TipsC: Tips and Corrections for programming MOOCs

Saksham Sharma, Pallav Agarwal, Parv Mor, and Amey Karkare

Indian Institute of Technology, Kanpur {sakshams, pallavag, parv, karkare}@cse.iitk.ac.in

Abstract. With the widespread adoption of MOOCs in academic institutions, it has become imperative to come up with better techniques to solve the tutoring and grading problems posed by programming courses. Programming being the new 'writing', it becomes a challenge to ensure that a large section of the society is exposed to programming. Due to the gradient in learning abilities of students, the course instructor must ensure that everyone can cope up with the material, and receive adequate help in completing assignments while learning along the way. We introduce TipsC for this task. By analyzing a large number of correct submissions, TipsC can search for correct codes resembling a given incorrect solution. Without revealing the actual code, TipsC then suggests changes in the incorrect code to help the student fix logical runtime errors. In addition, this also serves as a cluster visualization tool for the instructor, revealing different patterns in user submissions. We evaluated the effectiveness of TipsC's clustering algorithm on data

collected from previous offerings of an introductory programming course conducted at IIT Kanpur where the grades were given by human TAs. The results show the weighted average variance of marks for clusters when similar submissions are grouped together is 47% less compared to the case when all programs are grouped together.

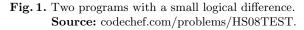
Keywords: Intelligent Tutoring System · Automated Program Analysis · MOOC · Clustering · Program Correction

1 Introduction

With Massively Open Online Courses (MOOCs) being widely adopted among academic institutions and online platforms alike, the number of students studying programming through such courses has sky-rocketed. In contrast, the availability of personalized help through Teaching Assistants (TAs) can not scale accordingly due to human limitations.

The challenge in this scenario is two-fold. Firstly, TAs have to manually grade a large number of incorrect submissions for partial grades, and this process is prone to a large bias and variance as we discovered through collected data [17]. Secondly, helping students stuck at a problem (by providing relevant tips and suggestions) is simply not tractable for MOOCs due to the scale involved.

```
int main() {
                                           int main() {
  int n; float f;
                                             float y; int x;
  scanf("%d %f", &n, &f);
                                             scanf("%d %f", &x, &y);
                                             if ((x%5==0) && (x+0.5)<=y)
  if (n%5==0 && (n+.5)<=f && f<=2000)
    printf("%0.2f", f-n-.5);
                                               printf("%0.2f", y-x-.50);
  else
                                             else
                                               printf("%0.2f", y);
    printf("%0.2f", f);
                                           }
}
```



We introduce TipsC, a tool to parse, analyze, and cluster programming MOOC submissions, in order to tackle the above challenges.

Motivational Example

Consider the two submissions in an offering of a programming course as shown in Fig 1. It would be ideal if the author of the second program could be informed about the missing bound check, once the author has tried enough. Using a large number of submissions available for each problem, **TipsC** finds programs similar to the incorrect one, and suggests granular changes.

The algorithm to find similar submissions allows TipsC to cluster the programs together. This aids in manual analysis, allowing instructors and TAs to obtain a bird's-eye view of the spectrum of solutions received from the students and also helps in creating customized feedback and grading rubrics for individual clusters.

Our Contributions

TipsC solves a very practical use-case, which has not been explored enough in the past. The contributions of this paper are:

- 1. A technique to normalize C program Abstract Syntax Trees (ASTs) to a linear representation, with an intention to make them amenable to similarity analysis. This includes various approximations and domain-specific heuristics.
- 2. An edit distance metric for normalized programs, which is a set of specialized modifications upon Levenshtein distance for two lists.
- 3. We demonstrate the effectiveness of our distance metric by clustering similar programs (distance within a certain threshold) together and comparing the variance in marks awarded by TAs within a cluster.
- 4. An open source tool, TipsC, which implements the above ideas in the context of a MOOC teaching the C language.

