ArduCode: Predictive Framework for Automation Engineering

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Abstract
Automation engineering is the task of integrating, via software, various sensors, actuators, and controls for automating a real-world process. Today, automation engineering is supported by a suite of software tools including integrated development environments (IDE), hardware configurators, compilers, and runtimes. These tools focus on the automation code itself, but leave the automation engineer unassisted in their decision making. This can lead to increased time for software development because of imperfections in decision making leading to multiple iterations between software and hardware. To address this, this paper defines multiple challenges often faced in automation engineering and propose solutions using machine learning to assist engineers tackle such challenges. We show that machine learning can be leveraged to assist the automation engineer in classifying automation, finding similar code snippets, and reasoning about the hardware selection of sensors and actuators. We validate our architecture on two real datasets consisting of 2,927 Arduino projects, and 683 Programmable Logic Controller (PLC) projects. Our results show that paragraph embedding techniques can be utilized to classify automation using code snippets with precision close to human annotation, giving an $F_1$-score of 72%. Further, we show that such embedding techniques can help us find similar code snippets with high accuracy. Finally, we use autoencoder models for hardware recommendation and achieve a $p@5$ of 0.79 and $p@5$ of 0.95.

1 Introduction
Industrial automation is undergoing a technological revolution of smart production enabled by recent breakthroughs in intelligent robotics, sensors, big data, advanced materials, edge supercomputing, internet of things, cyber-physical systems, and artificial intelligence. These systems are currently being integrated by software into factories, power grids, transportation systems, buildings, homes, and consumer devices. The lifecycle of industrial automation systems is divided into two phases: engineering and runtime. Engineering refers to all activities that occur before the system is in operation. These engineering activities include hardware selection, hardware configuration, automation code development, testing, and simulation. Runtime, on the other hand, refers to all activities that occur during the system’s operation. These runtime activities include control, signal processing, monitoring, prognostics, etc.

Applications of AI in industrial automation have been focused mainly on the runtime phase due to the availability of large volumes of data from sensors. For example, time series forecasting algorithms have been very successful in signal processing. Planning and constraint satisfaction are used in controls and control code generation. Anomaly detection algorithms are becoming very popular in cyber-attack monitoring. Probabilistic graphical models and neural networks for prognostics and health management of complex cyber-physical systems such as wind and gas turbines.

The use of AI in the engineering phase, on the other hand, has remained relatively unexplored. There may be several reasons for this. First, engineering data is very scarce because of its proprietary nature. Second, the duration of the engineering phase is short compared to the runtime phase; some industrial automation systems are in operation for more than 30 years. Therefore, the engineering phase is often considered less important than the runtime phase. Third, acquiring human intent and knowledge is difficult. Capturing engineering know-how in expert systems has been shown to be time consuming and expensive.

There are three tasks that can greatly benefit the automation engineering of the future:

1. **Code classification.** As production demands change rapidly, there is a need to efficiently integrate new functionality into production. Code classification can help organize existing and new code into functional libraries with code functions for different categories: signal processing, signal generation, robot motion control, etc.

2. **Semantic code search.** Frequent reconfigurations of the production system demand a much higher degree of code reusability. Semantic code search can help the productivity of engineers by allowing them to find functionally equivalent code. Similar code can inform their decision making when writing software to automate hardware they never experienced before.

3. **Hardware recommendation.** Automation engineering is the task of integrating various hardware components in software to achieve a production goal. Therefore, selecting good hardware configurations is a critical activity.
Hardware recommendation can assist the engineers with hardware configuration auto-completion. That is, given a partial hardware configuration, predict the full hardware configuration.

1.1 Methodology and Contributions

This paper introduces the use of machine learning methods in AES to address the three tasks listed above. First, we demonstrate code classification on two real AES datasets. We learn representation of AES code via document embedding methods, using different artifacts such as function calls, includes, comments, tags, and the code itself. Then we train classifiers on code embeddings to categorize code projects. Our results show that our approach captures code structure and it is comparable to human annotation prediction performance. Second, using the resulting code embeddings, we demonstrate a semantic code search capability for AES code capable of finding functionally equivalent fragments of code. Third, we develop a hardware recommendation system to auto-complete partial hardware configurations. Our results show a 3× higher precision than the baselines. The original contributions of this paper are as follows:

• The introduction of three AES tasks where AI has a big impact potential: code classification, semantic code search, and hardware recommendation.

• An unsupervised learning AES code embedding approach based on bag of words suitable for code classification and semantic code search.

