Performance Optimization on a Supercomputer with cTuning and the PGI compiler

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CISL Computational & Information Systems Laboratory

About me

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About NCAR

- National Center for Atmospheric Research
- Federally funded R&D center
- Service, research and education in the atmospheric and related sciences
- Various “Laboratories”: NESL, EOL, RAL
- Observational, theoretical, and numerical
- CISL is a world leader in supercomputing and cyberinfrastructure

Disclaimer

Opinions, findings, conclusions, or recommendations expressed in this talk are mine and do not necessarily reflect the views of my employer.

Compiler's challenges

- Hardware is becoming more complex
- Some optimizations depend on frequently changing hw details
- Others are NP-complete
- Others are undecidable
- Hand-tuned heuristics are usually implemented in production compilers
- Other techniques provided better results

Need for speed

- Dramatic clock speed increase with Moore's law has stopped
- Science needs computation horsepower
- Hardware is becoming more complex
- Parallelism has become mainstream
- There is more interest in applying new research techniques to mainstream compilers.

Iterative compilation

- Compile a program with a set of different optimization flags
- Execute the binary
- Try again, until a satisfactory performance is achieved – of course this is a very long process
- … and more

Predict optimization flags

- Use "somehow" the knowledge from iterative compilation, to find best optimizations quicker
- For example, pick flags with a strategy
- Note that the best optimization for a particular program on a particular architecture strongly depends on the program and the architecture
- Try Machine Learning

Existing cTuning CC infrastructure

- Feature extraction with MILEPOST GCC (56 features)
- Training infrastructure CCC (Continuous Collective Compilation) and cBench set of 20 training programs
- Machine Learning prediction infrastructure
- … and more

Our contributions

- Implemented the PGI compiler in the framework
- Added a few benchmarks
- Reimplemented kNN
- Deployed on our system

PGI configuration file

```
1, 0, 4, -O
2, -fpic
2, -Mcache_align
3, 2, -Mnodse, -Mdse
3, 2, -Mnoautoinline, -Mautoinline
1, 20, 200, -Minline=size:
1, 5, 20, -Minline=levels:
2, -Minline=reshape
2, -Mipa=fast
3, 3, -Mnolre, -Mlre=assoc, -Mnolre=noassoc
3, 2, -Mnomovnt, -Mmovnt
2, -Mnovintr
3, 3, -Mnopre, -Mpre, -Mpre=all
1, 1, 10, -Mprefetch=distance:
1, 1, 100, -Mprefetch=n:
3, 2, -Mnopropcond, -Mpropcond
2, -Mquad
3, 2, -Mnosmart, -Msmart
3, 2, -Mnostride0, -Mstride0
1, 2, 16, -Munroll=c:
1, 2, 16, -Munroll=n:
1, 2, 16, -Munroll=m:
3, 2, -Mvect=noaltcode, -Mvect=altcode
3, 2, -Mvect=noassoc, -Mvect=assoc
3, 2, -Mvect=nofuse, -Mvect=fuse
3, 2, -Mvect=nogather, -Mvect=gather
1, 1, 10, -Mvect=levels:num
2, -Mvect=partial
2, -Mvect=prefetch
3, 2, -Mvect=noshort, -Mvect=short
3, 2, -Mvect=nosse, -Mvect=sse
```