2 TipsC

TipsC, implemented in Scala, can be plugged into a MOOC to realize the contributions mentioned above. The primary motivation behind the working of the software is the fact that most introductory programming assignments have a finite number of solution variants, with minor variations in between them. We assume that a student's solution would often resemble some previously existing solution(s). TipsC attempts to find programs which are similar to a user's attempt. It can then suggest changes to the user's program, which would involve fixing small logical runtime errors.

The software offers a *command line interface* (CLI), as well as a *web interface*, with an intersecting set of functionality available. It is intended to be run as a web service behind the scenes, in a MOOC. The CLI's purpose is to allow experimenting with program similarity metrics, and for producing illustrative figures to aid in visualization of the data.

Workflow

- 1. TipsC accepts C language programs as input, which it parses using an inbuilt parser. Relevant features are extracted from the parsed result, and the program is normalized and converted to a linear representation (Sections 3.1 and 3.1). All this information is serialized and stored in a database.
- 2. On every valid program insert request, edit distances (Section 3.2) between that program and all existing submissions (for that particular question) are computed, using the method described in Section 3.3.
- 3. Periodically, the distance matrix is consumed by a script which creates clusters out of the provided programs (Section 3.4). Such clusters are formed for each active problem in the MOOC. The number of clusters is ensured to be sub-polynomial in n.
- 4. TipsC provides an endpoint which accepts a valid C program, which is then linearized and normalized. Edit distance is computed between the input program and representative elements from our clusters, and then to each element of the closest clusters, which allows us to select the closest programs to our input program.
- 5. The edit distance metric discussed in Section 3.2 also returns a 'patch' to convert the normalized programs into each other. Thus, knowing the closest programs allows TipsC to provide personalized tips for the problem to the user. Of course, such tips must be filtered appropriately in order to prevent leaking solutions. This is discussed in section 4.

3 Algorithms

In this section, we provide details on the various algorithms used by the workflow in Section 2. The programs submitted by the students, can not be compared as is. To use our variation of the Levenshtein distance algorithm, we first normalize all the programs (into a linear form) by a series of transformations on the obtained AST of the program. After this, our metric for comparing programs, and our clustering technique, together allow **TipsC** to efficiently suggest changes in programs, as discussed above.

3.1 Program normalization

We now describe various stages of program normalization.

Linearization The program is first converted to a linear representation, rather than one with nested constructs. This is done to aid in the comparison step. For example, an if-else construct would be converted to:

IF(condition) BLOCK_START...BLOCK_END ELSE BLOCK_START...BLOCK_END. Ideally, each statement would translate to one or more tokens in the linear form.

Construct Normalization Since there are multiple loop constructs, they are replaced with the closest approximation of a single LOOP construct. For instance, a for loop may be split into an assignment, a while loop, and a update operation at the end of the while block. "for(expr1; cond1; expr2) BLOCK" becomes "expr1; loop(cond2); (BLOCK + expr2);") This allows for a better similarity measure between two programs. Similarly, other semantically similar constructs could be handled (for instance, renaming var++ to var=var+1).

Expression Linearization Just like the flow graph, we also need a linear representation of the expressions. For our purposes, we use the postfix notation for the expression linearization.

Expression normalization Since different students use different variable names, we rename the variables in the expression to generic names, based on their order of use *within that expression*. For instance, the expression (a + b/a) after normalization would become: $(var_1 + var_2/var_1)$. Or, in postfix: $var_1 var_2 var_1 / +$

3.2 Edit distance

After the linearization of the program, we use a variation of the Levenshtein edit distance algorithm to find the similarity between two programs. The edit distance algorithm is run on the linear representation of the programs, with each logical line of code considered as one token. We assign a constant value (W_{ad}) for additions and deletions, and a maximum value for $(W_r = W_{ad}/2)$ for replacements of most constructs.

Since it is not enough to compare just the equality of two statements/expressions, a granular edit cost is computed when the tokens being compared are both expressions. The edit cost inside the expressions is computed in exactly the same manner as the rest of the program (Levenshtein). Later, the edit cost when comparing expressions is normalized by the size of the expression and finally scaled to W_r , where an edit cost of W_r implies completely different expressions.

