Universal Learning Machine with Genetic Programming

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Abstract: This paper presents a proof of concept. It shows that Genetic Programming (GP) can be used as a "universal" machine learning method, that integrates several different algorithms, improving their accuracy. The system we propose, called Universal Genetic Programming (UGP) works by defining an initial population of programs, that contains the models produced by several different machine learning algorithms. The use of elitism allows UGP to return as a final solution the best initial model, in case it is not able to evolve a better one. The use of genetic operators driven by semantic awareness is likely to improve the initial models, by combining and mutating them. On three complex real-life problems, we present experimental evidence that UGP is actually able to improve the models produced by all the studied machine learning algorithms in isolation.

1 INTRODUCTION

According to the No Free Lunch Theorem (Wolpert and Macready, 1997), if averaged on all existing problems, all Machine Learning (ML) algorithms have the same performance. As a consequence, no algorithm is better than all the others on all existing problems and so discovering the most appropriate algorithm for solving one particular application is usually a difficult task. Typically, the choice of the ML technique involves an experimental comparison between several different algorithms. Besides time-consuming, this experimental phase has also, generally speaking, an uncertain outcome. In fact, the most appropriate algorithm for the considered problem may have not been included in the experimental comparison, or the results may lack statistical significance. This paper represents the first proof of concept that Genetic Programming (GP) (Koza, 1992) can be used as a universal learning machine, able to completely relieve the user from the choice of the ML algorithm. We do this by presenting a system, called Universal Genetic Programming (UGP), that integrates several different ML methods, called Basic Learners (BLs), and guarantees that the returned model is, in the worst case, the best among the ones generated by the BLs, or hopefully a significant improvement of it.

This is guaranteed thanks to the dynamics of evolution: in UGP the initial population is not random, as it is usual in GP, but is seeded using the models returned by the BLs. Such an idea has a major difficulty: all the models generated by the BLs should be represented using the same encoding, and that encoding must be usable by GP (for instance, they should be represented as trees). This may be very hard to obtain, given the diverse nature and characteristics of the various ML algorithms that could be used as BLs. However, UGP is able to completely avoid this work of encoding. In fact, UGP uses Geometric Semantic Genetic Programming (GSGP) (Moraglio et al., 2012), one of the most recent and powerful developments of GP. GSGP allows us to abstract from the solution representation since it bases the evolution purely on semantics. In the GP terminology, semantics is the vector of outputs of a model on the training observations. Each model generated by the BLs can be represented in the UGP population by its semantics. Hence, it is not needed to carry on its syntactic structure (that can be extremely large) during the evolution. In this way, any existing ML algorithm can be used by UGP as a BL, in a simple way and with no limitation. GSGP uses Geometric Semantic Operators (GSOs) instead of the traditional crossover and mutation. GSOs induce a unimodal error surface (i.e. a surface with no local optima) for any supervised learning problem. This fact bestows on UGP the ability to improve the BLs. Furthermore, UGP counteracts overfitting, thanks to some well studied theoretical properties of the GSOs (Vanneschi et al., 2014b). In this paper, which represents the first step in this

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promising research track, only three ML methods are used as BLs: linear regression, support vector regression and multi-layer perceptron regression. Furthermore, an extended version of UGP, called UGP with selection (UGP-SEL), aimed at further counteracting the overfitting of the BLs, is presented. The power of UGP and UGP-SEL is tested on three real-life symbolic regression problems. Their performance is compared to the one of GSGP and to the one of the BLs used in isolation.

2 GEOMETRIC SEMANTIC GENETIC PROGRAMMING

Even though the term semantics can have several different interpretations, it is a common trend in the Genetic Programming (GP) (Koza, 1992) community (and this is what we do also here) to identify the semantics of a solution with the vector of its output values on the training data (Vanneschi et al., 2014a). Under this perspective, a GP individual can be identified with a point (its semantics) in a multidimensional space that we call semantic space. The term Geometric Semantic Genetic Programming (GSGP) indicates a recently introduced variant of GP in which traditional crossover and mutation are replaced by so-called Geometric Semantic Operators (GSOs), which exploit semantic awareness and induce precise geometric properties on the semantic space.

GSOs, introduced by Moraglio et al. (Moraglio et al., 2012), are becoming more and more popular in the GP community (Vanneschi et al., 2014a) because of their property of inducing a unimodal error surface on any problem consisting in matching sets of input data into known targets (like for instance supervised learning problems such as regression and classification).

