CFaults: Model-Based Diagnosis for Fault Localization in C with Multiple Test Cases

Pedro Orvalho ¹, Mikoláš Janota ² and Vasco Manquinho ¹

¹INESC-ID, Instituto Superior Técnico, Universidade de Lisboa, Portugal ²CIIRC, Czech Technical University in Prague, Czechia

FM 24, Milan, Italy

Thursday 12th September, 2024









Motivation

 Debugging is one of the most time-consuming and expensive tasks in software development.

Motivation

- Debugging is one of the most time-consuming and expensive tasks in software development.
 - In 2000, the total cost of the work done in preparation for Year 2000 Problem likely surpassed 400 Billion US\$ [The Guardian, 2019];

Motivation

- Debugging is one of the most time-consuming and expensive tasks in software development.
 - In 2000, the total cost of the work done in preparation for Year 2000 Problem likely surpassed 400 Billion US\$ [The Guardian, 2019];
 - In 2024, the estimated global cost of Crowdstrike's error that hit Microsoft systems, is 24 Billion US\$ [The Sun UK, 2024].

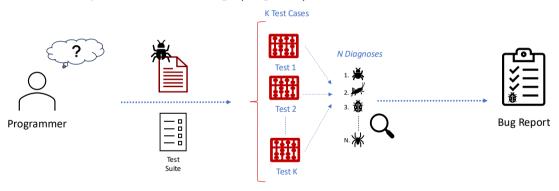
Fault Localization

• Given a buggy program, fault localization (FL) involves identifying locations in the program that could cause a faulty behaviour (bug).



Formula-Based Fault Localization (FBFL)

 FBFL methods encode the localization problem into several optimization problems to identify a minimal set of bugs (diagnoses).



Formula-Based Fault Localization

1: Faulty program example. Faulty lines: $\{4,6,8\}$.

```
int main(){
     int f,s,t;
     scanf("%d%d%d",&f,&s,&t);
    if (f < s && f >= t)
    printf("%d",f);
5
     if (f > s && s <= t)
    printf("%d",s);
     if (f > t && s > t)
       printf("%d",t);
     return 0;
10
11
```

Table 1: Test-suite.

	Input		
t0	1	2	3
t1	-1	-2	-3
t2	1	2	1

Output	
3	
-1	
2	

2: Faulty program example. Faulty lines: {4,6,8}.

```
int main(){
     int f,s,t;
     scanf("%d%d%d",&f,&s,&t);
     if (f < s \&\& f >= t)
        printf("%d",f);
5
     if (f > s && s <= t)
        printf("%d",s);
      if (f > t \&\& s > t)
        printf("%d",t):
     return 0;
10
11
```

	BugAssist	SNIPER
#Diagnoses t_0	8	8
#Diagnoses t_1	21	21
#Diagnoses t ₂	9	9
#Total Unique Diagnoses	32	1297
Final Diagnosis	{3,9}	{4,6,8}

Table 2: Number of diagnoses (faulty statements) generated by ${\rm BUGASSIST}$ [Jose et al., 2011] and ${\rm SNIPER}$ [Lamraoui et al., 2016] per test.

	BugAssist	SNIPER
#Diagnoses t_0	8	8
#Diagnoses t_1	21	21
#Diagnoses t ₂	9	9
#Total Unique Diagnoses	32	1297
Final Diagnosis	{3,9}	{4,6,8}

Table 3: Number of diagnoses (faulty statements) generated by $\rm BugAssist$ [Jose et al., 2011] and $\rm SNIPER$ [Lamraoui et al., 2016] per test.

Current Limitations

FBFL tools especially for programs with multiple faults:

	BugAssist	SNIPER
#Diagnoses t_0	8	8
#Diagnoses t_1	21	21
#Diagnoses t ₂	9	9
#Total Unique Diagnoses	32	1297
Final Diagnosis	{3,9}	{4,6,8}

Table 3: Number of diagnoses (faulty statements) generated by $\operatorname{BugAssist}$ [Jose et al., 2011] and SNIPER [Lamraoui et al., 2016] per test.