A simplified pseudocode of the algorithm is given in Fig 2.

In addition to the above, we intentionally penalize addition or deletion of BLOCK_OPEN and BLOCK_CLOSE constructs with thrice the usual penalty, so that the matching algorithm tries to align blocks with each other, wherever possible.

```
func EditModule(list1, list2: List[Item]):
    let head1, head2 = head(list1), head(list2)

if head1 == head2:
    return EditModule(tail(list1), tail(list2))

normalized_dist = 10
if type(head1) == Expr && type(head2) == Expr:
    partial_distance = EditModule(head1, head2)
    normalized_dist = normalize(partial_distance, head1, head2)

distance1 = 20 + EditModule(list1, tail(list2))
distance2 = 20 + EditModule(tail(list1), list2)
distance3 = normalized_dist + EditModule(tail(list1), tail(list2))
return min(distance1, distance2, distance3)
```

Fig. 2. Pseudo-code for edit distance algorithm

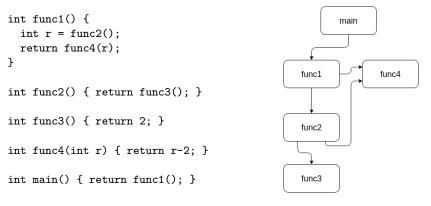


Fig. 3. Depth-First traversal: main \rightarrow func1 \rightarrow func2 \rightarrow func3 \rightarrow func4

This modification should make the suggestions much more meaningful since now loops and conditionals would be matched to corresponding constructs with a higher likelihood. This is because a higher penalty for block anchors incentivizes matching-up blocks between the codes.

3.3 Comparing Two Programs

TipsC uses a modified edit distance algorithm (Section 3.2) to compare normalized programs. This, alone, is not enough to capture the variations seen in programs. This is because naively detecting homomorphic reordering of statements (reordering content across functions or changing function order) would make the comparison algorithm very inefficient. We solve this issue by comparing each function separately.

if (0)	if (1)
helper1();	helper2();
else	else
helper2();	helper1();

Fig. 4. Example where first-use-based ordering does not work
func PairUpFunctions(fxns1, fxns2: List[Function]):
 let result = []

Fig. 5. Pseudo-code for function pairing algorithm

Each function is represented as a list of tokens, and a program is represented as a list of function representations. In addition, we do a Depth-First-Traversal on expressions in the 'main' function, to reorder all the functions in the program in the order they are first called. Such a traversal also removes any unused functions from the analysis. It is easy to imagine how introductory programming assignments could involve multiple functions which call each other, and how ordering them in first-use-order would compensate for the many possible ways students could choose to order their functions. An example of such a traversal is shown in Fig 3.

There are still two scenarios remaining. A user could choose to write a singleton 'main' function, which calls another helper function for the main logic. Another scenario where the first-use-ordering would be incorrect is shown in Fig 4.

Both these scenarios are taken care of by our algorithm, shown in Fig 5. The algorithm considers all permutations of the functions, assigning appropriate penalties in case the ordering is different or if some functions could not be matched. Note that this pairing algorithm is exponential in the number of functions present in the programs. Yet, it is practical since we do not expect more than a handful of functions in an introductory course. Even in cases where a large number of functions are expected in a program, the implementation of the algorithm can be forced to time out after a threshold.

3.4 Clustering programs

Since the distances obtained from the algorithm in Section 3.2 do not follow triangle inequality, we cannot map the programs onto a vector space that accu-

Fig. 6. Pseudo-code for creating hierarchical clusters

rately captures their distance matrix. Instead we use hierarchical/agglomerative clustering [15] which does not require assertion of the inequality. We perform clustering using the following four different linking criteria, which are: *single*, *complete*, *average* and *weighted*.

For each of these methods, we calculate cophenetic correlation coefficient [3] and select the linkage method which maximizes the coefficient. Based on this method we generate the hierarchical tree and create clusters using the algorithm in Fig 6. We define thresholdCount to be $\lfloor \sqrt{n} \rfloor$, where *n* is the number of programs and thresholdDist is the distance only below which creation of clusters will be allowed to filter out the outliers.

