Technische Universität Berlin

Cost Modelling for Vectorization on ARM

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Challenges of Auto-Vectorization in Compilers

1. Is it **possible** to vectorize the code?
   - Passes: Loop Level Vectorization (LLV), Superword-Level Parallelism (SLP) …
   - Algorithms: loop transformations, partial vectorization, SLP padding …
   - Challenges: dependences, missing instructions …

2. Is it **beneficial** to vectorize the code?
   - Transformations might add overhead
   - Code can run slower afterwards

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Short Introduction to Cost Modelling

```
int s121() {
   for (int i = 0; i < LEN; i++){
      j = i + 1;
      a[i] = a[j] + b[i];
   }
   return 0;
}
```

C Source

```
%indvars.iv.next = add nuw nsw i64 %indvars.iv, 1, !dbg !55
%1 = load float, float* %arrayidx, align 4, !dbg !56, !tbaa !22
%2 = load float, float* %arrayidx7, align 4, !dbg !57, !tbaa !22
%add8 = fadd fast float %2, %1, !dbg !58
store float %add8, float* %arrayidx10, align 4, !dbg !60, !tbaa !22
%exitcond = icmp eq i64 %indvars.iv.next, 31999, !dbg !61
```

LLVM's Intermediate Representation

$$C_{add,VF=1} = 1$$
$$C_{load,VF=1} = 1$$
$$C_{load,VF=1} = 1$$
$$C_{fadd,VF=1} = 2$$
$$C_{store,VF=1} = 1$$
$$C_{icmp,VF=1} = 1$$

Block Cost Calculation

$$C_{loop} = \frac{1}{VF} \sum C_{instr,VF}$$

$$S_{est} = \frac{C_{scalar}}{C_{vec}}$$

Estimate Benefit

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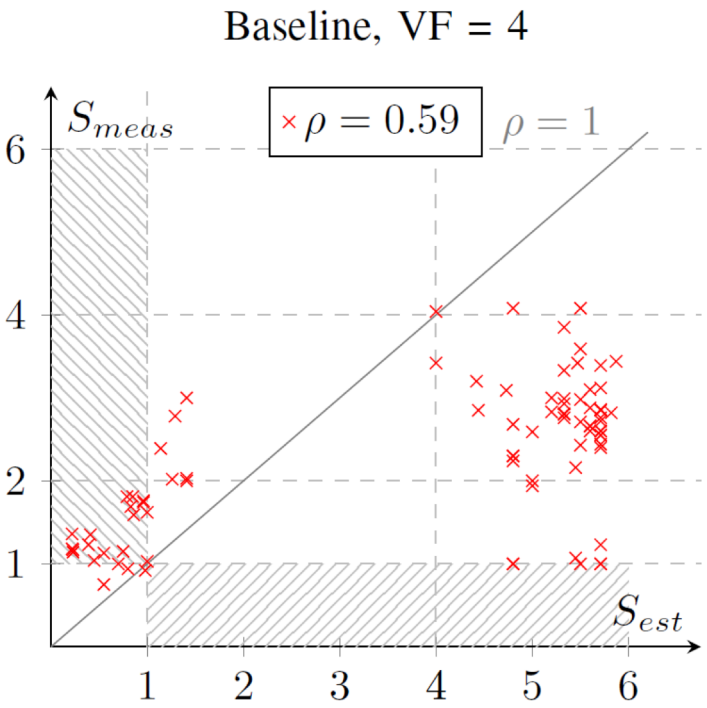
State of the Art Analysis

- LLV pass of LLVM 6.0 on ARMv8
- TSVC Benchmark: 151 basic loop patterns
- Vectorization with overwritten cost model
- No unrolling, no interleaving

Metric	Baseline
Vectorized loops	61
$f\ominus$	14
$f\oplus$	0
t_{norm}	117.2



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Linear Modelling Approach

- Formulate basic block as linear equation for each test pattern

$$c_{vec} = \sum n_i c_i$$

- Determine basic block target cost based on measurement

$$c_{target} = \frac{c_{scalar}}{S_{meas}} = \sum n_i c_{i'}$$

- Apply mathematical fitting to set of linear equations

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Linear Modelling: Example

```
for (int i = 0; i < LEN; i++){
      a[i] = b[k] + 1.0;
}
```

$c_{scalar} = 8 \quad S_{meas} = 2.76 \Rightarrow \quad c_{target} = 2.89$

```
for (int i = 0; i < LEN; i++){
      prod *= a[i];
}
```