Current Limitations

FBFL tools especially for programs with multiple faults:

 do not ensure a minimal diagnosis across all failing tests (e.g., BugAssist);

	BugAssist	SNIPER
#Diagnoses t_0	8	8
#Diagnoses t_1	21	21
#Diagnoses t ₂	9	9
#Total Unique Diagnoses	32	1297
Final Diagnosis	{3,9}	{4,6,8}

Table 3: Number of diagnoses (faulty statements) generated by $\operatorname{BugAssist}$ [Jose et al., 2011] and SNIPER [Lamraoui et al., 2016] per test.

Current Limitations

FBFL tools especially for programs with multiple faults:

- do not ensure a minimal diagnosis across all failing tests (e.g., BugAssist);
- may produce an overwhelming number of redundant sets of diagnoses (e.g., SNIPER).

Our Work

• We formulate the FL problem as a single optimization problem;

Our Work

- We formulate the FL problem as a **single optimization problem**;
- We leverage MaxSAT and the theory of Model-Based Diagnosis
 (MBD) [Reiter et al., 1987, Ignatiev et al., 2019], integrating all failing test cases
 simultaneously;

Our Work

- We formulate the FL problem as a single optimization problem;
- We leverage MaxSAT and the theory of Model-Based Diagnosis
 (MBD) [Reiter et al., 1987, Ignatiev et al., 2019], integrating all failing test cases
 simultaneously;
- We implement this MBD approach in a publicly available tool called CFAULTS.

• A system description P is composed of a set of components $C = \{c_1, \ldots, c_n\}$.

- A system description \mathcal{P} is composed of a set of components $\mathcal{C} = \{c_1, \dots, c_n\}$.
- Each component in C can be declared **healthy** or **unhealthy**.

- A system description \mathcal{P} is composed of a set of components $\mathcal{C} = \{c_1, \dots, c_n\}$.
- Each component in C can be declared **healthy** or **unhealthy**.
- For each component $c \in \mathcal{C}$, h(c) = 0 if c is unhealthy, otherwise, h(c) = 1.

- A system description \mathcal{P} is composed of a set of components $\mathcal{C} = \{c_1, \dots, c_n\}$.
- Each component in C can be declared **healthy** or **unhealthy**.
- For each component $c \in \mathcal{C}$, h(c) = 0 if c is unhealthy, otherwise, h(c) = 1.
- \mathcal{P} is described by a CNF formula, where \mathcal{F}_c denotes the encoding of component c:

$$\mathcal{P} \triangleq \bigwedge_{c \in \mathcal{C}} (\neg h(c) \vee \mathcal{F}_c) \tag{1}$$

• Observations represent deviations from the expected system behaviour.

- Observations represent deviations from the expected system behaviour.
- An observation, denoted as o, to be encodable in CNF as a set of unit clauses.

- Observations represent deviations from the expected system behaviour.
- An observation, denoted as o, to be encodable in CNF as a set of unit clauses.
- In this work, the failing test cases represent the set of observations.

- Observations represent deviations from the expected system behaviour.
- An observation, denoted as o, to be encodable in CNF as a set of unit clauses.
- In this work, the failing test cases represent the set of observations.
- A system \mathcal{P} is considered faulty if there exists an inconsistency with a given observation o when all components are declared healthy:

$$\mathcal{P} \wedge o \wedge \bigwedge_{c \in \mathcal{C}} h(c) \vDash \bot \tag{2}$$

 The problem of model-based diagnosis (MBD) aims to identify a set of components which, if declared unhealthy, restore consistency;

- The problem of model-based diagnosis (MBD) aims to identify a set of components which, if declared unhealthy, restore consistency;
- For a given MBD problem $\langle \mathcal{P}, \mathcal{C}, o \rangle$, a set of system components $\Delta \subseteq \mathcal{C}$ is a diagnosis iff:

$$\mathcal{P} \wedge o \wedge \bigwedge_{c \in \mathcal{C} \setminus \Delta} h(c) \wedge \bigwedge_{c \in \Delta} \neg h(c) \nvDash \bot$$
 (3)

- The problem of model-based diagnosis (MBD) aims to identify a set of components which, if declared unhealthy, restore consistency;
- For a given MBD problem $\langle \mathcal{P}, \mathcal{C}, o \rangle$, a set of system components $\Delta \subseteq \mathcal{C}$ is a diagnosis iff:

$$\mathcal{P} \wedge o \wedge \bigwedge_{c \in \mathcal{C} \setminus \Delta} h(c) \wedge \bigwedge_{c \in \Delta} \neg h(c) \nvDash \bot$$
 (3)

• A diagnosis Δ is minimal iff no subset of Δ , $\Delta' \subsetneq \Delta$, is a diagnosis, and Δ is of minimal cardinality if there is no other diagnosis $\Delta'' \subseteq \mathcal{C}$ with $|\Delta''| < |\Delta|$.