In particular[1], *geometric semantic crossover* generates, as the unique offspring of parents $T_1, T_2 : \mathbb{R}^n \to \mathbb{R}$, the expression:

$$T_{XO} = (T_1 \cdot T_R) + ((1 - T_R) \cdot T_2)$$

where T_R is a random real function whose output values range in the interval $[0,1]$. Analogously, *geometric semantic mutation* returns, as the result of the mutation of an individual $T : \mathbb{R}^n \to \mathbb{R}$, the expression:

$$T_M = T + ms \cdot (T_{R1} - T_{R2})$$

where T_{R1} and T_{R2} are random real functions with codomain in $[0,1]$ and *ms* is a parameter called mutation step.

Moraglio et al. (Moraglio et al., 2012) show that geometric semantic crossover corresponds to geometric crossover in the semantic space (i.e. the point representing the offspring stands on the segment joining the points representing the parents) and geometric semantic mutation corresponds to ball mutation in the semantic space (and thus induces a unimodal fitness landscape on the above mentioned types of problem).

The GSOs implementation presented in (Vanneschi et al., 2013; Castelli et al., 2015a) not only makes GSGP usable in practice by solving the drawbacks pointed out in the original work of Moraglio, but was also a source of inspiration for the work presented here. Given that the solutions semantics is enough to make GSGP work, the population can be seeded with any solution, even the ones returned by other ML algorithms. This can be done independently from the representation used by the ML algorithms to encode their models. In other words, GSGP allows us to abstract from the representation of the solutions (Moraglio et al., 2012).

GSOs have a known limitation (Vanneschi et al., 2014a; Castelli et al., 2015a): the reconstruction of the best individual at the end of a run can be a hard (and sometimes even impossible) task, due to its large size. This issue is even more visible in UGP, where the initial individuals may already be very large (assume for instance that the population is seeded with a model generated by a deep neural network). This basically turns UGP into a black-box system.

3 UNIVERSAL GENETIC PROGRAMMING (UGP)

As mentioned above, GSGP is able to induce a unimodal error surface for any supervised learning problem. Thus, GSGP is characterized by excellent optimization power. Furthermore, solid theoretical foundations (Vanneschi et al., 2013) allow us to state that GSGP is also able to limit overfitting, under some precise and well-studied circumstances. Taking into account these characteristics, a new idea comes naturally: seeding the initial population with a set of predictive models, that have been obtained by as many ML methods (Basic Learners, BLs), instead of randomly as customary in GP. This is possible and easy, simply running the BLs, storing the semantics of the generated models and using them in the initial population of GSGP. GSGP with this new initialization is called UGP (Universal GP) and presented in this

[1] Here we report the definition of the GSOs as given by Moraglio et al. for real functions domains, since these are the operators we will use in the experimental phase. For applications that consider other types of data, the reader is referred to (Moraglio et al., 2012).

paper. We can assert that UGP has the following characteristics: (1) With the simple use of elitism, well known in GP (Koza, 1992), UGP is able, in the worst case, to return the best model found by the BLs; (2) Thanks to the unimodal error surface induced by GSOs, UGP can easily improve the models found by the BLs; (3) Thanks to the theoretical properties of GSGP, UGP is able to limit overfitting.

3.1 Universal Genetic Programming with Selection Mechanism (UGP-SEL)

The fact that GSGP can limit overfitting has been demonstrated in the literature for a traditional randomly generated initial population (Castelli et al., 2014b). When, as it is the case for UGP, the initial population integrates randomly generated individuals with models that have already been trained (the models generated by the BLs), the picture can be different. Indeed, it is expected that the models generated by the BLs will have a much better training fitness than the randomly generated ones, and thus they will be selected for mating many times, at least in the first phase of the evolution. In such a situation, it is easy to imagine that if those models overfit training data, it will be very hard for UGP to return a final model that does not overfit. In simple words, we have to avoid to seed the population with overfitting models.