• The comparison of two hardware recommendation approaches using Bayesian Newtorks and Autoencoders.

• The evaluation of our AI models in two real AES datasets consisting of 2,927 Arduino projects, and 683 Programmable Logic Controller (PLC) programs.

• The ArduCode reference implementation in Python, and datasets for advancing the AI research in automation consisting of: (i) AES source code and meta-data; (ii) an expert evaluation of code structural and syntactic similarity for 50 code snippets; (iii) a manually curated silver standard for hardware recommendation systems with two levels of granularity.

2 Related Work

To the best of our knowledge, we are the first to investigate the use of machine learning in AES. Recently, however, the use of machine learning to support general purpose software engineering is becoming an active area of research.

Broadly, recent advances in code learning can be divided into two categories (Chen and Monperrus 2019): (i) language specific models, and (ii) language independent models. Language specific models use knowledge of the languages used in the code to generate low-dimensional representations. For example, code2vec (Alon et al. 2019) constructs abstract syntax tree from the code for Java language for the purpose of predicting a method’s name from its content. It deconstructs the tree into several paths and learns code embedding by aggregating the representations of these paths. func2vec (DeFreese, Thakur, and Rubio-González 2018) uses control flow graphs to generate embeddings of functions in C language. They utilize such representations to detect function clones. Similarly, Deeprepair (White et al. 2019) use a combination of word2vec on tokens and recursive encoder on abstract syntax tree for Java token embedding. They use the representation to automatically repair programs with bugs. Several other works, such as DeepFix (Gupta et al. 2017), use language specific code learning to identify bugs and programming errors in codes. DeepTyper (Hellendoorn et al. 2018) uses recurrent neural networks to perform type inference in dynamically typed languages such as Javascript and Python.

Language independent models focus on syntactic representation learning. For example, (Harer et al. 2018) utilize word2vec directly on tokens from code to learn their representations. They show that their model can help predict software vulnerabilities. (Chen and Monperrus 2018) utilize a similar approach for the task of automated program repair. (Allamanis et al. 2015) introduce a syntactic model based on logbilinear contexts to generate new method names using these embeddings. Such models which do not use language syntax to learn code representations are less widely used compared to language specific models and often do not perform as well. However, in this paper, we show that our proposed language independent model achieves high accuracy in automation engineering tasks.

3 ArduCode: Automation Engineering Software Learning

In this section, we introduce our predictive framework for three key tasks in AES (see Figure 1): (i) code classification, (ii) semantic code search, and (iii) hardware recommendation.

![Figure 1: AES code learning architecture.](https://create.arduino.cc/projethub)
category, title, abstract, tags, description, and hardware configuration. Each project is labeled by one category. In total, there are 12 categories as shown in Figure 2. We use these categories as the labels to predict in the code classification task. Makers are well known for helping and fostering collaboration in the DIY community. The documentation associated to the Arduino projects is extensive. Therefore, the project’s title, abstract, tags, and description metadata provide a upper bound baseline for label classification using human annotations.

The hardware configuration is a list of components required to build the project. In the 2,972 projects, there are 6,500 unique components. After manual inspection, we observed that different authors name the same component differently; e.g., “resistor 10k” and “resistor 10k ohm”. To clean the data, we manually curated the hardware configuration lists and renamed the 6,500 components according to their functionality. We defined functional levels of abstraction for the hardware. The level-1 functionality consists of 9 categories: Actuators, Arduino, Communications, Electronics, Human Machine Interface, Materials, Memory, Power, Sensors. The level-2 functionality further refines the level-1 into a total of 45 categories (e.g., Actuators, {acoustic, air, flow, motor}).

The OSCAT library is the largest publicly available library of PLC programs. The OSCAT-LIB is vendor independent and it provides reusable code functions in different categories such as signal processing (SIGPRO), geometry calculations (GEOMETRY), and string manipulation (STRINGS). These categories are extracted from the comment’s section of each file marked by the line “FAMILY: X”, where “X” is the category associated to that function. This line is eliminated from the dataset during training. In total, the OSCAT-LIB Basic version 3.21 contains 683 functions and 28 category labels. The OSCAT-LIB does not contain hardware configuration, and therefore it is only suitable for the tasks of code classification and semantic code search. All the code is written in SCL language.

3.2 Code Classification

Given a code snippet, the task of code classification is to predict its label. Our pipeline consists of four steps: preprocessing, feature selection, code embeddings, and classification.