$c_{scalar} = 6 \quad S_{meas} = 2.30 \quad \Rightarrow \quad c_{target} = 2.61$

$$\mathbf{2.89} = \mathbf{1} \times c_{load} + \mathbf{1} \times c_{fadd} + \mathbf{0} \times c_{fmult} + \cdots$$

$$\mathbf{2.61} = \mathbf{1} \times c_{load} + \mathbf{0} \times c_{fadd} + \mathbf{1} \times c_{fmult} + \cdots$$

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Modelling Speedup Instead of Cost

Problem:

- Target costs vary significantly, i.e. data has to be fitted across large interval
- But: fitting benefits from smaller target intervals

Idea:

- Model speedup instead of cost
- Limits interval to (0, vectorization factor)
- Linear equations become $S_{meas} = \sum n_i w_i$

  with n_i = numer of instructions of same type, w_i = corresponding weight

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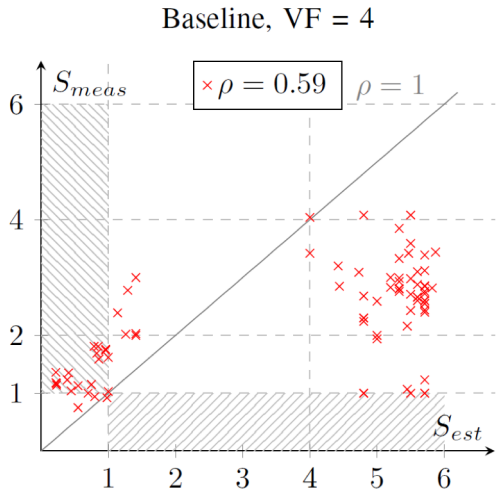
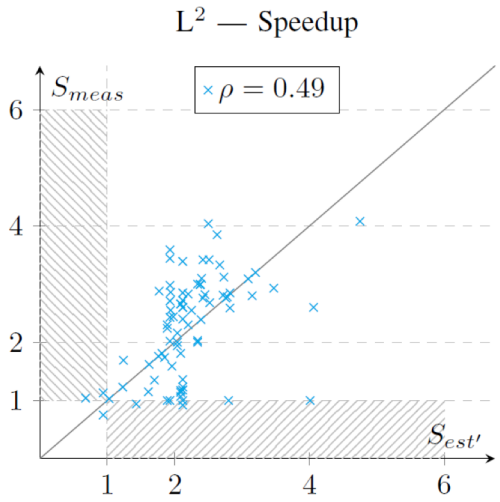
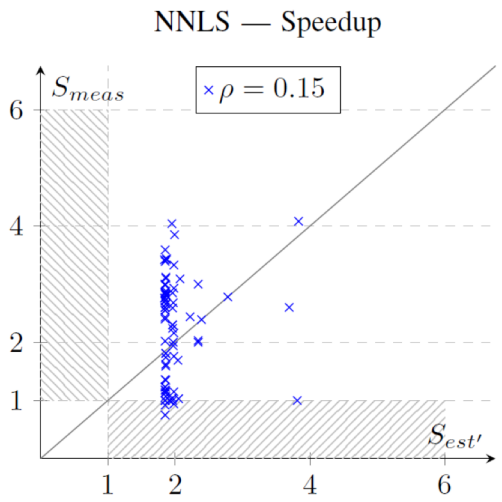
Results: Fitted for Speedup







- L2: Least Squares (minimizes Euclidian L2 Norm)
- NNLS: Non-Negative Least Squares (all coefficients > 0)

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Adding Block Composition as Feature

Problem:

- Current cost model only cares about individual instructions
- Arithmetic intensity can have major impact on speedup, e.g. if code is memory bound

Idea:

- Replace count of instruction type with overall percentage, e.g. 20% load, 10% cmp, …