- The problem of model-based diagnosis (MBD) aims to identify a set of components which, if declared unhealthy, restore consistency;
- For a given MBD problem $\langle \mathcal{P}, \mathcal{C}, o \rangle$, a set of system components $\Delta \subseteq \mathcal{C}$ is a diagnosis iff:

$$\mathcal{P} \wedge o \wedge \bigwedge_{c \in \mathcal{C} \setminus \Delta} h(c) \wedge \bigwedge_{c \in \Delta} \neg h(c) \nvDash \bot$$
 (3)

- A diagnosis Δ is minimal iff no subset of Δ , $\Delta' \subsetneq \Delta$, is a diagnosis, and Δ is of minimal cardinality if there is no other diagnosis $\Delta'' \subseteq \mathcal{C}$ with $|\Delta''| < |\Delta|$.
- A diagnosis is redundant if it is not subset-minimal [Ignatiev et al., 2019].

To encode the MBD problem with one observation with partial MaxSAT:

• The set of clauses that encode P represents the set of hard clauses;

To encode the MBD problem with one observation with partial MaxSAT:

- The set of clauses that encode \mathcal{P} represents the set of hard clauses;
- The soft clauses consists of unit clauses that aim to maximize the set of healthy components, i.e.,:

$$\bigwedge_{c\in\mathcal{C}}h(c);$$

To encode the MBD problem with one observation with partial MaxSAT:

- The set of clauses that encode P represents the set of hard clauses;
- The soft clauses consists of unit clauses that aim to maximize the set of healthy components, i.e.,:

$$\bigwedge_{c\in\mathcal{C}}h(c);$$

 This encoding enables enumerating subset minimal diagnoses, considering a single observation;

We **integrate all failing test cases** in a single MaxSAT formula.

We integrate all failing test cases in a single MaxSAT formula.

• We **generate only minimal diagnoses** capable of identifying all faulty components within the system, in our case, a C program;

We **integrate all failing test cases** in a single MaxSAT formula.

- We generate only minimal diagnoses capable of identifying all faulty components within the system, in our case, a C program;
- Given m observations, $\mathcal{O} = \{o_1, \dots, o_m\}$, a distinct replica of the system, denoted as \mathcal{P}_i , is required for each observation o_i ;

We integrate all failing test cases in a single MaxSAT formula.

- We generate only minimal diagnoses capable of identifying all faulty components within the system, in our case, a C program;
- Given m observations, $\mathcal{O} = \{o_1, \dots, o_m\}$, a distinct replica of the system, denoted as \mathcal{P}_i , is required for each observation o_i ;
- The hard clauses, ϕ_h , in our MaxSAT formulation correspond to:

$$\phi_h = \bigwedge_{o_i \in \mathcal{O}} (\mathcal{P}_i \wedge o_i);$$

We integrate all failing test cases in a single MaxSAT formula.

- We **generate only minimal diagnoses** capable of identifying all faulty components within the system, in our case, a C program;
- Given m observations, $\mathcal{O} = \{o_1, \dots, o_m\}$, a distinct replica of the system, denoted as \mathcal{P}_i , is required for each observation o_i ;
- The hard clauses, ϕ_h , in our MaxSAT formulation correspond to:

$$\phi_h = \bigwedge_{o_i \in \mathcal{O}} (\mathcal{P}_i \wedge o_i);$$

The soft clauses are formulated as:

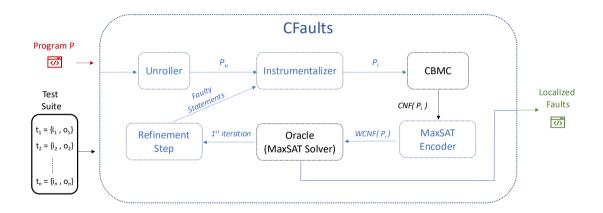
$$\phi_s = \bigwedge_{c \in \mathcal{C}} h(c).$$

• The set of unhealthy components (h(c) = 0), corresponds to a **subset-minimal** aggregated diagnosis.