The objective of UGP-SEL is to minimize the possibility of having overfitted models in the initial population. This is obtained by means of a pre-evolutionary selection procedure aimed at estimating the generalization ability of BLs before adding them to the initial population. This is done using a validation dataset which is separated from the dataset used for training the BLs. The selection procedure we introduce works by partitioning the entire dataset in three subsets: training, validation and testing datasets. The training dataset is used to train the BLs. The validation is used to estimate the performance of the models generated by the BLs, with the objective of discarding the overfitting ones. Training can then take place again using both the training and validation datasets. The output performances are then measured on the testing dataset, which is completely unknown to the models. In this scheme, different selection procedures can be adopted, for example discarding BLs that have excessively poor validation performance when compared to training. This procedure scales well with the number of models used to construct the BLs, as it requires a single training and a single validation for each learner, and can be adopted once a strategy for evaluating the performance and discarding BLs is defined. In our case, to obtain robust statistical evidence, we adopt a nested K-fold cross-validation procedure, which involves testing which combination of models yields the best performance after a short run of UGP. The winning combination of models is then used for a long run of UGP.

More precisely, let $\mathcal{D}$ be the entire dataset and p_i its i-th partition. Then, in K-fold cross-validation, the datasets used in the k-th fold are defined as $d_k^v = p_k$ and $d_k^t = \mathcal{D} \setminus p_k$, for $1 \leq k \leq K$. Similarly, we perform nested J-fold cross-validation by defining the datasets n_{kj}^v and n_{kj}^t, obtained by partitioning d_k^t instead of $\mathcal{D}$, having $n_{kj}^t \cup n_{kj}^v = d_k^t$ for $1 \leq j \leq J$. Given a set of $\mathcal{M}$ models generated by the BLs, the pre-evolutionary selection procedure we used first involved training all the models over n_{kj}^t, then take every combination of models and performing a short UGP run, using the same dataset n_{kj}^t to compute fitness values, and evaluating their performances over n_{kj}^v. The results of these runs are averaged across the J-folds, and the best combination of models is selected to be used in the next phase. Once a combination of models is selected, it is used to perform a long run of UGP: models are trained again over d_k^t, which is also used to compute the fitness during the evolution, while d_k^v is used for evaluation purposes (test set). Note that this procedure is repeated K times and then averaged.

UGP-SEL, as we defined it, is computationally expensive: it requires to train models multiple times over different datasets, suffers from a combinatorial explosion when $\mathcal{M}$ increases and requires to execute a large number of (short) UGP runs. However, the use of UGP-SEL gave us some useful insights, as it will appear clear when we will present our experimental study (Section 4).

4 EXPERIMENTAL STUDY

4.1 Test Problems and Experimental Settings

For each model, 60 runs were performed adopting a 5-fold cross-validation scheme and, where applicable, a nested 4-fold cross-validation. Each run used a population of 200 individuals and a total of 200000 fitness evaluations were performed. When UGP-SEL was used, the brief evolutionary stage consisted of 4000 fitness evaluations. The population was initialized with the ramped half and half method (Koza, 1992), except for UGP, where the population is seeded using the three models evolved by Multilayer Perceptron, Support Vector Regression and Linear Regression, while the remaining 197 individuals are initialized using the ramped half and half algorithm, with an initial maximum height of 6. No height constraints were in place after initialization. For UGP-SEL the initialization is done using the models chosen by the selection mechanism described in Section 3.1, plus the remaining individuals generated randomly using ramped half and half. Besides those parameters, the primitive operators were addition, subtraction, multiplication, and division protected as in (Koza, 1992). The terminal symbols included one variable for each feature in the dataset and no constants. Parent selection was done using tournaments of size 4. Crossover rate and mutation rate were equal to 70% and 30% respectively. These values were selected after a preliminary tuning phase aimed at discovering the most suitable values of the parameters, and since a manual tuning of the parameters showed no (statistically significant) difference in terms of performance with respect to other configurations tested. This is related to the fact that it has become increasingly clear that GP is very robust to parameter values once a good configuration is determined, as suggested by a recent large and conclusive study (Sipper et al., 2018). The error measure adopted to measure the fitness of one semantic against the train semantic was the Mean Absolute Error (MAE).

Table 1: Description of the test problems. For each dataset, the number of features and the number of instances are reported.