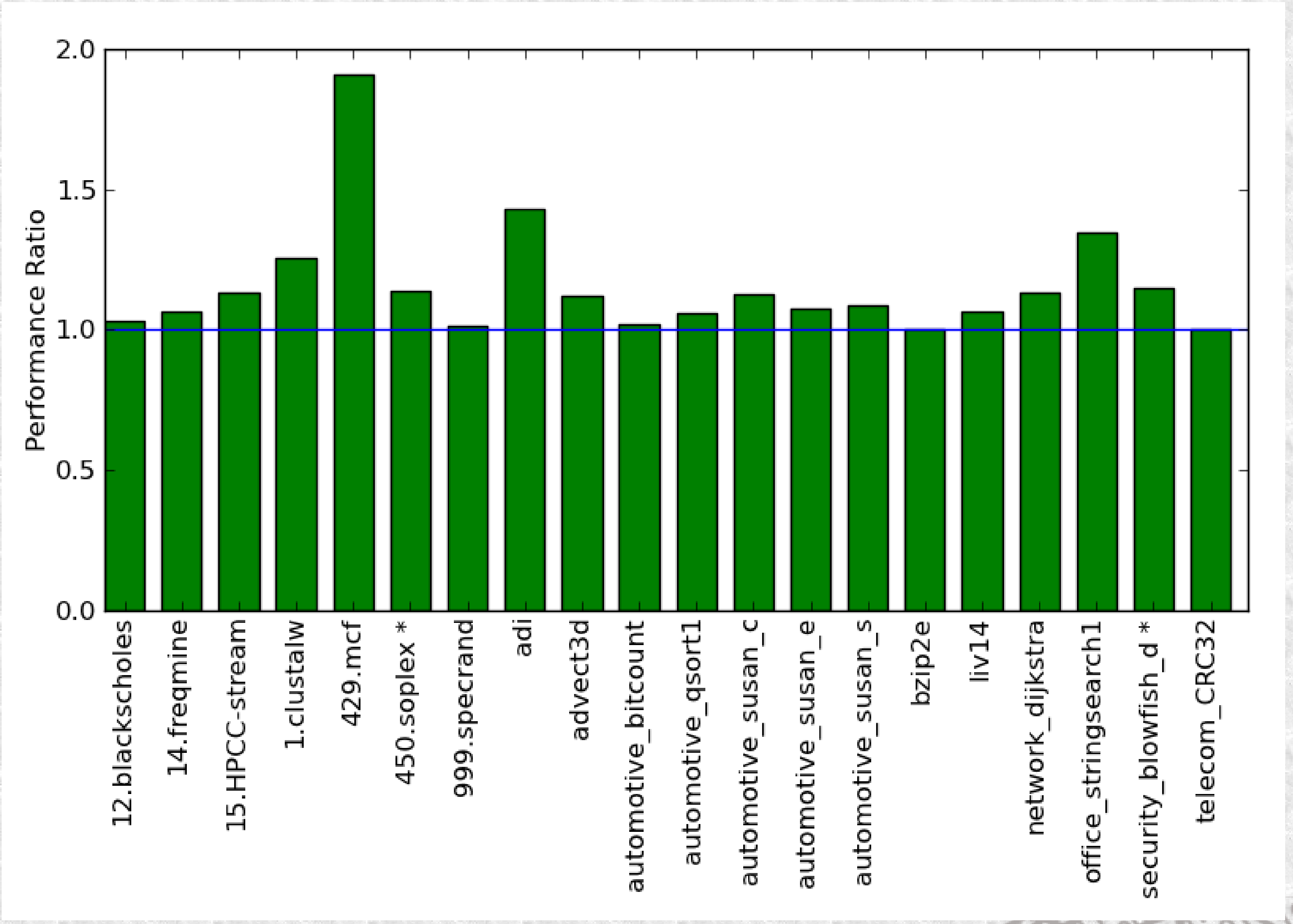
Training programs

	benchmark	suite
1.	automotive_bitcount	cBench [12]
2.	automotive_qsort1	cBench [12]
3.	automotive_susan_c	cBench [12]
4.	automotive_susan_e	cBench [12]
5.	automotive_susan_s	cBench [12]
6.	bzip2e	cBench [12]
7.	network_dijkstra	cBench [12]
8.	office_stringsearch1	cBench [12]
9.	security_blowfish d	cBench [12]
10.	telecom_CRC32	cBench [12]
11.	12.blackscholes	PARSEC [6]
12.	14.freqmine	PARSEC [6]
13.	15.stream	HPCC [3]
14.	429.mcf	SPEC CINT2006 [8]
15.	450.soplex	SPEC CFP2006 [8]
16.	999.specrand	SPEC [8]
17.	adi	Livermore benchmarks kernel
18.	liv14	Livermore loops
19.	1.clustalw	BioBench [11]
20.	advect3d	kernel from COMMAS [5]

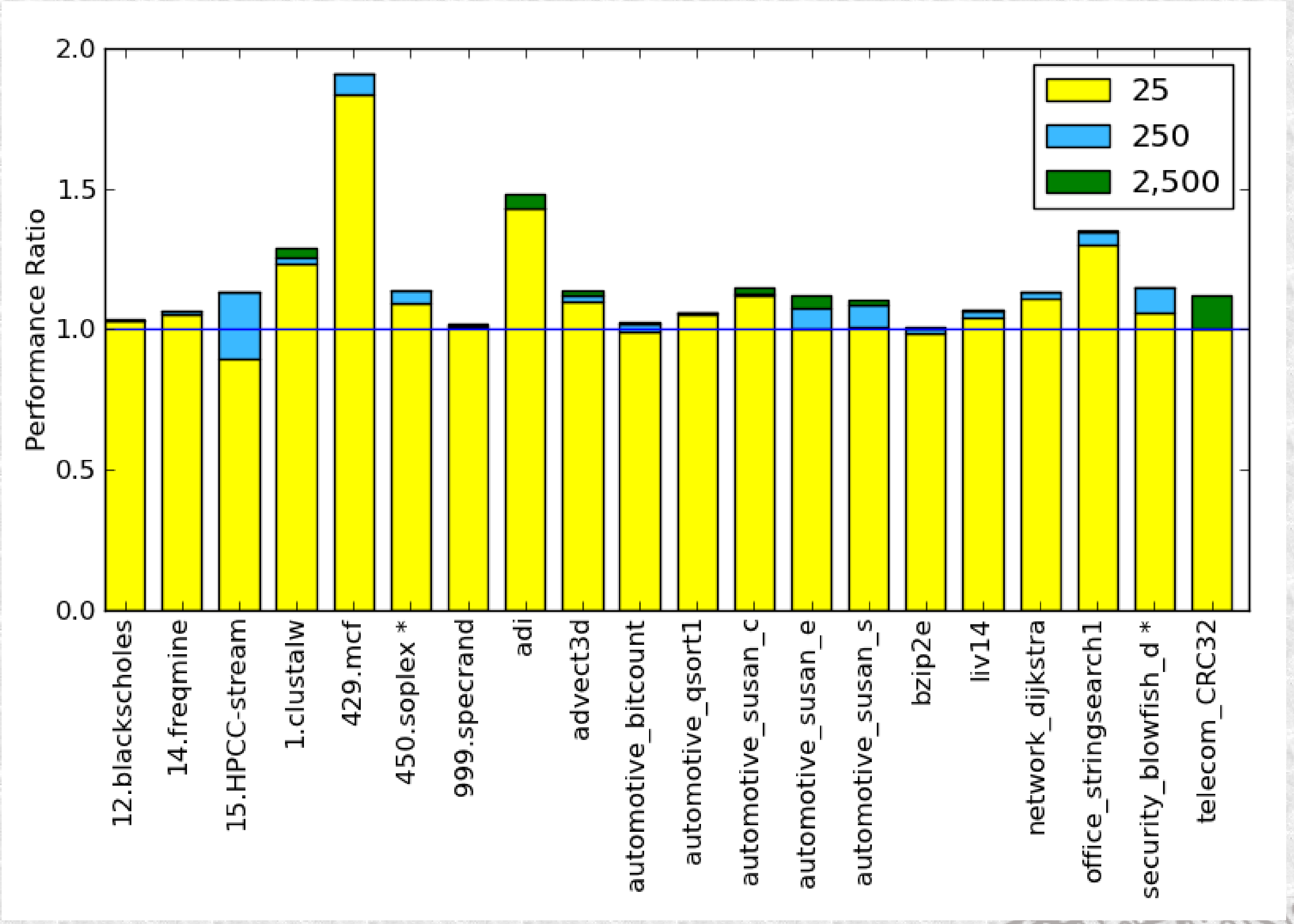
Deployment

- Reimplemented kNN in python
- Boring details of job submission and management on our machine
- Some glue from output of cTuning CCC to our data analysis, plots, etc