- The set of unhealthy components (h(c) = 0), corresponds to a **subset-minimal** aggregated diagnosis.
- This diagnosis is a subset-minimal of components that, when declared unhealthy (deactivated), make the system consistent with all observations, as follows:

$$\bigwedge_{o_i \in \mathcal{O}} (\mathcal{P}_i \wedge o_i) \wedge \bigwedge_{c \in \mathcal{C} \setminus \Delta} h(c) \wedge \bigwedge_{c \in \Delta} \neg h(c) \nvDash \bot$$
 (4)

CFaults



Program unrolling

- An unrolled program is the original program expanded m times;
- It encodes the execution of all failing tests within the program;

```
float _input_f0[3] = {1, 2, 3};
    char out 0[2] = "3";
    int ioff f0 = 0, ooff 0 = 0;
    // ... inputs and outputs for the other tests
    int main(){
       scope 0:{
         int f_0, s_0, t_0;
         f_0 = \inf_{f \in \mathcal{F}} f(f) = \inf_{f \in \mathcal{F}} f(f) = f(f)
         s_0 = input_f0[ioff_f0++];
         t 0 = input_f0[ioff_f0++];
10
         if ((f \ 0 < s \ 0) \ \&\& \ (f \ 0 >= t \ 0))
11
              ooff 0 = printInt( out 0, ooff 0, f 0);
12
         if ((f \ 0 > s \ 0) \&\& (s \ 0 <= t \ 0))
13
14
              ooff 0 = printInt( out 0, ooff 0, s 0);
         if ((f \ 0 > t \ 0) \ \&\& \ (s \ 0 > t \ 0))
15
16
              _ooff_0 = printInt(_out_0, _ooff_0, t_0);
         goto scope_1;
17
18
       // ... scope_1 and scope_2
19
       final step:
20
       assert(strcmp( out 0, "3") != 0 // other assertions);
21
22
                                                                38 / 65
```

Program unrolling

For each scope, CFAULTS:

- generates fresh variables and functions;
- establishes variables representing the inputs and outputs;
- embeds an assertion capturing all the specifications.

```
float _input_f0[3] = {1, 2, 3};
    char out 0[2] = "3";
    int ioff f0 = 0, ooff 0 = 0;
    // ... inputs and outputs for the other tests
    int main(){
       scope 0:{
         int f 0, s 0, t 0:
         f_0 = \inf_{f \in \mathcal{F}} f(f) = \inf_{f \in \mathcal{F}} f(f) = f(f)
         s_0 = input_f0[ioff_f0++];
         t_0 = input_f0[ioff_f0++];
10
         if ((f \ 0 < s \ 0) \ \&\& \ (f \ 0 >= t \ 0))
11
              ooff 0 = printInt( out 0, ooff 0, f 0);
12
         if ((f \ 0 > s \ 0) \&\& (s \ 0 <= t \ 0))
13
14
              ooff 0 = printInt( out 0, ooff 0, s 0);
         if ((f \ 0 > t \ 0) \ \&\& \ (s \ 0 > t \ 0))
15
              _ooff_0 = printInt(_out_0, _ooff_0, t_0);
16
         goto scope_1;
17
18
       // ... scope_1 and scope_2
19
       final step:
20
       assert(strcmp( out 0, "3") != 0 // other assertions);
21
22
                                                                39 / 65
```

Program Intrumentalization

3: Program statements.

```
int i;
   int n;
   int s;
4
   s = 0:
   n = input f0[ioff f0++];
7
   if (n == 0)
       return 0:
9
10
   for (i=1; i < n; i++){
11
  s = s + i:
12
13
```

4: Program statements relaxed.

```
1 //main scope
   bool rv1, rv2, rv3, rv5;
   bool ru6[UNWIND],..., ru8[UNWIND];
   int los; // loop1 offset
6 //test scope
   bool ev4;
   int i,n,s;
    los=1;
10
   if (rv1) s = 0:
11
   if ( rv2) n = _input_f0[_ioff_f0++];
    if (rv3 ? (n == 0) : ev4)
       return 0:
14
15
    for (_{rv5} ? (i = 1) : 1;
17 ! rv6[ los] || (i<n):
        rv8[ los] ? i++ : 1, los++){
18
19 if (rv7[los]) s = s + i:
20
```