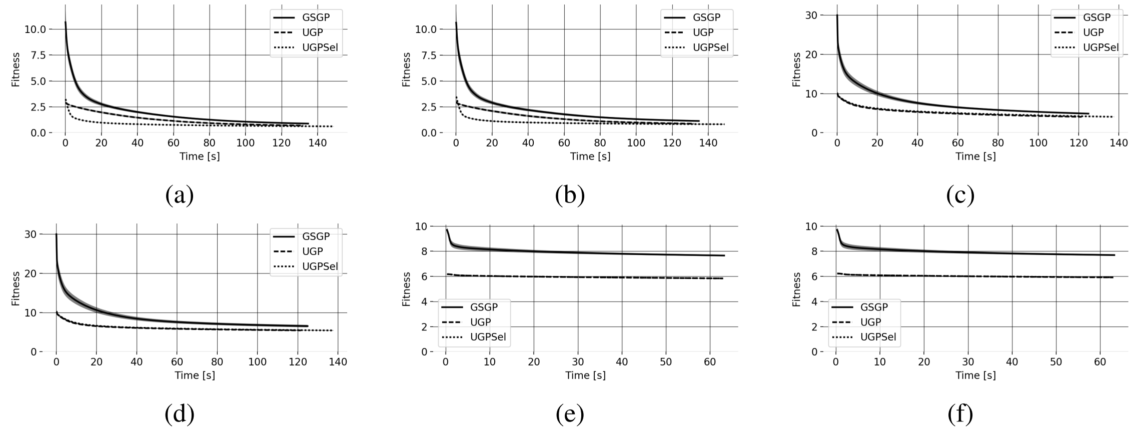
Dataset	# Features	# Instances
Parkinson (Castelli et al., 2014a)	26	5875
Energy (Castelli et al., 2015b)	8	768
Concrete (Castelli et al., 2013)	8	1029

The test problems that we have used in our experimental study are three symbolic regression real-life applications. The first one (Parkinson) aims at predicting the value of the unified Parkinson's disease rating scale as a function of several patients features, mainly extracted from their voice. The second problem (Energy) has the objective of forecasting the value of the energy consumption in some particular geographic areas and on some particular days, as a function of some of the observable characteristics of that (and previous) day(s) (for instance meteorologic characteristics and others). Finally, the Concrete problem aims at predicting the value of the concrete strength, as a function of some features of the material. All these problems have already been used in previous GP studies (Castelli et al., 2014b; Castelli et al., 2014a; Castelli et al., 2013; Castelli et al., 2015b). Table 1 reports, for each dataset, the number of features (variables) and the number of instances (observations). For a complete description of these datasets, the reader is referred to the references reported in the same table.

4.2 Experimental Results

The experimental study aims at understanding the real advantage of using GP as a universal learning method. To accomplish this task, we analyzed different aspects. We initially compared the performance over training and unseen instances of three different GP-systems: GSGP, UGP, and UGP-SEL. The results of this analysis are reported in Figure 1. Focusing on the performance achieved on the training instances, and considering the three benchmark problems, it is possible to observe a common trend: UGP and UGP-SEL produce results that are comparable between each other and outperform GSGP on all the studied test problems. Interestingly, the models produced by the BLs are effectively improved in the evolutionary process. In fact, both UGP and UGP-SEL have steady improvement in terms of fitness during the whole evolution. Additionally, UGP-SEL is able to reduce the computational time needed for obtaining good quality models for the Energy benchmark. Hence, the selection of the best models produced by the BLs, that is typical of UGP-SEL, is not detrimental and, on the contrary, can speed up the search process for some problems. Also, GSGP produces a standard deviation (grey area surrounding the GSGP line in the plots) that, while presenting an acceptable magnitude, is larger than the one produced by UGP and UGP-SEL. We conclude that using GP for evolving models obtained from other ML techniques provides a beneficial effect on the final model, that is characterized by a lower error and a lower standard deviation with respect to the one produced by GSGP.

While results achieved on the training instances are important, the performance on the test set is a fundamental indicator to assess the robustness of the model with respect to its ability in generalizing over unseen data. This is a property that must be ensured in order to use an ML technique for addressing a real-world problem. As one can observe from Figure 1, in all the considered benchmarks, UGP and UGP-SEL are able to generalize well over unseen instances, outperforming GSGP on all the studied problems. Also on the test set, UGP and UGP-SEL are able to improve the performance of the models produced by the BLs and, even more interesting, are able to combine



(a) (b) (c) (d) (e) (f)

Figure 1: Results on training (a,c,e) and test sets (b,d,f). Median over 30 runs. Plot (a,b): Energy dataset. Plot (c,d): Concrete dataset. Plot (e,f): Parkinson dataset.

these models for obtaining a final solution that corresponds to a "blend" of different ML techniques. The final solution produces good performance over the training data as well as a good generalization ability and it is characterized by a lower standard deviation with respect to GSGP. All in all, the idea of using GP as a universal learning method seems very promising.