Preprocessing We preprocess the automation projects and code snippets to expose the various features shown in Table 1. The Arduino dataset contains more features than the PLC dataset. Therefore, not all features are available in the PLC dataset. For example, PLC code does not have includes, and project data such as tags, title, descriptions, and components is not available.

| Feature   | Arduino | PLC | Description |
|-----------|---------|-----|-------------|
| Includes  | ✓       | ✗   | C/C++ includes |
| Functions | ✓       | ✓   | Function names |
| Comments  | ✓       | ✓   | Comments in code |
| Tokens    | ✓       | ✓   | All code tokens |
| Code      | ✓       | ✓   | Code keywords |
| LOC       | ✓       | ✓   | Lines of code |
| Tags      | ✓       | ✗   | Project tags |
| Title     | ✓       | ✗   | Project title |
| Descriptions | ✓   | ✗  | Project descriptions |
| Labels    | ✓       | ✓   | Labels to predict |
| Components| ✓       | ✗   | Hardware configuration |

Table 1: Features exposed by preprocessing.

Feature Selection The purpose of feature selection is to provide the ArduCode framework with a feature space exploration mechanism to compare the performance of different code representations in the task of code classification and semantic code search. The quality of the code embeddings is expected to vary according to the provided features. Therefore, the feature selection generates different experiments by combining different sets of features. For example, code can be represented by different combinations of includes, functions, comments, tokens, keywords. Code documentation can be represented by combinations of tags, titles, and descriptions. Or both code representations and code documentation features can be combined.

Code Embeddings The next step is to embed the textual representations generated by the feature selection. We compare the performance of the embeddings generated by gensim doc2vec (Le and Mikolov 2014) with the embeddings generated by the term frequency-inverse document frequency (tf-idf). The doc2vec’s hyperparameters of interest are the embedding dimension, and the training algorithm (distributed memory and distributed bag of words). We run all our experiments with negative sampling of 5.

Classification The final step is to train a supervised model for code classification using the code embeddings as the input samples, and the code labels as the target values. We compare the performance of logistic regression and random forest classifiers using the $F_1$-score metric.

Results First, we established the lower and upper bounds for code label classification. The lower bound is given by training the code label classifier using random embeddings. The upper bound is given by training the code label classifier...
using human annotations. The Arduino dataset provides human annotations in the form of tags and descriptions that can be combined in three configurations: tags, descriptions, and descriptions+tags. We first embed these three configurations using tf-idf and doc2vec, and compare the label classification performance using the $F_1$-score. As shown in Figure 3, doc2vec yields a better performance than tf-idf. The embedding dimension for doc2vec was set to 50, and the tf-idf models generated embedding dimensions of 1,469 for tags, 66,310 for descriptions, and 66,634 for descriptions+tags. Intuitively, the descriptions+tags configuration provides the upper bound $F_1$-score of 0.8213.

![Figure 3: Human annotation prediction performance.](image)

We establish the lower bound by generating 50-dimensional random embeddings and predicting the labels using the LR classifier. Figure 4 shows that with both tf-idf and doc2vec the lower bound is 0.3538. After establishing the upper and lower bounds, we use different code features to predict labels. Figure 4 shows that embedding includes and functions provide a slightly better performance than the random baseline due to the very limited amount of information contained in these: 1.82 includes and 4.70 functions on average. Other code features improve the classification accuracy significantly. For example, tokens and code are similar representations and give a similar $F_1$-score of 0.63 and 0.67. These results also show that comments contain valuable information that can be used to predict the code label with a score of 0.67. Embedding code+comments and code+titles yield the highest $F_1$-scores of 0.71. These results show that the prediction performance with code feature embeddings is comparable to human annotation embeddings with improvements of $2.03 \times$ and $2.32 \times$ over the random baseline, respectively.

![Figure 4: Code label prediction using code.](image)

Since the PLC dataset does not have any human annotation features, we can only compare the performance of code feature embeddings (against the random baseline. The $F_1$-score for the code embeddings is 0.9024 and for the random baseline is 0.2878; a $3.13 \times$ improvement. Compared to the Arduino dataset, the PLC dataset has less samples (683 vs 2,927), more category labels (28 vs 12), and less lines of code per file on average (55 vs 177). These are three factors that influence the higher prediction accuracy of ArduCode on the PLC dataset.

### 3.3 Semantic Code Search

Given a code snippet, the goal of semantic code search is to find similar programs. For automation engineering, similarity is defined in terms of syntax and functionality. Syntax similarity helps engineers find useful functions in a given context, and functional similarity informs engineers on how other automation solutions have been engineered.

