *Group of Reasoning on Planning and Scheduling* (GRPS, <http://users.dsic.upv.es/grupos/grps/>), that is part of the *Department of Computer Systems and Computation* of the UPV. In the last 10 years, the GRPS has led 3 research projects of the Spanish national research plan on *AI planning*. Further, the GRPS has developed its own AI planner, that is participating at the International Planning Competition (IPC-2018, <https://ipc2018.bitbucket.io>).

The research group for this project comprises: 1 principal investigator, 1 senior researcher and 1 PhD student. All of them are GRPS members.

### 1.1 Principal Investigator: Sergio Jiménez Celorrio

Sergio is a *Ramón y Cajal* fellow at the Universitat Politècnica de València (2017-2022). Previously, Sergio was a post-doc at the University of Melbourne and a *Juan de la Cierva* fellow at the Universitat Pompeu Fabra de Barcelona. From 2004 to 2013 Sergio was assistant lecturer at the Universidad Carlos III de Madrid where he obtained the *Distinguished Thesis Award 2011*. Sergio is co-organizer of the 7<sup>th</sup> *International Planning Competition* and program committee at top international conferences on Artificial Intelligence.

His research addresses complex *decision-making* problems with innovative integrations of two *Artificial Intelligence* paradigms: *Machine Learning* and *AI Planning*. His research trajectory on this topic has produced a novel approach to the synthesis of programs, grammars and controllers for autonomous behavior and is the recipient of the *2016 distinguished paper award* at the International Joint Conference on Artificial Intelligence (IJCAI)<sup>1</sup>, the main international conference on *Artificial intelligence*.

His top five scientific contributions are:

1. Inductive programming with classical planning. [1], [2], [3].
2. Generalization in AI planning. [4], [5], [6].
3. Learning to relieve the *knowledge acquisition bottleneck* in AI planning. [7], [8], [9], [10], [11].
4. Machine learning for addressing the *curse of dimensionality* in AI planning. [12], [13], [14].
5. Evaluation in AI planning. [15], [16], [17].

General quality indicators of scientific research: **373 citations** (287 since 2013) and **h-index 11**. *Source google scholar*.

### 1.2 Senior Researcher: Eva Onaindia

Eva Onaindia is a *Full Professor* at the Universitat Politècnica of València. She leads the GRPS where she conducts research in Artificial Intelligence, Automated Planning, Causal Model Learning and Recommender Systems.

<sup>1</sup> IJCAI is ranked as *A+* by the CORE rank and with *h5-index* 43 at Google Scholar

Eva has published numerous articles in top-tier specialized conferences such as the International Joint Conference on Artificial Intelligence (IJCAI), Autonomous Agents and Multi Agent Systems (AAMAS), International Conference on Planning and Scheduling (ICAPS) or European Conference on Artificial Intelligence (ECAI), among others; and scientific journals related to topics of Artificial Intelligence, Planning, Argumentation and Recommender Systems such as IEEE Intelligent Systems, Information Sciences, Engineering Applications of Artificial Intelligence, Knowledge and Information Systems or Applied Intelligence, among others.

She has led several National Research Projects as well as served on multiple ICAPS, AAAI, IJCAI and ECAI conferences as a member of the Program Committee and as a senior member. Eva is Editor-in-Chief of the journal AI Communications, a Review Board member of the journal Applied Intelligence and she will be Program co-chair of ICAPS 2019 (the main international conference on AI planning).

Eva Onaíndia has supervised so far a total of 9 PhD theses and she is currently supervising four doctoral students. She has also participated in many diverse scientific evaluation committees at national and international level. In the national scene, she has collaborated with National Agencies such as ANEP and ANECA and she has been member of different expert boards and scientific committees. At an international level, she has participated in the evaluation of research projects for Israel, Italy or Czech Republic.

Eva has also participated in several R&D and Innovation contracts: with the firm DESTINIA S.L. for the development of a tourist recommender system, and currently in the construction of a system for Electricity Price Forecasting aimed at energy savings (Ayuntamiento Llíria) using neural networks and data analysis techniques.