To assess the statistical significance of the results presented in Figure 1, a statistical validation was performed. First of all, given it is not possible to assume a normal distribution of the values obtained by running the different techniques, we ran the Lilliefors test, using $\alpha = 0.05$. The null hypothesis of this test is that the values are normally distributed. The result of the test suggests that the null hypothesis should be rejected. Hence, we used the Mann-Whitney U test for comparing the results returned by the different techniques considered under the null hypothesis that the distributions are the same across repeated measures. Also in this test, a value of $\alpha = 0.05$ was used and the Bonferroni correction was considered. Table 2 reports the p-values returned by the Mann-Whitney test. A bold font is used to denote values suggesting that the alternative hypotheses cannot be rejected (statistically significant results). According to this study, for all the studied benchmarks, UGP and UGP-SEL obtained models that are better (i.e., with lower error) than the ones produced by GSGP and the differences in terms of error are statistically significant on both training and test data.

To gain a full comprehension of the dynamics of UGP, the second part of the experimental phase analyzes the contribution provided by the different BLs in the construction of the final model. The objective is to understand what are the sub-components of the final solution that were formed thanks to a blend of different ML techniques. To answer this question, we perform the following analysis: we associate to each candidate solution a vector, whose length is equal to the number of used BLs, plus one. Each component of this vector will be associated with a different BL, and the further component will be associated to GP. For all the individuals initialized randomly (with the ramped-half-and-half technique in our case), the position of the vector corresponding to GP is initialized with a value equal to 1, while all the other positions are initialized with a value equal to 0. For each model generated by a BL, the vector is initialized with a value equal to 1 in the position corresponding to that BL, and 0s in all other positions. After each crossover

Table 2: P-values returned by the Mann-Whitney test for the benchmarks considered. Bold values used to denote statistically significant results.

	Energy			
	Training		Test	
	UGP	UGP-SEL	UGP	UGP-SEL
GSGP	**3.6E-21**	**3.6E-21**	**3.6E-21**	**3.6E-21**
UGP	-	**4.4E-21**	-	**3.2E-12**
	Concrete			
	Training		Test	
	UGP	UGP-SEL	UGP	UGP-SEL
GSGP	**3.6E-21**	**3.6E-21**	**3.6E-21**	**3.6E-21**
UGP	-	0.52	-	0.53
	Parkinson			
	Training		Test	
	UGP	UGP-SEL	UGP	UGP-SEL
GSGP	**3.6E-21**	**3.6E-21**	**3.6E-21**	**3.6E-21**
UGP	-	0.27	-	0.04

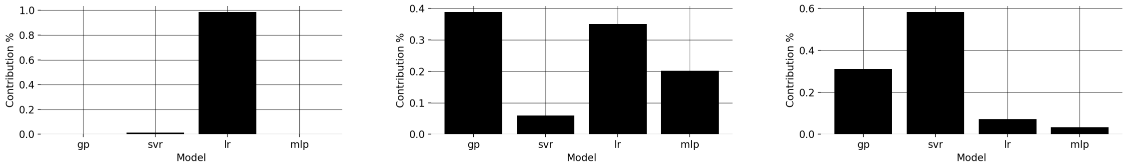
event, we summed up the vectors of the parents to obtain a new vector that can, in some senses, be interpreted as the "fingerprint" of the child. In this way, at the end of the evolutionary process, we are able to quantify the contribution of each BL and of GP itself to the construction of the final solution. Theoretically, an individual that has a value equal to the number of crossover events in the position of the vector corresponding to GP, and a value equal to 0 is all other positions is a model that has been generated purely by GP, without any contribution from any of the BLs. On the other hand, the values in the positions corresponding to the BLs quantify the contribution of the various BLs in the formation of that individual. The results of this analysis are reported in Figure 2 and in Figure 3, where the values contained in the vector associated to the best individual at the end of the evolution are reported, after having been normalized in a $[0,1]$ scale. Figure 2 reports the results for UGP, while Figure 3 shows the analogous results for UGP-SEL.