Doc2vec attempts to bring similar documents close to each other in the embedding space. For a given code embedding of a code snippet, the nearest neighbors are expected to be similar and are used as the basis of our semantic code search. While this approach is intuitive for syntactically similar documents, it is unclear whether functional structure is captured in the embeddings.

#### Results

To validate the quality of our code embeddings, we randomly sampled 50 Arduino code snippets, and tasked a group of 6 software engineers to score the similarity of each code snippet to its top-3 nearest neighbors. For every code snippet pair, two similarity ratings for code syntax and code structure are given. A rating of 1 represents similarity, and a rating of 0 represents the lack of similarity. Code syntax refers to the use of similar variables and function names. Code structure refers to the use of similar code arrangements such as if-then-else and for loops. In addition, every rating has an associated expert’s confidence score from 1 (lowest confidence) to 5 (highest confidence) that represent the expert’s self-assurance during the evaluation. During the expert evaluation we eliminated 5 out of 50 samples where one of the top-3 nearest neighbors was either an empty file, or it contained code in a different programming language. We found three code snippets written in Python and Javascript.

Table 2 shows the average code syntax and code structure similarity scores given by experts. We only report the high confidence ratings (avg. confidence $\geq 4.5$) in order to eliminate the influence of uncertain answers. We also measure the experts’ agreement via the Fleiss Kappa. These results show that the similarity scores for both syntax and structure are high for the top-1 neighbors (0.68 and 0.61 respectively) but reduce significantly (under 0.50) for the top-2 and top-3 neighbors. The experts are in substantial agreement (0.61 $\leq \kappa < 0.80$) in their syntax similarity scores, and in moderate agreement (0.41 $\leq \kappa < 0.60$) in their structure similarity scores. While these results confirm that doc2vec code embeddings capture syntactic similarity, they also show that some structure similarity is captured in the top-1 neighbor.

To further gain insight into our experiment, we selected...
perform the same task of creating a heatmap for a sensor value using LEDs. While there are some syntactic similarities, or semantic code search is also able to capture semantic and functional similarities.

| Similarity   | Top 1 (κ) | Top 2 (κ) | Top 3 (κ) |
|--------------|-----------|-----------|-----------|
| Syntax       | 0.61 (0.75) | 0.48 (0.70) | 0.32 (0.61) |
| Structure    | 0.68 (0.53) | 0.40 (0.44) | 0.33 (0.66) |

Table 2: Average code structure and code syntax similarity and Fleiss Kappa values for high confidence raters.

four similar and three not similar code snippets, and measured the cosine similarity of their embeddings as shown in Table 3. The selected code snippets have a strong agreement among the experts, and a high confidence in the similarity and lack of similarity across the top-3 nearest neighbors. These results confirm that the code snippets considered very similar by the experts are close to each other in the embedding space. On the other hand, code snippets considered not similar are far apart in the embedding space.

| Nearest neighbors | Top 1 | Top 2 | Top 3 |
|-------------------|-------|-------|-------|
| Similar code snippets | #2696 | 0.8768 | 0.7527 | 0.7642 |
|                    | #547  | 0.8719 | 0.8705 | 0.8506 |
|                    | #2815 | 0.9465 | 0.9445 | 0.9126 |
|                    | #54   | 0.8513 | 0.8056 | 0.7815 |
| Not Similar code snippets | #4512 | 0.5967 | 0.5497 | 0.5643 |
|                    | #4345 | 0.5415 | 0.4175 | 0.5192 |
|                    | #1730 | 0.5970 | 0.5035 | 0.5511 |

Table 3: Code embedding cosine similarity for similar and not similar code snippets.

Figure 5 shows two similar Arduino code snippets (#54 and #2689) produced by ArduCode. There are similarities between these two programs at different levels. First, all Arduino programs are required to have the setup() and loop() functions to initialize the program, and to specify the control logic executed on every cycle. Syntactically, the two programs use the same standard functions: pinMode() to configure the Arduino board pins where the hardware connects as inputs or outputs; analogRead() to read an analog value from a pin; Serial.print() to print an ASCII character via the serial port; delay() to pause the program for the amount of time (in ms) specified by the parameter; and analogWrite() to write an analog value to a pin. Semantically, the two programs read sensor values (only 1 value in #54 and 3 values in #2689), scale the sensor value to a range (from 300-1024 to 0-255 using map() in #54 and to $(x + 100)/4$ in #2689), print the scaled sensor value via the serial port, write the analog value to a LED (a single LED in #54 and three LEDs in #2689), and pause the program (10ms in #54 and 100ms in #2689). Note that the order in which these operations are scheduled is different in the two programs. Functionally, the two programs

Figure 5: Arduino semantic code search result.