General quality indicators of scientific research: **1521 citations** (977 since 2013) and **h-index 22**. *Source google scholar.*

### 1.3 Researcher in training period: Diego Aineto

## 2 Estado del arte y objetivos específicos ( Apartado 5.2.i, bases de la convocatoria)

This research project will **investigate the integration of *AI planning* into the *Test Driven Development* paradigm for the automatic synthesis and validation of programs**. Here we briefly introduce the technology we will rely on along the project:

- **AI Planning (AIP)** is the Artificial Intelligence component that studies the synthesis of sets of actions to achieve some given objectives [18]. AIP arose in the late '50s from converging studies into *combinatorial search*, *theorem proving* and *control theory* and now, is a well formalized paradigm for problem solving with algorithms that scale-up reasonably well. State-of-the-art planners are able to synthesize plans with hundreds of actions in seconds time [19]. The mainstream approach for AIP is *heuristic search* with heuristics derived automatically from the problem representation [20, 21]. Current planners add other ideas to this like *novelty exploration* [22], *helpful actions* [23], *landmarks* [24], and *multiqueue best-first search* [25] for combining different heuristics.
- **Test driven development (TDD)** [26] is a popular paradigm for software development that is frequently used in *agile methodologies* [27]. In TDD, test cases are created before the program code is written and they are run against the code during the development, e.g. after a code change via an automated process. When all tests pass, the program code is considered *complete* while when a test fails, it pinpoints a *bug* that must be fixed from the program code. Tests cases are a natural form of program specification, programmers often claim '*code that is difficult to test is poorly written*'. Further, tests alert programmers of bugs before handing the code off to clients (the cost of finding a bug when the code is first written is considerably lower than the cost of detecting and fixing it later). Last but not least, writing a thorough set of tests cases forces programmers to think through inputs, outputs, and error conditions of programs.

Now we review the two most successful approaches for program synthesis:

- **Programming by Example (PbE)**. PbE techniques have already been deployed in the real world and are part of the FLASH FILL feature of Excel in Office 2013 that generates programs for string transformation [28]. In this case the set of synthesized programs are represented succinctly in a restricted Domain-Specific Language (DSL) using a data-structure called version space algebras [29]. The programs are computed with a domain-specific search that implements a divide and conquer approach. The approach posed in this research project falls into this category.
- **In Programming by Sketching (PbS)** programmers provide a partially specified program, i.e. a program that expresses the high-level structure of an implementation but that leaves low level details undefined to be determined by the synthesizer [30]. This form of program synthesis relies on a programming language called SKETCH, for sketching partial programs. PbS implements a counterexample-driven iteration over a synthesize-validate loop built from two communicating SAT solvers, the

inductive synthesizer and the validator, to automatically generate test inputs and ensure that the program satisfy them. Despite, in the worst case, program synthesis is harder than NP-complete, this counterexample-driven search terminates on many real problems after solving only a few SAT instances [31].

Closely related to the aims of the project is also the work on the synthesis and validation of *Finite State Controllers* (FSCs) [32]. The state-of-the-art algorithms for computing FSCs follow a *top-down* approach that interleaves *programming* the FSC with validating it [33]. To keep the computation of FSCs tractable, they limit the space of possible solutions bounding the maximum size of the FSC. The computation of FSCs includes works that compile this task into another forms of problem solving so they benefit from the last advances on off-the-shelf solvers (e.g. *classical planning* [34], *conformant planning* [35], *CSP* [36] or a *Prolog program* [37]).

Finally the generation of programs from examples is a research question also addressed in the classic AI field of *Inductive Logic Programming* (ILP) [38, 39]. ILP arises from the intersection of *Machine Learning* and *Logic Programming* and deals with the development of inductive techniques to learn a given target concept, expressed as a logic program, from examples and background knowledge, that are expressed as logic facts.

(Please find the full list of *references* at the end of the document)

### 3 Metodología y Plan de Trabajo ( Apartado 5.2.ii, bases de la convocatoria)

Our current research already shows that AI planners can synthesize programs for non trivial tasks like sorting lists, traversing graphs or manipulating strings [3, 34, 40, 33]. Table 1 reports the time invested by the AI planner FD [24] to solve the following programming tasks: computing the  $n^{th}$  term of the *summatory* and *Fibonacci* series, *reversing* a list, *finding* an element (and the *minimum* element) in a list, *sorting* a list and traversing a binary tree.

Programming Task	Time (seconds)
Summatory	1
Fibonacci	5
Reverse	22
Find	336
Minimum	284
Sorting	30
Tree	165

Tab. 1: Time to synthesize the programs with the AI planner FD [24] on a processor *Intel Core i5 3.10GHz x 4* and with a 4GB memory bound.