Iterative compilation



Convergence



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Training

- The output of iterative compilation is fed to a machine learning algorithm

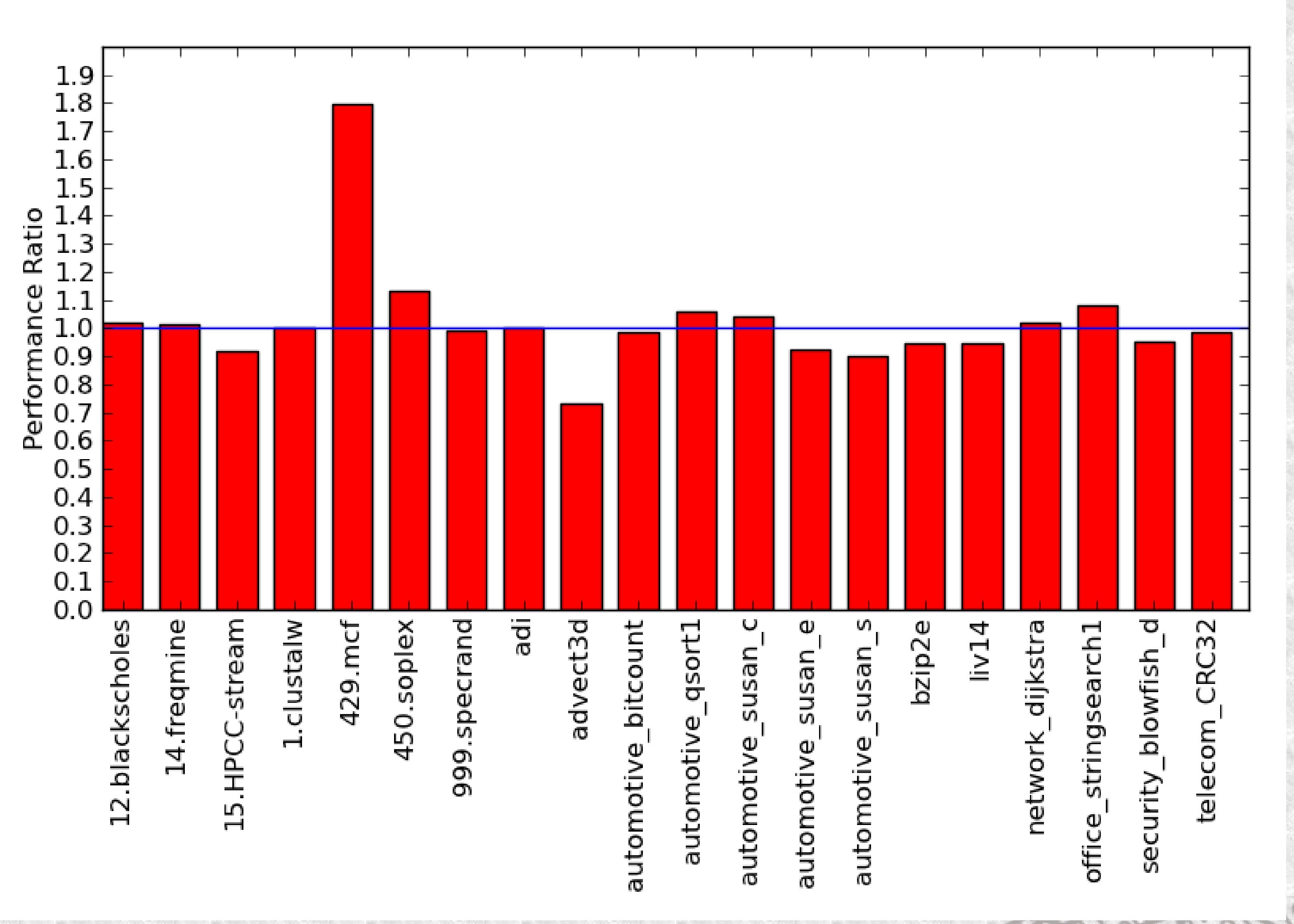
- In our case is simply kNN with k=1

- So the kNN learner is trained to select the “best” set of optimization flag, among the 20 sets (each for each example program)