3.5 Finding representative elements of clusters

In TipsC, the concept of representative elements is introduced to avoid computing distance with all the programs in the database with the input program. Clustering the tree using algorithm in Fig 6 ensures that we have $\Omega(\sqrt{n})$ clusters with each cluster having $\mathcal{O}(\sqrt{n})$ elements. As a result to find the nearest program we compare the input program first with representative elements of each of the $\Omega(\sqrt{n})$ clusters. Then filter out on the second level with every element of the starting best clusters.

To find out the representative element of a cluster we the take the program from it which gives the least root mean square error with all elements of the cluster.

4 Usage in a MOOC environment

TipsC approach is particularly suited for a programming MOOC. MOOCs usually allow a few days of time for solution submission. Students may start attempting the problem early on, which would ensure that a large number of correct solutions populate the database in some time. Students having difficulty with the problem may be unable to submit a correct solution in time, since they may find themselves stuck on minor errors. When a particular amount of

time has passed, the instructor may choose to activate TipsC, which would allow slower students to get hints using the already processed correct solutions. The instructor may choose to penalize all submissions after that particular time, which is a standard practice in many university courses even without TipsC.

The above approach would ensure that students do not stay stuck at a particular problem and give up, but rather can take advantage of automated and personalized hints to proceed further in their assignments, thus hopefully lowering the drop-out rate. Also, since this algorithm can potentially scale to very large courses, this would also reduce the number of TAs required for MOOCs.

There is a fine line between helping and spoon-feeding, and TipsC tries its best not to cross it. The suggestions provided by TipsC are not plug-and-play, but are rather hints. The difference between programs is on a processed version of the program and does not contain exact variable names or even syntax. For example, a user may notice that there is a missing conditional check, which may bring their attention to that part of the code, but they would not see an already complete solution. They would also not be shown large differences, thus preventing a leak of program logic or structure.

5 Implementation and Scaling

TipsC is an open source software, released under the Apache 2.0 License, on GitHub.¹. The major implementation is in Scala, using the Akka framework for the backend. The clustering algorithm used is implemented in SciPy and is run using Python scripts. A web playground has been deployed publicly, which allows users to see the algorithm live in action on different problems.²

The performance was tested on a Linux desktop running OpenJDK8, with 16 GB RAM, and an Intel(R) Core(TM) i7-4470 CPU @ 3.40GHz with 4 cores.

Program Addition This entails a simple addition into the database, fetching the distance matrix for the background distance update job, and starting the background jobs. Thus, there is no noticeable time required for this step.

Updating the Distance Matrix For every new program addition, distances with existing programs must be computed. Requests are handled sequentially to avoid race conditions. If the database has n programs, then this part of the algorithm takes O(n) time to compute the distance for each of those programs.

This step is only run for correct submissions. This is bounded by the number of students enrolled in the course, and thus would be quite infrequent. Yet, this step is amenable to parallelization. This makes its performance very practical for MOOCs, as is shown in Fig 7(a)

¹ The source code is available at https://github.com/HexFlow/tipsy

² The web playground for TipsC is deployed at http://tipsy.hexflow.in

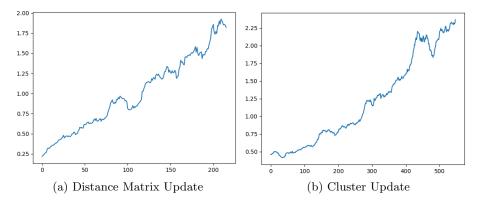


Fig. 7. Performance on an average of 50 lines of code per program. The x-axis denotes the number of already submitted programs. Y-axis denotes the time taken in seconds to update the data structures on adding a new program.