 CFAULTS generates a weighted partial MaxSAT formula aiming to minimize the necessary code alterations;

- CFAULTS generates a weighted partial MaxSAT formula aiming to minimize the necessary code alterations;
- The soft clauses are the relaxation variables used to instrument the C program, expressed as

$$S = \bigwedge_{c \in \mathcal{C}} (rv_c);$$

- CFAULTS generates a weighted partial MaxSAT formula aiming to minimize the necessary code alterations;
- The soft clauses are the relaxation variables used to instrument the C program, expressed as

$$S = \bigwedge_{c \in \mathcal{C}} (r v_c);$$

 We assign a hierarchical weight to each relaxation variable based on the height of its sub-AST (abstract syntax tree);

- CFAULTS generates a weighted partial MaxSAT formula aiming to minimize the necessary code alterations;
- The soft clauses are the relaxation variables used to instrument the C program, expressed as

$$S = \bigwedge_{c \in \mathcal{C}} (r v_c);$$

- We assign a hierarchical weight to each relaxation variable based on the height of its sub-AST (abstract syntax tree);
- CFAULTS enumerates all MaxSAT solutions to identify all subset-minimal diagnoses.

Experimental Results

 CFAULTS has been evaluated using two benchmarks of C programs: TCAS [Do et al., 2005] and C-PACK-IPAS [Orvalho et al., 2022];

- CFAULTS has been evaluated using two benchmarks of C programs: TCAS [Do et al., 2005] and C-PACK-IPAS [Orvalho et al., 2022];
- TCAS, from Siemens, comprises 41 versions of a program with introduced faults;

- CFAULTS has been evaluated using two benchmarks of C programs: TCAS [Do et al., 2005] and C-PACK-IPAS [Orvalho et al., 2022];
- TCAS, from Siemens, comprises 41 versions of a program with introduced faults;
- C-PACK-IPAs is a set of **introductory programming assignments**. It consists of ten programming assignments, comprising **486 faulty programs**.

- CFAULTS has been evaluated using two benchmarks of C programs: TCAS [Do et al., 2005] and C-PACK-IPAS [Orvalho et al., 2022];
- TCAS, from Siemens, comprises 41 versions of a program with introduced faults;
- C-PACK-IPAs is a set of **introductory programming assignments**. It consists of ten programming assignments, comprising **486 faulty programs**.
- All the experiments were conducted using:

- CFAULTS has been evaluated using two benchmarks of C programs: TCAS [Do et al., 2005] and C-PACK-IPAS [Orvalho et al., 2022];
- TCAS, from Siemens, comprises 41 versions of a program with introduced faults;
- C-PACK-IPAs is a set of **introductory programming assignments**. It consists of ten programming assignments, comprising **486 faulty programs**.
- All the experiments were conducted using:
 - a memory limit of **32GB**;

- CFAULTS has been evaluated using two benchmarks of C programs: TCAS [Do et al., 2005] and C-PACK-IPAS [Orvalho et al., 2022];
- TCAS, from Siemens, comprises 41 versions of a program with introduced faults;
- C-PACK-IPAs is a set of **introductory programming assignments**. It consists of ten programming assignments, comprising **486 faulty programs**.
- All the experiments were conducted using:
 - a memory limit of **32GB**;
 - a timeout of **3600 seconds** (1 hour).

BUGASSIST and SNIPER:

 are either unavailable or no longer maintained, prototypes of their algorithms were implemented;

BUGASSIST and SNIPER:

- are either unavailable or no longer maintained, prototypes of their algorithms were implemented;
- in this experiment, **handle ANSI-C programs**, as their algorithms are built on top of CFAULTS's unroller and instrumentalizer modules.

Results

Benchmark: TCAS

	Valid Diagnosis	Memouts	Timeouts
BugAssist	41 (100.0%)	0 (0.0%)	0 (0.0%)
SNIPER	7 (17.07%)	34 (82.93%)	0 (0.0%)
CFaults	41 (100.0%)	0 (0.0%)	0 (0.0%)
CFaults-Refined	41 (100.0%)	0 (0.0%)	0 (0.0%)

Table 4: BUGASSIST, SNIPER and CFAULTS fault localization results on TCAS.