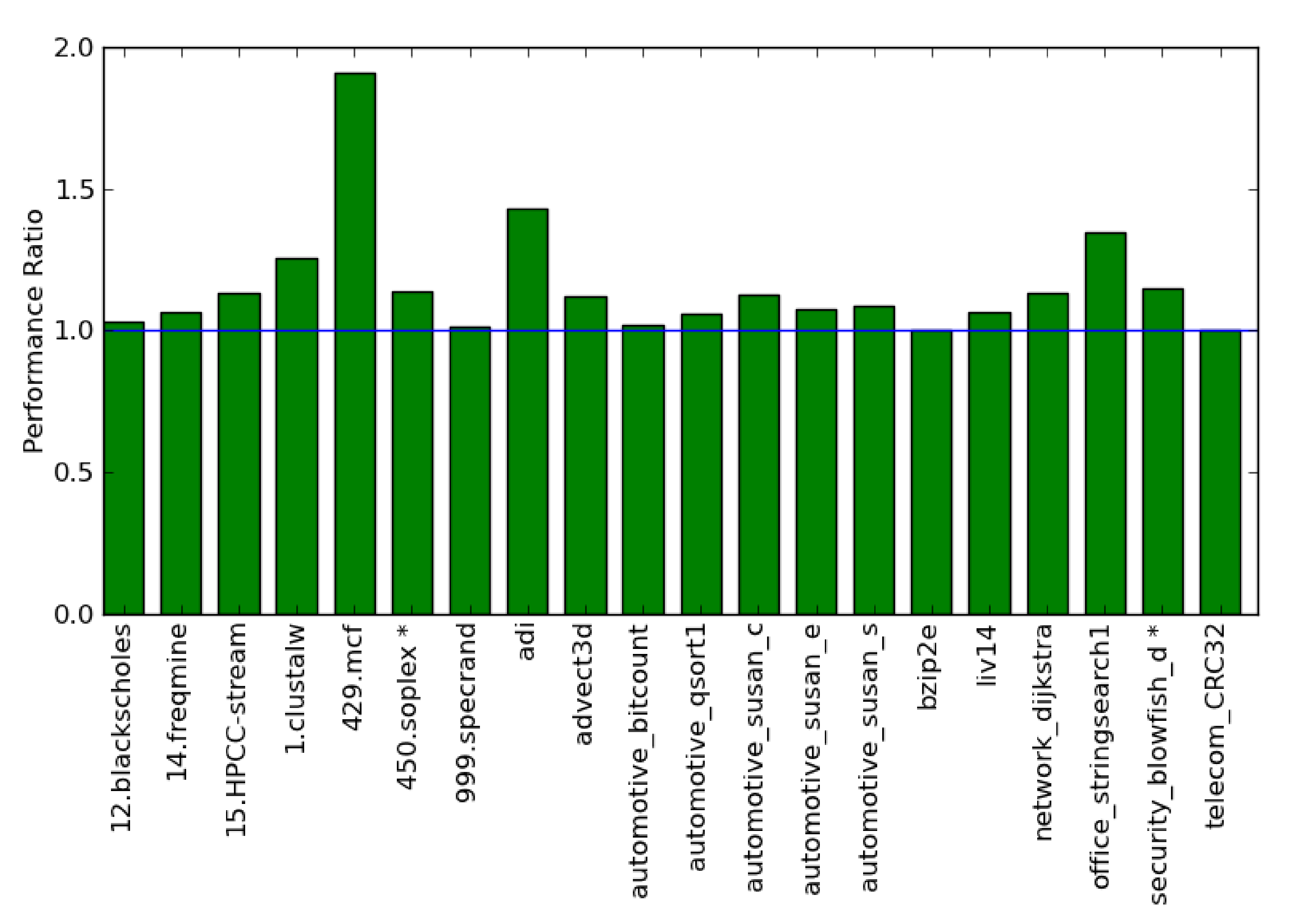
Crossvalidation

- Leave-one-out crossvalidation is a commonly used technique to estimate ML
- Each training example is left out, the learner is retrained and used to predict the missing example
- It has a bias, but it is simple and still provides a useful evaluation so it is commonly used

Crossvalidation



Iterative compilation



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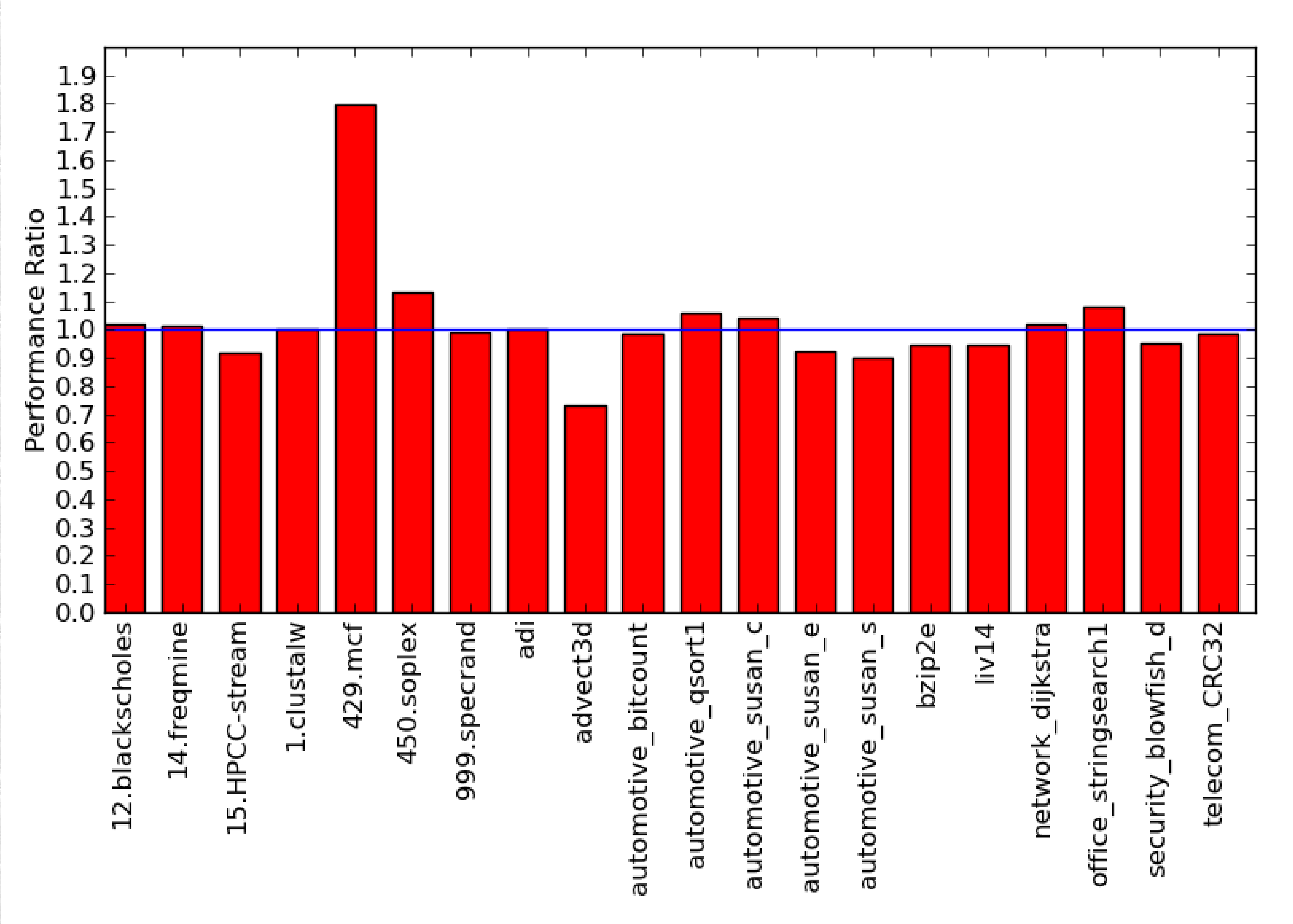
A different look at the data (1)

- What can we learn from this result? How can we process it to learn more?
- Is the training set too limited?
- Do the features characterize correctly the example and instances (programs)?
- Are there too many features (kNN)?
- Could a different ML algorithm perform better?