Updating Clusters This part of the algorithm is not run frequently, since it only provides more programs to be matched against, for correction fetching. This part is fast enough on practical database sizes, but it scales as $O(n^2)$. This is not a major overhead, as is shown in Fig 7(b)

Providing Corrections Corrections are served by matching against representative elements of each cluster, and later by comparing against all elements of 4 best clusters. Since the number of programs in a cluster is bounded (See Section 3.4), and the number of clusters is expected to be small. The worst case is still O(n) where all submissions are very far away from each other. This scenario is expected to be very rare for usual introductory problems of programming. On real data, from the Introduction to Programming course at IIT Kanpur, we see 30-40 clusters among 100 submissions for each problem, around 20-30 of which are singleton clusters of outliers. These numbers are from Week 3 and Week 4 problems, which contain simple recursion problems, multiple nesting loops, and conditionals, among other things.

In the scenario described above, requests for fetching corrections for non-trivial codes (35-45 lines of code) take 0.6-0.8 seconds end-to-end. This is expected to scale slowly with the number of programs in the database and thus is quite feasible for MOOCs. The major overhead is due to the comparison with representative elements of each cluster, and this task can be made faster with more parallelism.

6 Experiments

TipsC was run on data from previous iterations of the Introduction to Programming course at the authors' institute. Some observed trends are described in Fig 8, Fig 9 and Table 1.

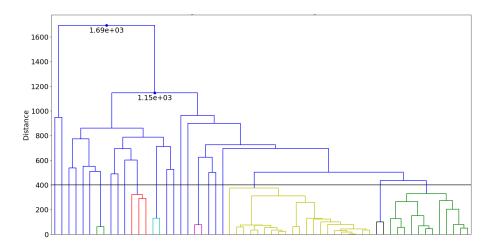


Fig. 8. Dendrogram from the clustering algorithm. X-axis represents unique programs.

Clustering followed by manual inspection of the clusters revealed some inconsistency in manual grading by TAs (among partially correct submissions). We inspected the variance of marks in each non-trivial cluster, which was often low (since many submissions got full marks). On inspecting clusters with high marks variance, we noticed programs with minor differences, but with disparate marks. Clustering on 85 submissions to a fairly advanced problem containing loops, conditionals and arrays, yielded a small number of interrelated clusters, as verified by manual inspection (Fig 8)

To compare the effectiveness of the clustering by TipsC, we computed the variance of marks in each cluster for several problems as shown in Table 1 (Problem ID is a unique ID given to each assignment for the course). The results show that variance within a cluster is much less (47% less on average) than when all the submissions are considered together. This suggests that TipsC is indeed able to group similar programs together, a fact that can help in effective grading by assigning similar programs to the same TA.

TipsC also generates force-layout based images for visualization purposes of the submissions. Figure 9 shows an example, when run on 100 submissions to a problem requiring solutions with 4-5 nested loops and conditionals. It also helps pinpoint outliers, which can be inspected manually by the instructor later.

Problem ID	# submissions	Variance (overall)	Average cluster variance
Lab3-1633	84	1.54	0.78
Lab4-1822	68	2.15	0.70
Lab6-2012	64	3.33	1.97
Lab8-2289	68	1.92	1.30
Exam1-1938	69	6.93	3.74

Table 1. Comparison of variance of marks with and without clustering

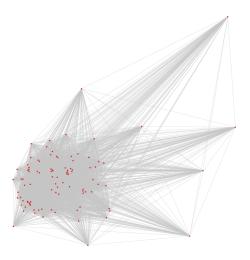


Fig. 9. Force-graph visualization of submissions to a problem

7 Related Work

Automated repair and feedback generation for introductory programming courses is attracting plenty of attention in recent years due to plethora of online courses available on MOOC platforms, and due to growing number of students in traditional classrooms. The repair or feedback can be produced at two different stages for student programs: (a) when a student is struggling to fix compile time errors, and (b) when the program is running, but the student is unable to match the behavior expected by the instructor (typically specified through unit tests).