The first important observation is that none of the best-evolved models (neither the ones evolved by UGP nor the ones evolved by UGP-SEL) is a purely GP-evolved individual. All of them have an important contribution by the BLs. Furthermore, only in one case, the final model is formed by a 100% contribution from only one BL. It is the case of UGP-SEL in the Energy dataset, reported in Figure 3(a), where the final model was formed by a 100% contribution of SVR. In all other cases, the final model is formed by a blend between different BLs and GP. Before continuing with the analysis of Figures 2 and 3, it is important to point out that if an individual is formed by a 100% contribution of one BL, this does not necessarily mean that the final model was the one generated by that BL, and used to initialize the GP population. Indeed, in GP it is possible to have a crossover between one individual and itself, and when GSOs are used (as in this work), the offspring is an individual that is very different from the parent. Indeed, what happened with UGP-SEL in the case of the Energy dataset (Figure 3(a)) is that the final model was obtained by various crossovers between individuals that, although different between each other, are all descendants from the model generated by SVR. This is proven by the fact that the curve of the evolution of UGP-SEL for this problem is not constant (see Figure 1(a)), but the error is steadily decreasing along with the evolution. Thus, the final model is not the one generated by SVR and used in the initialization, but an improvement of it.

Analyzing Figures 2 and 3 more in detail, one can remark that on the Energy dataset the final model was only influenced by SVR in the case of UGP-SEL (Figure 3(a)), while the best solution is obtained by a blend of LR and SVR in the case of UGP (Figure 2(a)). In the latter case, the model consists of a contribution of 98% given by LR and the remaining 2% by SVR. Looking back at Figure 1, it is interesting to notice that while UGP and UGP-SEL performed in a comparable manner, the best solutions they produced have been formed by combining different BLs. This observation further corroborates the importance of semantics: despite the solutions having completely different structures, because they are formed by recombinations of models generated by different BLs, they have a similar *behaviour*, that is what matters for assessing the models' performance. Taking into account the Concrete dataset, it is possible to see that the final model of UGP (Figure 2(b)) was generated using a contribution of approximately 40% of GP, 35% of LR, 20% of MLP, and 5% of SVR. On the same problem UGP-SEL (Figure 2(c)) behaves similarly but, with respect to UGP, a more important contribution to the construction of the best model is given by GP and LR, while MLP and SVR decreased their contribution. Finally, on the Parkinson benchmark, we have a similar situation where both UGP and UGP-SEL built a final model with a contribution of approximately 55% of SVR, 30% of GP, 10% of LR, and 5% of MLP (Figures 2(e) and 2(f)).

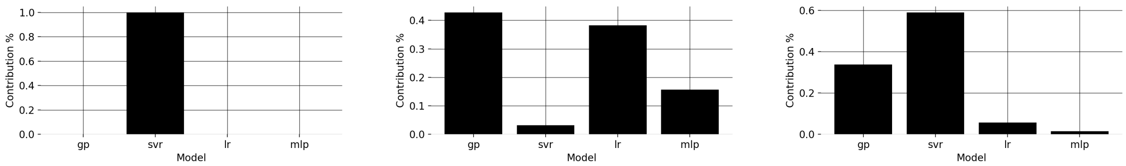
To conclude the experimental study, we focused on UGP-SEL and we analyzed the number of times in which the model generated by a BL was selected to be inserted in the initial population, using the selection process described in Section 3.1. This analysis is reported in Figure 4.

Remembering that each one of the independent runs that we have performed uses a different training/test partition of the data, and thus also the initial models generated by the BLs are different between each other in the different runs, we can observe that for the Energy problem (Figure 4(a)), in more than 60% of the runs both the models generated by LR and SVR are inserted in the initial population, while in the remaining runs only the model generated by SVR was selected and inserted in the initial population. On the Concrete dataset (Figure 4(b)), in more than 40% of the runs all the studied BL models (SVR, LR and MLP) were selected to be part of the initial population, and in more than 30% of the runs the models that were selected and inserted in the initial population were the ones generated by LR and MLP. Looking back at the results of Figure 3, we can see that the evolutionary process is able to combine the solutions composed by the aforementioned BLs, improving them; but, despite that, the final model was