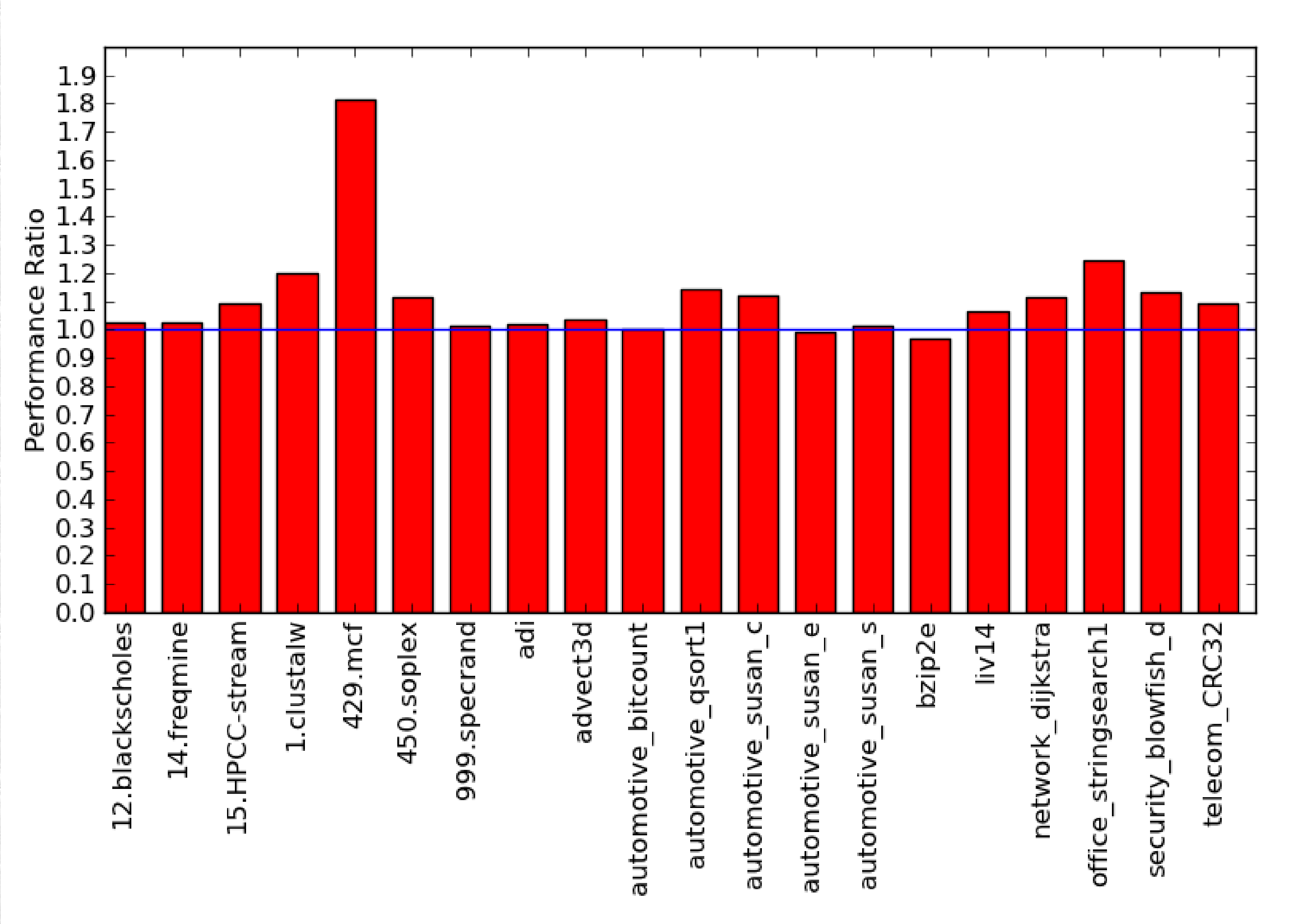
A different look at the data (2)

- To answer these questions
- We ran an exhaustive search among the database of 19 “good” sets of optimization flags, for each leave-one-out program
- And selected the best
- This is the best that kNN can do for this dataset (e.g. changing or weighting the features)

