Skill Evaluation as a Computer Science Question: Opportunities and Challenges

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Aspiring Minds

CACM Special Section Workshop – India Region

Opportunities and challenges

- Large number of students graduating every year, huge variation in quality, no signals – **3.5 million students enrolled in 2017-18**

- Capacity issues - Dearth of qualified teachers in universities – **Automatic evaluation/feedback systems**

- Services economy, Huge Hiring Numbers, Need for standardization – **Need automation in recruitment**

We conduct standardized computer based assessment to judge '<u>employability</u>'

AMCAT

GRE/SAT for Jobs

3 million assessments annually, 3000+ companies

Grading programs

Automata – Automatic program evaluation engine

Machine Learning based scoring engine

A model to predict the logical correctness of a program, given the control and data dependencies it possesses

Evaluation of programming best practices

Lint-styled rule-based system to detect programs not following programming best practices.

Asymptotic complexity evaluation

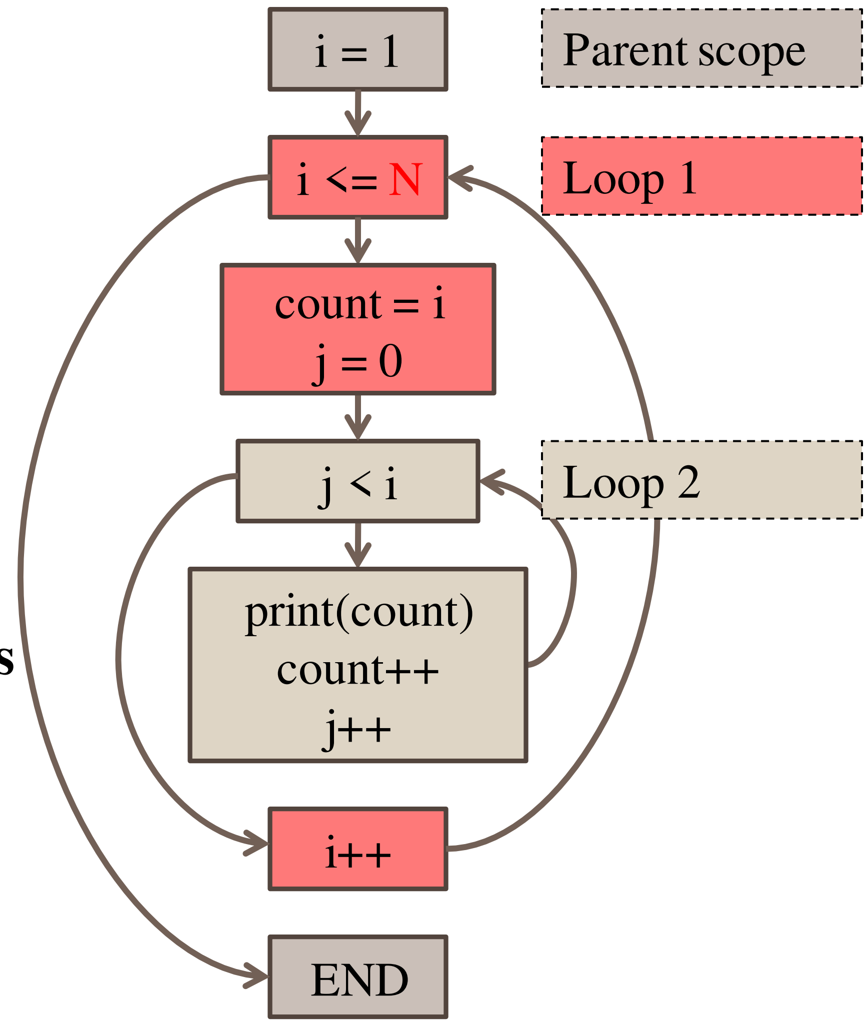
measures the run-time of the code for various input sizes and empirically derives the complexity

KDD 2014: A system to grade computer programming skills using machine learning
- Shashank Srikant, Varun Aggarwal

TARGET PROGRAM

```
void print(int  N){
for(i =1 ; i<=N; i++){
   print  newline;
        count  = i;
       for(j=0;  j<i;  j++)
     print  count;  count++;
       }
}
```