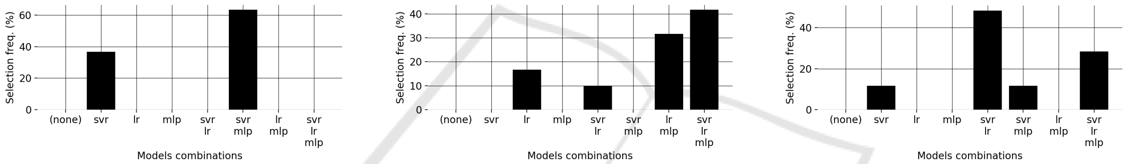
(a) (b) (c)

Figure 2: Percentage contribution provided by the different BLs for building the best final model for UGP. Plot (a): Energy dataset. Plot (b): Concrete dataset. Plot (c): Parkinson dataset.



(a) (b) (c)

Figure 3: Percentage contribution provided by the different BLs for building the best final model for UGP-SEL. Plot (a): Energy dataset. Plot (b): Concrete dataset. Plot (c): Parkinson dataset.



(a) (b) (c)

Figure 4: Techniques that provided the best model after the initial selection phase. Plot (a): Energy dataset. Plot (b): Concrete dataset. Plot (c): Parkinson dataset.

built also with a 40% contribution of GP. Hence, also for the Concrete dataset, the evolutionary process seems to be able to improve the performance of "simple" models (i.e. generated with the contribution of only one technique) more easily with respect to "hybrid" models (i.e. formed thanks to a blend of more than one technique). Finally, Figure 4(c) presents the results obtained on the Parkinson dataset. In this case, we can observe that the models generated by SVR are always selected to be inserted in the initial population. More than 40% of the times, the models that are inserted in the initial population are the one generated by SVR and the one generated by LR, while approximately 30% of the times the models inserted in the initial population are the ones generated by the three studied BLs (i.e. SVR, LR, and MLP). This result is consistent with the one reported in Figure 3(f), where the most important contribution for the construction of the final best model for this problem is provided by SVR. Anyway, also for this dataset, an important contribution to the final model is provided by GP itself. This observation strengthens the previous conjecture: for GP, improving "simple" models is easier than improving "hybrid" ones. In conclusion, the experimental study allowed us to discover interesting insights about UGP and UGP-SEL. In particular, UGP and UGP-SEL behave similarly to ensemble techniques for their ability in producing robust models, as well as reducing the variance bias. Additionally, the best model returned by both UGP and UGP-SEL always consists of a composition of different contributions from more than one ML technique.

5 CONCLUSIONS AND FUTURE WORK

The objective of this paper was to present a proof of concept, and the paper was conceived as a beginning step in a long and promising research track. The scientific question behind this work is if Genetic Programming (GP) can be used as a "universal" Machine Learning (ML) system. In this context, with the term universal, we mean a system able to join several (and potentially even all existing) ML algorithms (called Basic Learners – BLs –), and, in the worst case, always return the best model generated by any of these algorithms. The idea developed in this work consists of using several ML models to seed a GP population. The major obstacle to this idea is bound to representation: all the used models should employ the same representation, and this representation should be "usable" by GP. This obstacle is bypassed by the use of Geometric Semantic GP (GSGP), that is able to completely abstract from the representation. These ideas have been implemented in two systems that were presented in this paper: a first system called Universal GP (UGP), and its variant, called selective UGP (UGP-SEL), where only a subset of the models generated by the BLs are selected and retained in the initial population, in order to limit overfitting. The suitability of UGP and UGP-SEL has been tested on three real-life symbolic regression problems. UGP and UGP-SEL have been compared with GSGP and the BLs themselves, that in this preliminary work were linear regression, support vector regression and multi-layer Perceptron. UGP and UGP-SEL have clearly outperformed all these methods in a statistically significant way. Furthermore, our experimental study has clearly shown that the final models returned by UGP and UGP-SEL are often obtained by a blend of different models generated by different ML algorithms.

In spite of the very promising results presented in this paper, the work is still in an initial phase, and a lot of work is expected in the near future. First, given that this work was just intended as a first proof of concept, only three BLs were used so far. On the other hand, in order to exploit the potentiality of the idea, many different BLs have to be used. Also, better ways of joining the models generated by the BLs, by means of specific and new types of crossover, deserve investigation.

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