Crossvalidation



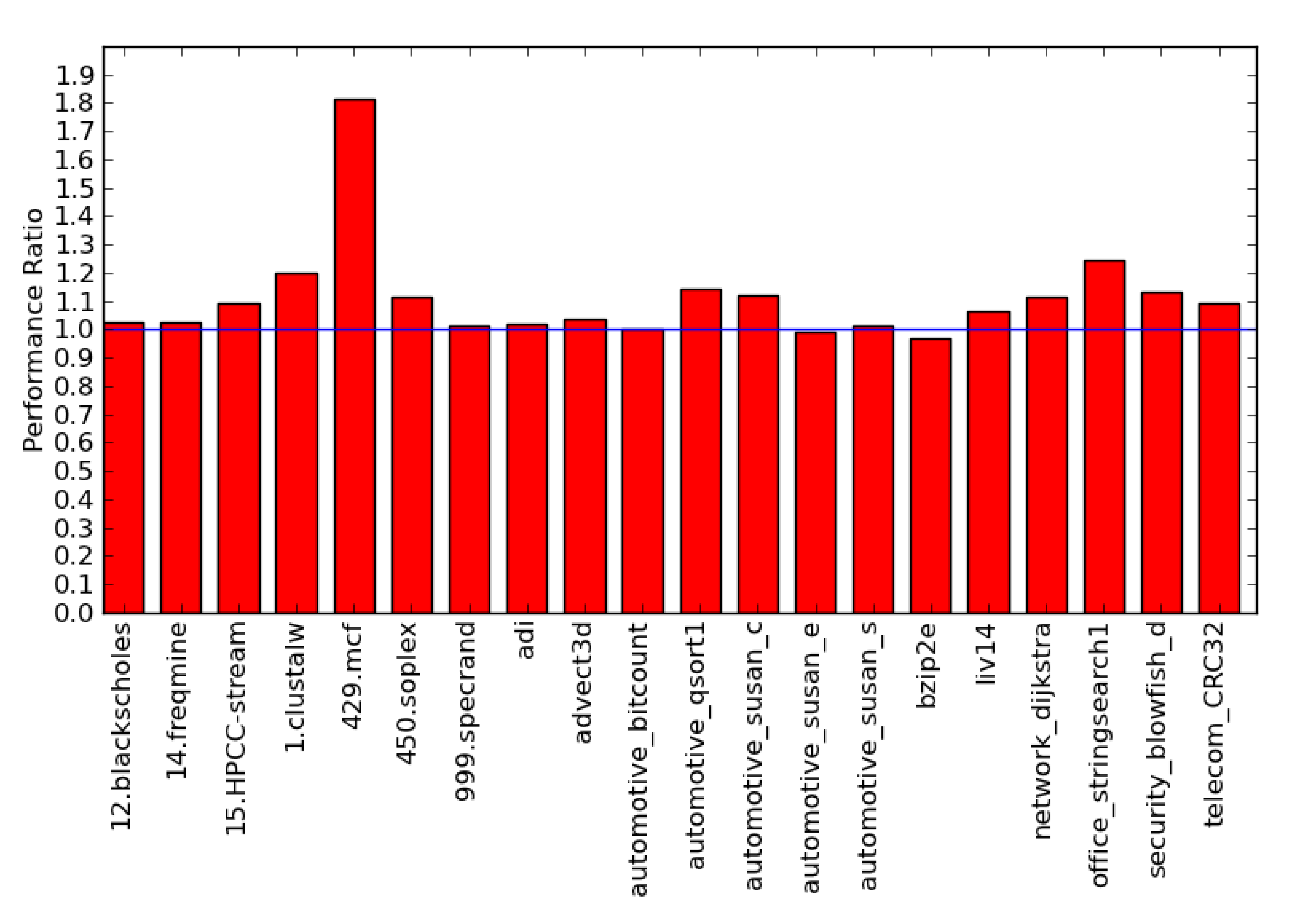
Upper limit to kNN cross-validation



First result

- Changing the way in which the distance is measured (e.g. removing irrelevant features) can improve performance

Upper limit to kNN cross-validation



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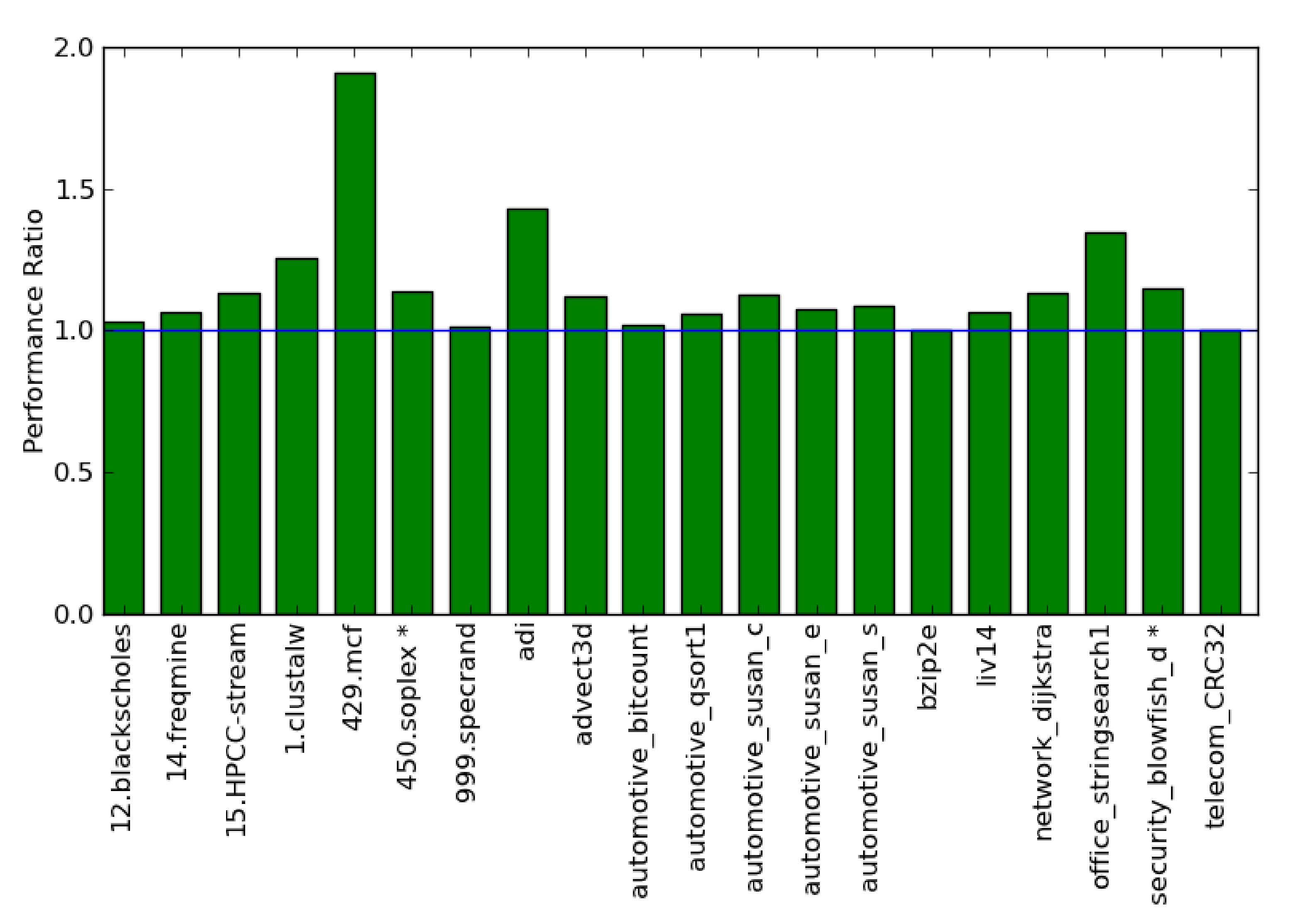
Iterative compilation