CONTROL FLOW GRAPH



CONTROL FEATURES – COUNTS

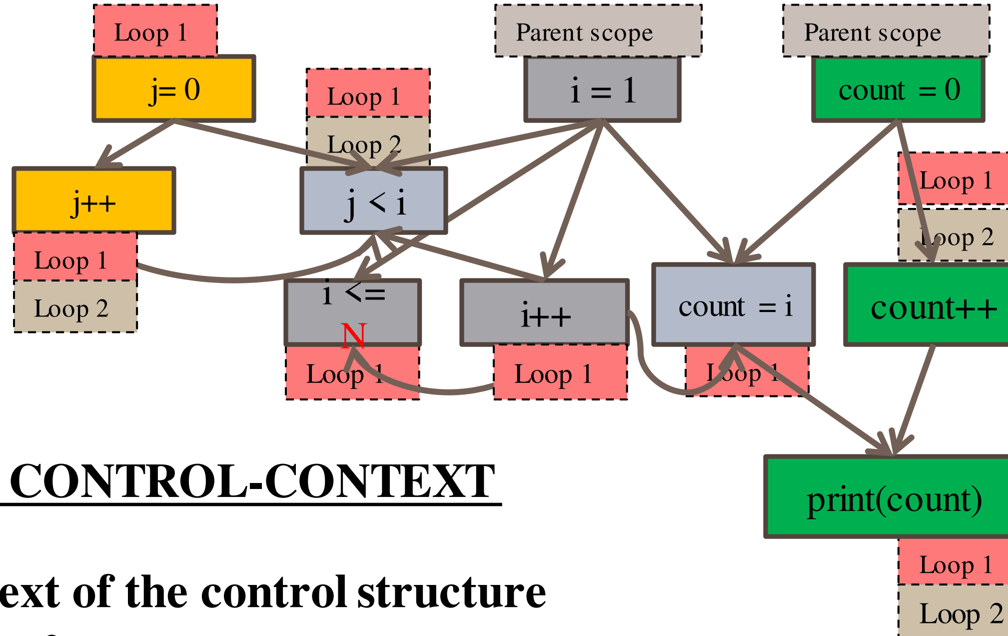
Counts of control-related keywords/tokens

E.g. count(**for**) = 2
count(**for-in-for**) = 1
count(**while**) = 0

Control-context of these keywords

- The Print command as loop(loop(**print**)))

CONTROL FLOW INFORMATION ANNOTATED IN A D-D GRAPH



DATA OPERATION FEATURES IN CONTROL-CONTEXT

Counts of data-related tokens in context of the control structure

E.g. count(**block1** :**loop(loop(++)))** = 2

count(**block1** :**loop(loop_cond(<)))** = 1

Capture control-context of data-dependencies in groups of expressions

- i++ → j < i : **var** (i) **related to var** (j) **: appearing in a loop(loop_cond)**

previously incremented : appearing in a loop

The relation and the increment happen in the same block

Results: Question Specific Models

PROBLEM	# of features	Cross-val correl	Train correl	Validation correl	Test Case Score
1	80	0.61	0.85	**0.79**	**0.54**
2	68	0.77	0.93	**0.91**	**0.80**
3	193	0.91	0.98	**0.90**	**0.64**
4	66	0.90	0.94	**0.90**	**0.80**
5	87	0.81	0.92	**0.84**	**0.84**

Validation correlation >= 0.79

Matches inter-rater correlation between two human raters

(Published at KDD 2014)

ML Models are question specific

Binary search

```
int binarySearch(params)
{
    // Initializations
    for(;first <= last;) {
        if(array[middle] < search)
            // Look in the 2nd half
            first = middle + 1;
        else
            // Look in the first half
            last = middle - 1;
        middle = (first + last)/2;
    }
}
```

if-in-for

Bubble sort

```
int bubbleSort(params)
{
  for (i=0 ; i<n; i++)
  {
    for (j=0 ; j <n-i; j++)
    {
      if (array[j] > array[j+1])
      {
        // Swap elements
      }
    }
  }
}
```