3.4 Hardware Recommendation
Given a partial list of hardware components, the task of the hardware recommendation is to give a prediction of other hardware components typically used in combination with the partial list. The hand curated silver standard described above is used to learn the joint probability distribution of the hardware components. The hardware recommendation task is then to compute the conditional probability of missing hardware components given a partial list of components.

We compare two approaches for the hardware recommendation task. Our baseline consists of the predictions given on random hardware configurations. First, we learn a Bayesian network where the random variables are the hardware component categories. We use the Pomegranate Python package to learn the structure of the Bayesian network and fit the model with 70% of the hardware configuration data. The Bayesian network for level-1 components consists of 9 nodes and the one for level-2 components consist of 45 nodes. However, we were only able to fit the level-1 Bayesian network as the initialization of the Bayesian network takes exponential time with the number of variables. Typically, this cannot be done with more than two dozen variables due to the super-exponential time complexity with respect to the number of variables, and the level-2 hardware configuration consists of 45 variables. To overcome this limitation, we use an autoencoder implemented in Keras where the encoder learns a lower dimensional representation of the hardware configuration data, and the decoder learns to reconstruct the original input from the lower dimensional rep-
representation. To avoid overfitting, we use L1 and L2 regularizers.

Results  In hardware recommendation, we are interested in recommending the top-k hardware components. Therefore, we evaluate our models in terms of precision@k. Precision@k is the portion of recommended hardware components in the top-k that are relevant. For each hardware configuration in the test data, we leave one hardware component out, and measure its precision@k. Table 4 shows the results for the random baseline, the Bayesian network, and the autoencoder. As expected, the performance of the random baseline improves linearly from p@1 = 0.1, p@3 = 0.32, and p@5 = 0.54 to p@9 = 1 for the level-1 hardware predictions. The Bayesian Network also improves linearly from p@1 = 0.32, p@3 = 0.59, and p@5 = 0.79. The autoencoder provides both the best performance and the best improvements from p@1 = 0.36, p@3 = 0.79, and p@5 = 0.95. Note that the autoencoder’s p@3 is the same performance as the Bayesian Network’s p@5, 0.79. Furthermore, the autoencoder achieves > 0.95 precision at p@5, and the Bayesian network at p@8.

| p@k       | Random Baseline | Bayesian Network | Autoencoder |
|-----------|-----------------|------------------|-------------|
| p@1       | 0.10            | 0.32             | 0.36        |
| p@3       | 0.54            | 0.79             | 0.95        |
| p@5       | 1.00            | 1.00             | 1.00        |

Table 4: p@k results for level-1 hardware predictions.

Learning a Bayesian Network for level-2 hardware components is computationally unfeasible. Therefore, we rely on an autoencoder to accomplish this task and the p@k results are reported in Table 5. The overall p@k performance of the autoencoder for level-2 is comparatively lower than for level-1. The reason is that the level-2 hardware configuration is sparser than level-1. On average, level-2 configurations have 4/40 components and level-1 configurations have 4/12 components. However, the improvement over the random baseline is of 10× for p@1, 5× for p@3, 4× for p@5, and 3× for p@10.

| p@k       | Random Baseline | Autoencoder |
|-----------|-----------------|-------------|
| p@1       | 0.02            | 0.21        |
| p@3       | 0.06            | 0.34        |
| p@5       | 0.11            | 0.45        |
| p@10      | 0.21            | 0.69        |

Table 5: p@k results for level-2 hardware predictions.

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4 Conclusion

In this paper, we introduced and studied three automation engineering predictive tasks. First, we showed that our code classification approach based on doc2vec code embeddings and logistic regression achieves an F1-scores of 72% and 90% on two real datasets. Second, a group of 6 experts validated the semantic code search task by assessing the syntax and structure similarity of 50 code snippets. Third, we demonstrated a p@3 of 79% and p@5 of 95% for the hardware recommendation task using an autoencoder.

Future research directions are as follows. Evaluate ArduCode’s doc2vec approach against recent approaches such as code2vec that are likely to better capture code structure and improve the code classification and semantic code search tasks. In addition, ArduCode’s hardware recommendation is limited to hardware components. This task would be even more useful if it incorporated software elements such as library or API recommendations. One promising idea is to model software elements as random variables in the Bayesian Network and use expert know-how to define their conditional probabilities and combine this expert knowledge with data.

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