#### 3.1 Synthesis and validation of TDD programs as AI planning

Given a *TDD programming* task our approach is modeling and solving it as it were an *AI planning* task.

Briefly the state variables of this AIP task are *fluents* of the kind:

- `var:=value`, that encode the program variables).
- `program(line):=instruction`, that encode the program lines.
- `pcounter:=line`, encoding the current program line.

The initial/goal states of the AIP task encode the initial/final values of the program variables according to the input/output tests of the TDD programming task.

Finally, program instructions are encoded using two kinds of AIP actions:

- *Programming actions*, that set an instruction on a given program line.
- *Execution actions*, execute the instruction set on a given program line.

We implement this encoding using standard planning languages, such as PDDL [41], so the AIP tasks resulting from our encoding can be solved with off-the-shelf planners, like FD [24]. The programs synthesized with this approach are guaranteed to be bug-free over given sets of *input-output* tests cases.

Interestingly, our PDDL encoding allows also program validation by (1), specifying the lines of the program to validate in the initial state of the AIP task and (2), disabling the mentioned *programming actions*.

### 3.2 Evaluation

The performance of our approach for the synthesis and validation of TDD programs will be evaluated in two kinds of programming tasks:

- *Theoretical benchmarks*: Programming tasks for the computation of mathematical/logic series, string manipulation and for the management of classic data structures such as *lists*, *queues*, *stacks*, *trees*, *heaps*, ...
- *Real-world benchmarks*: Practical programming tasks coming from *activity recognition* and *recommendation* domains. The GRPS group is currently leading a four-year research project from the Spanish National plan in which *activity recognition* and *activity recommendation* are applied to different real-world domains such as *tourism*, *domotics*, *traffic control* and *robotics*. We plan to evaluate our approach in programming and validation tasks that result from these domains.

### 3.3 Two-year workplan

We designed a 24-month workplan plan for the **development of a user-interactive program synthesizer** that (1), takes as input a set of test cases that specify the TDD programming task to solve and (2), outputs a program source code that passes these tests with a bug-free guarantee. Figure 1 details the proposed 24-month timeline for the project.

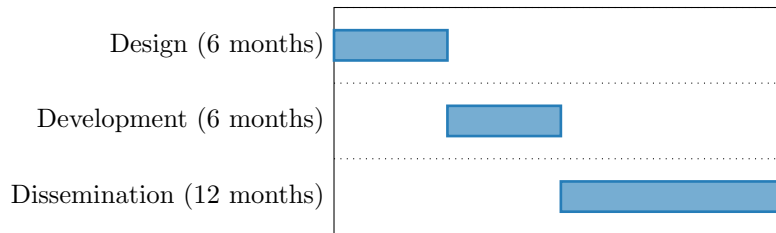


Fig. 1: Workplan for developing a user-interactive program synthesizer/validator.

#### 1. T1. System design (months 1-6)

- Design of the user-interaction for the test-case specification. Programming tasks are specified as a set of *input-output* tests cases plus the available instruction set.
- Experimental design. Experiments will comprise taking time and memory measurements to evaluate the resources required by our approach to solve the given TDD programming tasks.
- Evaluation of different AI planners available, with special attention to the planners that get the best results at the IPC-2018.

**Deliverable:** Technical report with the specifications of the system design.

#### 2. T2. Development of the system architecture (months 7-12)

- The programming-into-planning compiler (*Compiler 1*). This component parses the *TDD programming task* and produces an *AIP task* encoded in the standard planning language PDDL.

- (b) The plan-into-program compiler (*Compiler 2*). This component extracts the program code and the corresponding validation certificate from the solution plan produced by an off-the-shelf AI planner.

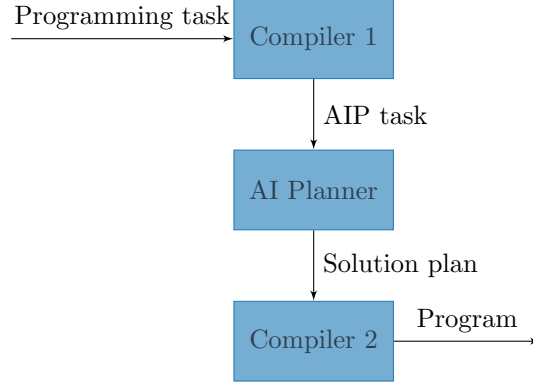


Fig. 2: The system architecture.