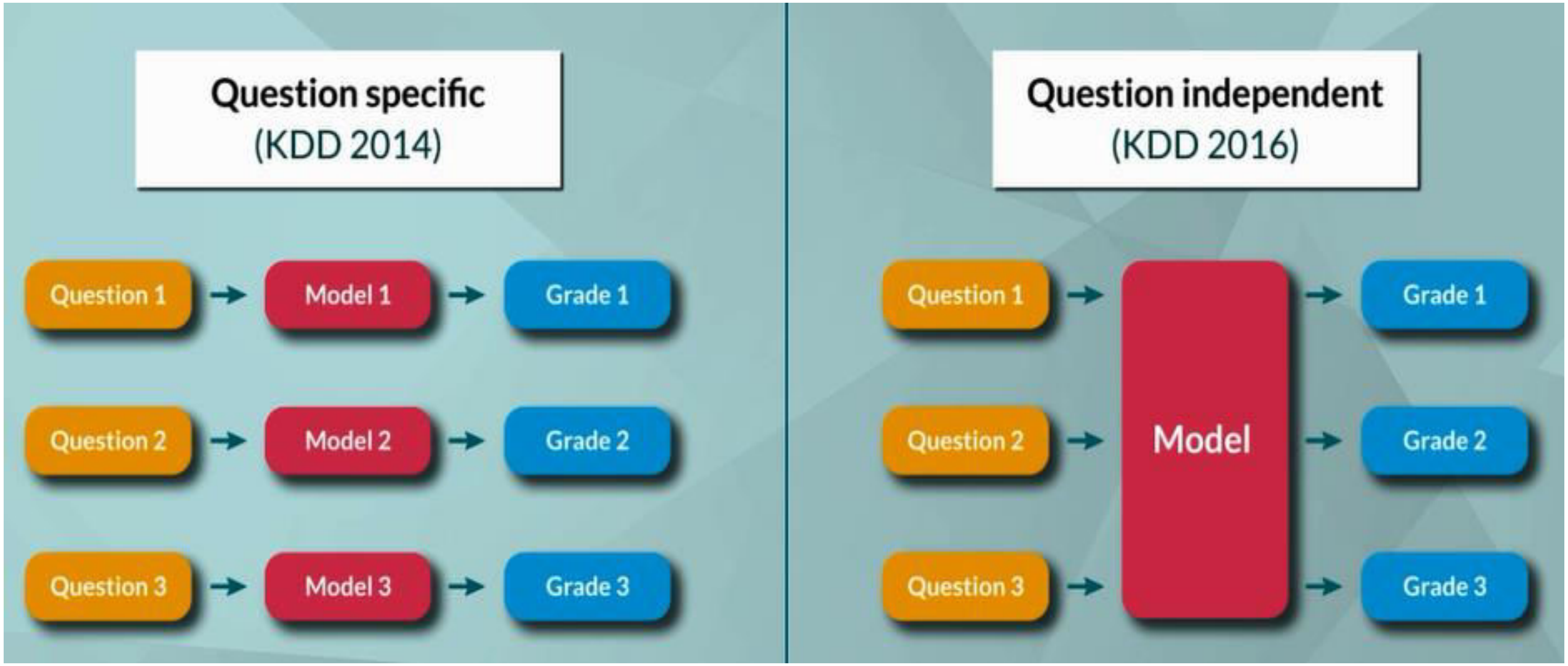
for-in-for

Solving for the industry needs scale

- The solution doesn't scale!!!
- We have 500+ questions in our database and support 35+ languages

How to get question independent models?