TRACER [1] learns fixes for compile time errors from existing code submissions (possibly for a different problem statement) and performs targeted repair. The learning is performed by comparing an erroneous version and a later errorfree version of the same program. Other methods [8,2,20] learn repairs by observing a large corpus of correct programs to learn possible correct sequences of tokens. HelpMeOut [9] generates feedback for compilation error by maintaining a database of errors encountered by other students. In case of a compiler error, it provides both the erroneous line of the other student, as well as the modified line which resulted in successful compilation as a hint. *GradeIT* [17] uses simple rewrite rules to repair common compilation errors. Their study show that even these simple repairs can be effective for feedback generation and automated grading of assignments.

The Software Engineering community has developed a number of Automated program repair $(APR)^3$ tools (GenProg [12], AE [25], Angelix [14], and Prophet [13] to name a few) that automatically fix software bugs. These tools have been shown to fix the bugs of large real-world software effectively. However, a recent study [26] has concluded that these repairs are not directly suitable to be

³ http://program-repair.org/

used as hints for novice students programmers. On the other hand, they can be an effective aid for improving grading by teaching assistants (typically student programmers with few years of experience).

REFAZER [24] uses program synthesis, particularly programming-by-example technique, to synthesize syntactic program transformations to fix logical errors in the program. It uses a corpus of code edits made by students to fix incorrect programs to generate transformers that can be used later on similar incorrect programs submitted by other students. Other approaches [22,21,23,19] use reference solution(s) from the instructor and correct/incorrect programs from other students to construct a solution space containing the different states (correct and incorrect) that students have created. Then, a path from an incorrect state to some nearest correct state is used to generate hints.

Another common approach to feedback generation is clustering where students submissions having similar features are grouped together in clusters. The clusters are created either by using a fixed set of rules or by using machine learning techniques [16,18,5] or by using techniques based on program analysis [6,7,11,4,10]. The feedback is typically generated manually for a representative program in each cluster, and it is customized to other members of the cluster automatically. Our tool **TipsC** belongs to the category of rule-based clustering tools. However, it differs significantly from others in the use of linearized ASTs that are amenable to efficient distance computation between two programs. Comparisons with TA marks show that these distances can be used as a measure of correctness for these programs.

8 Conclusion and Future Work

In this paper, we have described **TipsC** in the context of programming and logical error corrections. It is a scalable system, which can be plugged into any existing MOOC, to allow aiding students who are having difficulty in the course without any manual intervention. The system requires a very reasonable number of submissions to become practical, and can easily be modified to handle many other programming languages as well. It works in a fully automated manner and does not require any special effort to accommodate different problems.

We plan to deploy TipsC in an offering of the Introduction to Programming course at our institution, and conduct user surveys to evaluate its usefulness. We believe that TipsC rules can be easily mapped to create helpful feedback messages and rubrics to grade programs with minimum human intervention. Also, some lightweight semantic analysis, and inlining of non-recursive functions, can be used to improve the similarity matrix. We plan to implement these in a future iteration of the software. Use of TipsC as a plagiarism detector can also be explored.