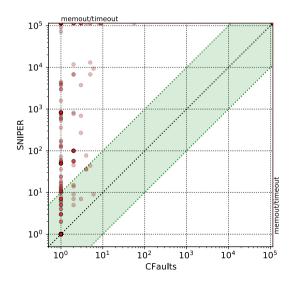
Results

Benchmark: C-Pack-IPAs

	Valid	Memouts	Timeouts
	Diagnosis		
BugAssist	454 (93.42%)	0 (0.0%)	32 (6.58%)
SNIPER	446 (91.77%)	4 (0.82%)	36 (7.41%)
CFaults	483 (99.38%)	1 (0.21%)	2 (0.41%)
CFaults-Refined	482 (99.18%)	1 (0.21%)	3 (0.62%)

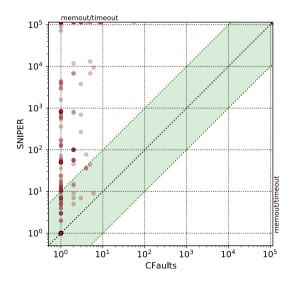
Table 5: BUGASSIST, SNIPER and CFAULTS fault localization results on C-PACK-IPAS.

Diagnoses Enumerated



1. CFAULTS needs to enumerate all MaxSAT solutions due to the weighted MaxSAT formula;

Diagnoses Enumerated



- CFAULTS needs to enumerate all MaxSAT solutions due to the weighted MaxSAT formula;
- 2. SNIPER generates significantly more diagnoses.

 We tackle the FL problem in C using Model-Based Diagnosis (MBD) with multiple failing test cases, formulating it as a unified optimization problem;

- We tackle the FL problem in C using Model-Based Diagnosis (MBD) with multiple failing test cases, formulating it as a unified optimization problem;
- We only generate subset-minimal aggregated diagnosis to identify all faulty program components;

- We tackle the FL problem in C using Model-Based Diagnosis (MBD) with multiple failing test cases, formulating it as a unified optimization problem;
- We only generate subset-minimal aggregated diagnosis to identify all faulty program components;
- We present CFAULTS, a fault localization tool for ANSI-C programs, that:

- We tackle the FL problem in C using Model-Based Diagnosis (MBD) with multiple failing test cases, formulating it as a unified optimization problem;
- We only generate subset-minimal aggregated diagnosis to identify all faulty program components;
- We present CFAULTS, a fault localization tool for ANSI-C programs, that:
 - allows refinement of localized faults to pinpoint the bugs' location more precisely;

- We tackle the FL problem in C using Model-Based Diagnosis (MBD) with multiple failing test cases, formulating it as a unified optimization problem;
- We only generate subset-minimal aggregated diagnosis to identify all faulty program components;
- We present CFAULTS, a fault localization tool for ANSI-C programs, that:
 - allows refinement of localized faults to pinpoint the bugs' location more precisely;
 - is **fast and only produces subset-minimal diagnoses**, unlike other SOTA FBFL tools.

References



Reiter, Raymond (1987)

A Theory of Diagnosis from First Principles.

Artif. Intell. 1987.



Do, Hyunsook and Elbaum, Sebastian G. and Rothermel, Gregg (2005)

Supporting Controlled Experimentation with Testing Techniques: An Infrastructure and its Potential Impact.

Empir. Softw. Eng. 2005.



Manu Jose and Rupak Majumdar (2011)

Cause clue clauses: error localization using maximum satisfiability.

PLDI 2011.



Lamraoui, Si-Mohamed and Nakajima, Shin (2016)

A Formula-based Approach for Automatic Fault Localization of Multi-fault Programs.

J. Inf. Process. 24(1), 88 – 98.

References



Ignatiev, Alexey and Morgado, António and Weissenbacher, Georg and Marques-Silva, João (2019) Model-Based Diagnosis with Multiple Observations.

IJCAI 2019.



Orvalho, P. and Janota, M. and Manquinho, V. (2022)

C-Pack of IPAs: A C90 Program Benchmark of Introductory Programming Assignments. arXiv:2206.08768.



The Guardian - Year 2000 Problem

https://www.theguardian.com/comment is free/2019/dec/31/millennium-bug-face-fears-y2k-it-systems

The Guardian 2019.



The Sun UK - Crowdstrike Meltdown

https://www.thesun.co.uk/tech/27223882/microsoft-crowdstrike-meltdown-trillions-cost-world-economy.

The Sun UK.

CFaults

Thank you!





https://github.com/pmorvalho/cfaults