Question independent ML models



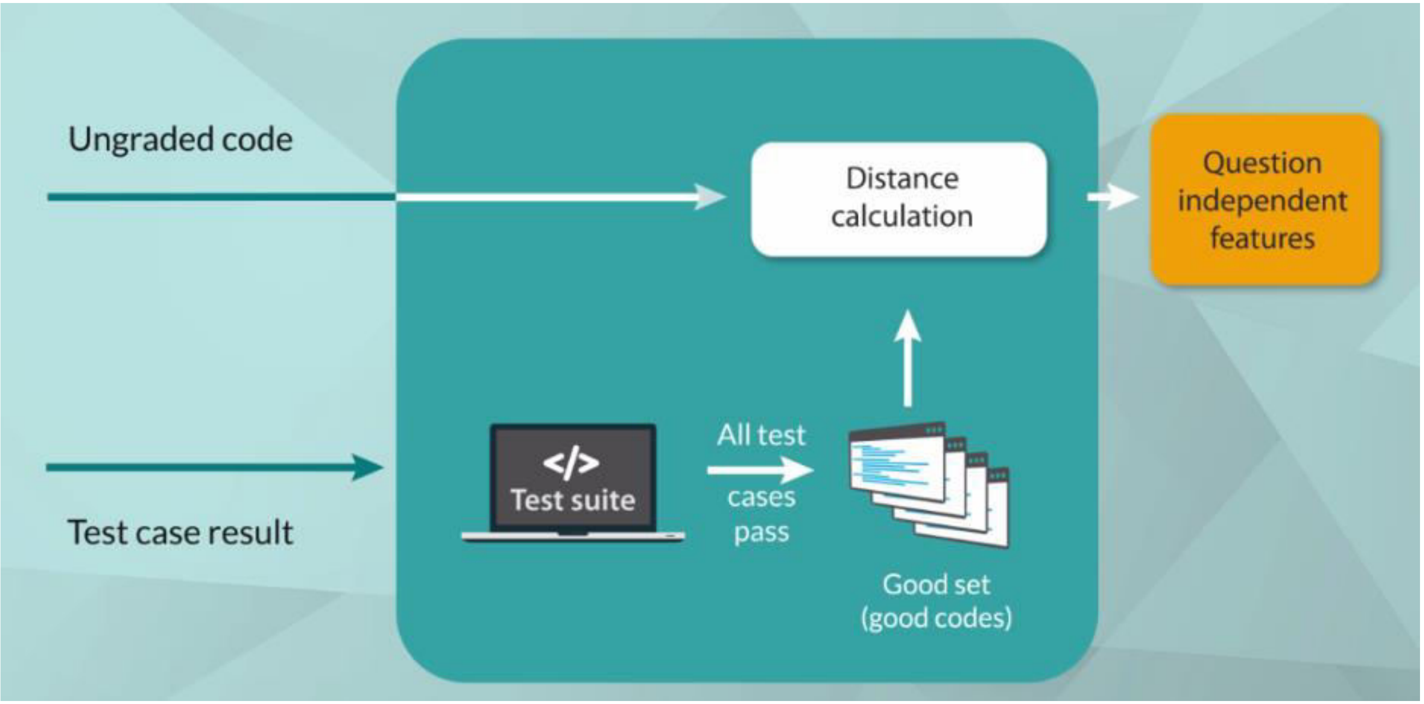
Two main ideas

Feature transformation - Convert original features into ‘structurally invariant’ features

How?

Exploit Automatic identification of good responses –Test cases can tell us this.

How does it work?



We just need a set of good codes for a new question, no labeled sample….

Results

Ques Set	Metric	QuesSpec	QuesIndep-N1	QuesIndep-N0	Baseline-TC
All questions	Correl	0.84	0.8	0.76	0.65
	Bias	0.14	0.24	0.28	0.35
	MAE	0.41	0.58	0.66	0.85
Unseen questions	Correl	0.85	0.8	0.76	0.65
	Bias	0.14	0.27	0.34	0.31
	MAE	0.43	0.62	0.7	0.84

- Question-independent **vs** test-case baseline
- Question-independent **vs** question-specific
- Performance on unseen problems

(Published at KDD 2016)

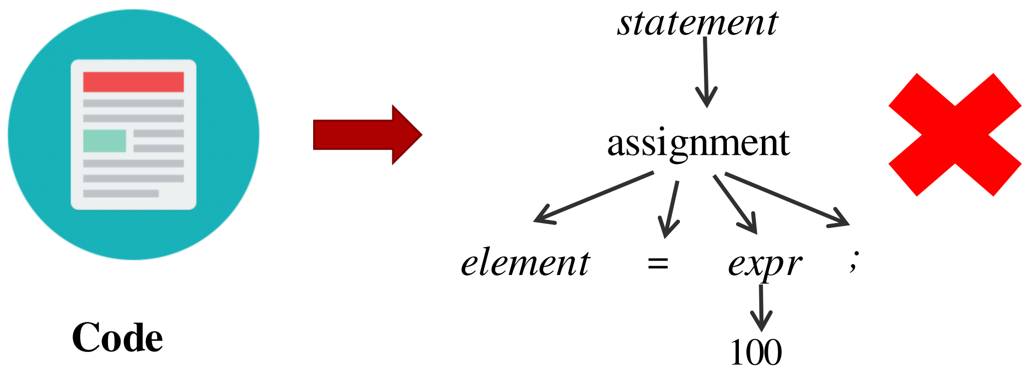
- Correl – Pearson coefficient (r)
- Bias – Average $(y_e - y_p)$
- MAE – Average$(|y_e - y_p|)$

Quality difference - Programmers

Country	% Uncompilable Codes	% Completely Correct
US	18.5%	44.5%
India	58%	16.8%

16% of candidates with uncompilable code had near correct logic!

For programs with syntax errors



Code

Syntax Tree

- **26% more candidates were shortlisted for interviews**
- **19% more were hired**

(Published at IAAI 2019)

Various AI-led products

- Automatic Grading of essays
- Automatic Grading of emails
- A tab based motor skills test
- Simulated Chat customers

Lessons

- Problems are multi-disciplinary – spawn fields
- Problems need novel theoretically plausible features
- Small data-sets; Expensive to get labels; Need to create good balanced data sets
- Need generalized solutions for problem space which scales
- Format assumptions of solution may break – need to handle by novel means
- Design of experiments and result interpretation is key

Discussion?