References

- Ahmed, U.Z., Kumar, P., Karkare, A., Kar, P., Gulwani, S.: Compilation error repair: For the student programs, from the student programs. In: ICSE-SEET '18. (2017) 13–22
- 2. Bhatia, S., Singh, R.: Automated Correction for Syntax Errors in Programming Assignments using Recurrent Neural Networks. arXiv:1603.06129 [cs.PL] (2016)
- Farris, J.S.: On the cophenetic correlation coefficient. Systematic Zoology 18(3) (1969) 279–285
- Glassman, E.L., Scott, J., Singh, R., Guo, P.J., Miller, R.C.: Overcode: Visualizing variation in student solutions to programming problems at scale. ACM Trans. Comput.-Hum. Interact. 22(2) (2015) 7:1–7:35
- Gross, S., Zhu, X., Hammer, B., Pinkwart, N.: Cluster based feedback provision strategies in intelligent tutoring systems. In Cerri, S.A., Clancey, W.J., Papadourakis, G., Panourgia, K., eds.: ITS '12. (2012)
- Gulwani, S., Radicek, I., Zuleger, F.: Feedback generation for performance problems in introductory programming assignments. In: FSE '14. (2014) 41–51
- Gulwani, S., Radicek, I., Zuleger, F.: Automated clustering and program repair for introductory programming assignments. CoRR abs/1603.03165 (2016)
- Gupta, R., Pal, S., Kanade, A., Shevade, S.: DeepFix: Fixing Common C Language Errors by Deep Learning. In: Proceedings of the 31st AAAI Conference on Artificial Intelligence (AAAI). (2017)
- Hartmann, B., MacDougall, D., Brandt, J., Klemmer, S.R.: What Would Other Programmers Do? Suggesting Solutions to Error Messages. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM (2010) 1019–1028
- Head, A., Glassman, E., Soares, G., Suzuki, R., Figueredo, L., D'Antoni, L., Hartmann, B.: Writing reusable code feedback at scale with mixed-initiative program synthesis. In: L@S '17. (2017)
- Kaleeswaran, S., Santhiar, A., Kanade, A., Gulwani, S.: Semi-supervised verified feedback generation. In: FSE '16. (2016) 739–750
- Le Goues, C., Nguyen, T., Forrest, S., Weimer, W.: Genprog: A generic method for automatic software repair. IEEE Transactions on Software Engineering 38(1) (Jan 2012) 54–72
- Long, F., Rinard, M.: Automatic Patch Generation by Learning Correct Code. In: Proceedings of the 43rd Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages (POPL). (2016) 298–312
- 14. Mechtaev, S., Yi, J., Roychoudhury, A.: Angelix: scalable multiline program patch synthesis via symbolic analysis. In: ICSE. (2016) 691–701
- Murtagh, F.: A survey of recent advances in hierarchical clustering algorithms. The Computer Journal 26(4) (1983) 354–359
- Nguyen, A., Piech, C., Huang, J., Guibas, L.J.: Codewebs: scalable homework search for massive open online programming courses. In: WWW '14. (2014) 491– 502
- Parihar, S., Dadachanji, Z., Singh, P.K., Das, R., Karkare, A., Bhattacharya, A.: Automatic grading and feedback using program repair for introductory programming courses. In: ITiCSE '17. (2017) 92–97
- Piech, C., Huang, J., Nguyen, A., Phulsuksombati, M., Sahami, M., Guibas, L.: Learning program embeddings to propagate feedback on student code. In: ICML '15. (2015) 1093–1102

- Price, T.W., Dong, Y., Barnes, T.: Generating data-driven hints for open-ended programming. In: EDM '16. (2016) 191–198
- Pu, Y., Narasimhan, K., Solar-Lezama, A., Barzilay, R.: Sk_P: A Neural Program Corrector for MOOCs. In: Companion Proceedings of the 2016 ACM SIGPLAN International Conference on Systems, Programming, Languages and Applications: Software for Humanity. SPLASH Companion 2016, New York, NY, USA, ACM (2016) 39–40
- 21. Rivers, K., Koedinger, K.R.: Automatic generation of programming feedback; A data-driven approach. In: Proceedings of the Workshops at AIED '13. (2013)
- Rivers, K., Koedinger, K.R.: Automating hint generation with solution space path construction. In: ITS '14. (2014) 329–339
- Rivers, K., Koedinger, K.R.: Data-driven hint generation in vast solution spaces: a self-improving python programming tutor. I. J. Artificial Intelligence in Education 27(1) (2017) 37–64
- Rolim, R., Soares, G., D'Antoni, L., Polozov, O., Gulwani, S., Gheyi, R., Suzuki, R., Hartmann, B.: Learning syntactic program transformations from examples. In: Proceedings of the 39th International Conference on Software Engineering, ICSE 2017, Buenos Aires, Argentina, May 20-28, 2017. (2017) 404–415
- 25. Weimer, W., Fry, Z.P., Forrest, S.: Leveraging program equivalence for adaptive program repair: Models and first results. In: ASE '13. (2013) 356–366
- Yi, J., Ahmed, U.Z., Karkare, A., Tan, S.H., Roychoudhury, A.: A Feasibility Study of Using Automated Program Repair for Introductory Programming Assignments. In: ESEC/FSE '17. (2017)