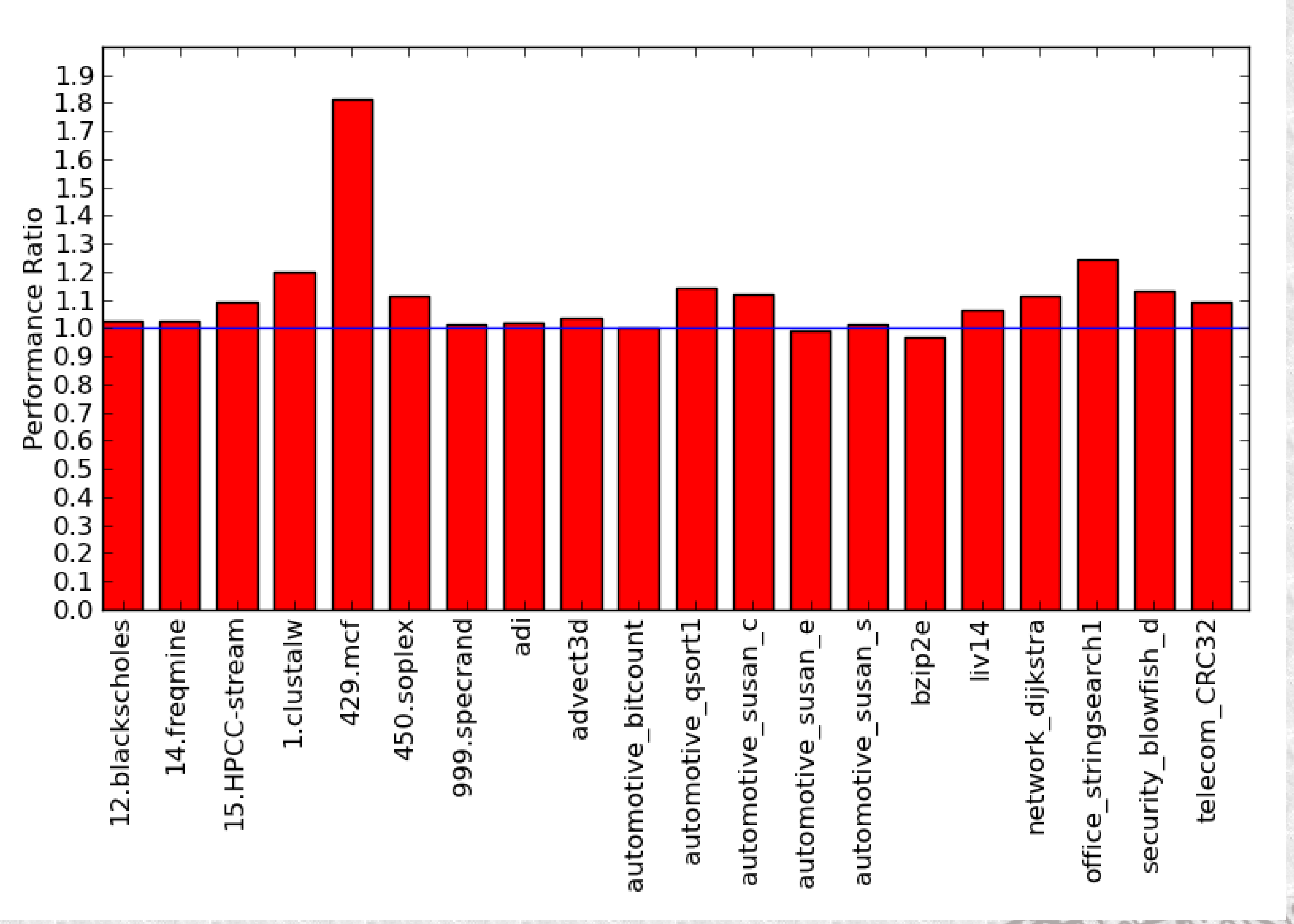
More results (1)

- When exhaustive search is less performant than iterative compilation...
- Upper limit of kNN, regardless of distance evaluation is not competitive
- Adding more example programs might improve these cases
- Changing to an algorithm doing individual flag prediction (like SVN) might also improve these cases

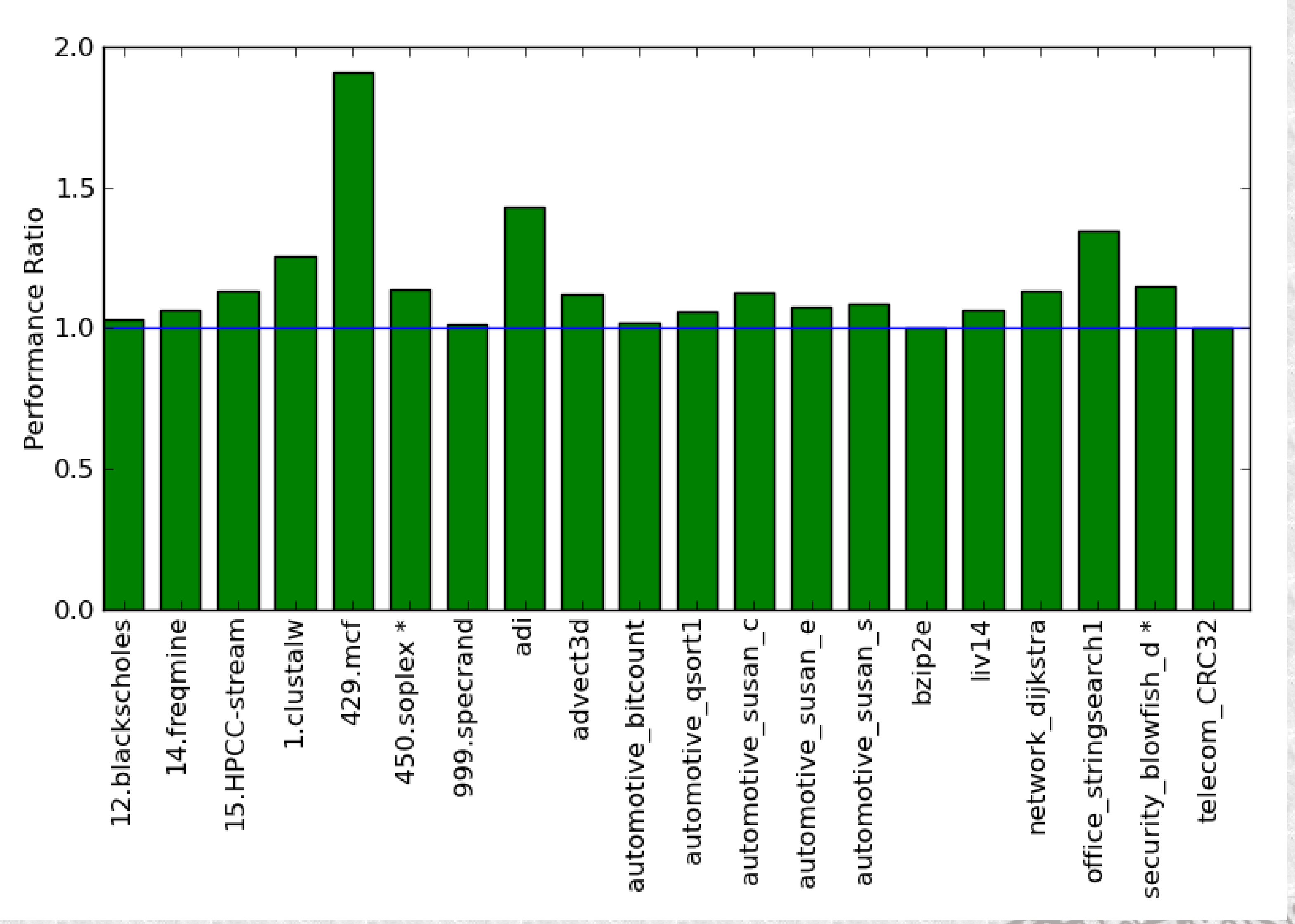
More results (2)