**Deliverable:** Open repository with the source code of the system architecture.

### 3. T3. Experiments and dissemination of results (months 13-24).

- (a) Reporting the experimental performance of our AIP approach for solving TDD programming tasks.
- (b) Dissemination of the obtained theoretical and empirical results by submitting papers to top international conferences and journals in AI.

**Deliverable:** Final report with the obtained conclusions and produced publications.

Tasks (**T1-T3**) will be developed by the three mentioned members of the research group: Sergio Jiménez, Eva Onaindia and Diego Aineto. In addition, we plan to hire a master student to assist in the completion of task **T3(a)**.



#### 4 Objetivos específicos del Proyecto ( Apartado 5.2.iii, bases de la convocatoria)

Figure 3 shows a synthesized program for traversing linked lists. The program is pictured as a *finite state machine*: The machine nodes mount to the different program lines while edges are tagged with a *condition/instruction* label, that denotes the condition (over the program variables) under which program instructions are taken.

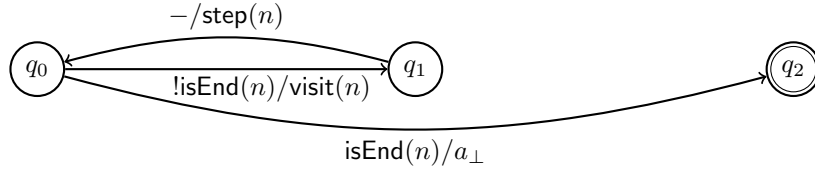


Fig. 3: Synthesized program to solve the programming task of traversing a linked list ( $n$  is a variable that points to a node of the linked list).

The objective of this project is to study the performance of our approach for the automated synthesis and validation of programs that are characterized by these tree dimensions: number of *program lines*, number of *program variables* and size of the available *instruction set*. For instance, the program of Figure 3 is generated using three program lines, one observable variable `isEnd(n)` with Boolean domain, and a instruction set that comprises two instructions (`visit(n)` that marks the list node assigned to  $n$  as *visited* and `step(n)` that advances  $n$  to the next node in the linked list).

In more detail, the two specific objectives of this project are:

- To study the performance of our Artificial Intelligence approach for the **synthesis of programs** up to: **10 program lines**, **10 variables** with binary domain and, an instruction set that comprises **10 instructions**.
- To study the performance of our Artificial Intelligence approach for the **validation of programs** up to: **15 program lines**, **20 variables** with binary domain and, an instruction set that comprises **10 instructions**.

In both cases the performance of our approach will be evaluated with regard to the **computation time** and **memory** invested in the synthesize and the validation of the aimed programs.

Despite setting bounds for the programs size and kind, note that challenging programming tasks can be addressed using *problem decomposition*. With this regard, our AIP encoding already supports callable procedures to decompose a given programming task into simpler modules and to enable recursive solutions [34, 33].

## 5 Beneficios del proyecto. Difusión y Explotación en su caso de los Resultados.

AIP has recently shown successful in *program testing* to generate *attack plans* that completed non-trivial software security tests [42, 43, 44, 45]. Promising research opportunities come from the application of AIP to *program synthesis* given that, *program synthesis* with a tests base, can also be seen as a dual to *program testing*.

This project will provide new insights into the current understanding of how Artificial Intelligence can assist programmers in the software development. Research in AI algorithms is too often tested with laboratory problems and AIP is not an exception. Most of the new planning algorithms are only tested within the benchmarks of the International Planning Competition [46]. This project will also help to meet the computational and expressiveness limits of AI planners when addressing real-world programming tasks.

The expected benefits of this project are three-fold:

1. The definition of **effective metrics for assessing how well a given program covers a set of input-output test cases.**
2. An empirical study on the performance of the state-of-the-art AI planners for the *Synthesis and Validation of Programs*.
3. The development, evaluation and dissemination of **open source software for the *Synthesis and Validation of Programs*.**

Our current work on *program synthesis* with AIP already produced **publications at top international conferences on Artificial Intelligence** [47, 40, 33, 34] and is the recipient of the *2016 distinguished paper award* at the International Joint Conference on Artificial Intelligence, the main international conference on *Artificial intelligence*.

The scientific results obtained during the development of the project will also be submitted to top Artificial Intelligence conferences (such as IJCAI, AAAI, ICML and ICAPS) and to the main journals in the AI field (such as AIJ, JMLR and JAIR).

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