- When exhaustive search is more performant than iterative compilation...
- We have discovered an important area of the optimization space not covered by iterative compilation
- Exploration of the optimization space with techniques different from the pure random space might find better results

Upper limit to kNN cross-validation



Iterative compilation



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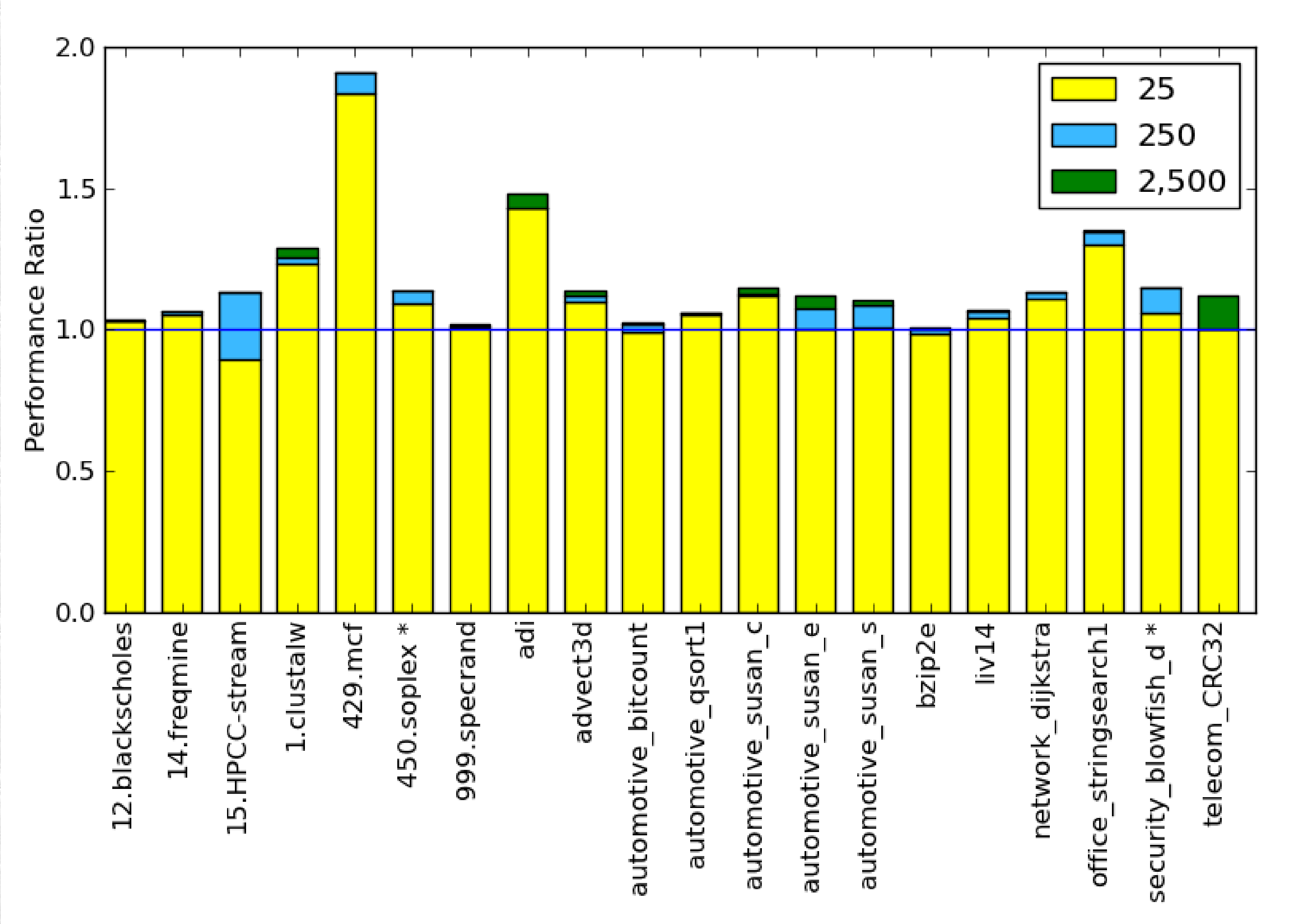
Convergence



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Conclusions

- We are interested in having an autotuning compiler deployed in production
- We demonstrated that there is potential to improve performance, even of an already aggressively optimized compiler such as PGI
- There is more work to do

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Questions?