$$S_{meas} = \sum \frac{n_i}{n_{total}} w_i$$

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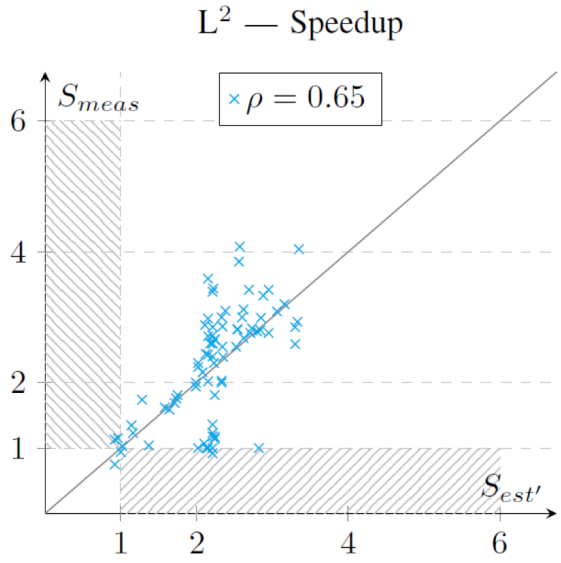
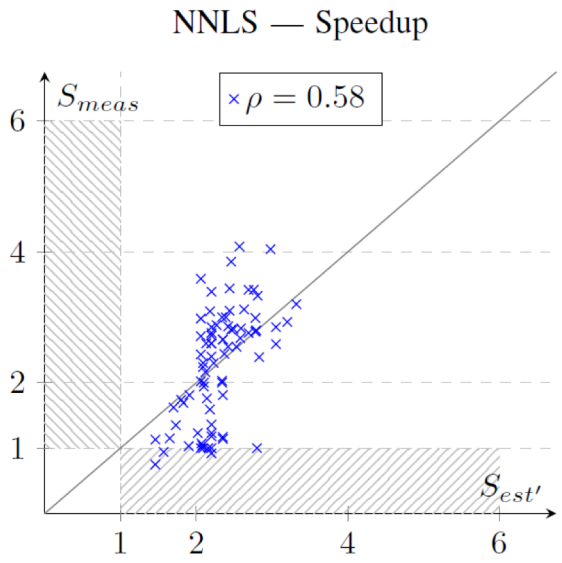
Results: Fitted with Rated Instruction Count





Metric	Baseline	L^2	$NNLS$
Vectorized loops	61	76	80
$f\ominus$	14	2	0
$f\oplus$	0	1	3
t_{norm}	117.2	113.2	113.4

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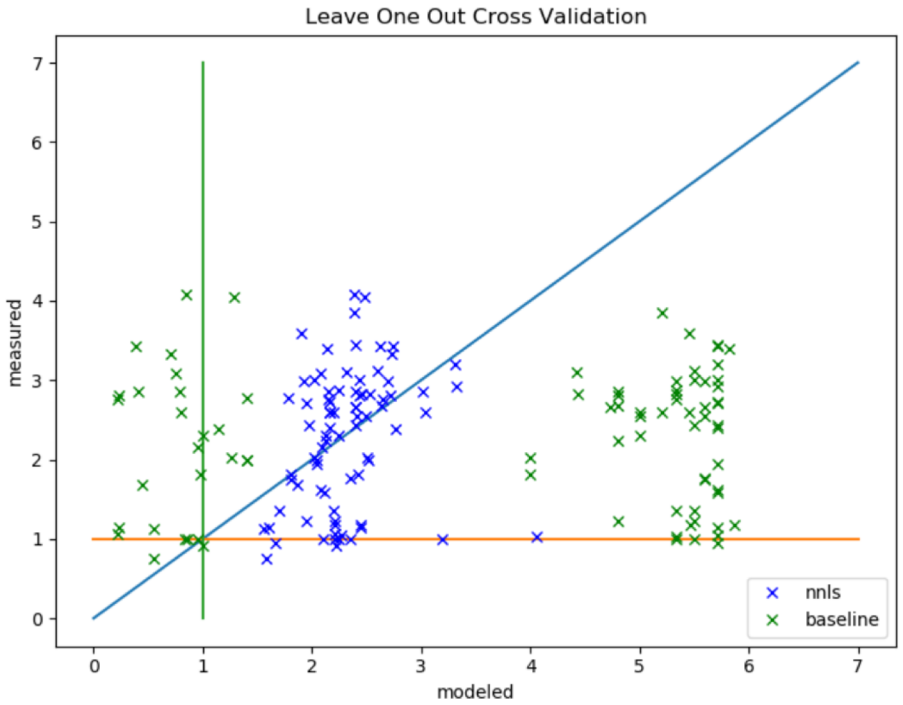
Leave One Out Cross Validation: NNLS

- Fitting is done with whole training data set except for one kernel
- Kernel is then predicted with that model



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Conclusion

- Compilers need more accurate cost models to avoid mispredictions
- Aligned cost models enable comparison of different transformation options
- With our refined cost model we
  - Increase the correlation between estimated and measured speedup
  - Decrease the number of false predictions
  - Lower execution times
- Next steps: add more code features and tests to cover all instruction types

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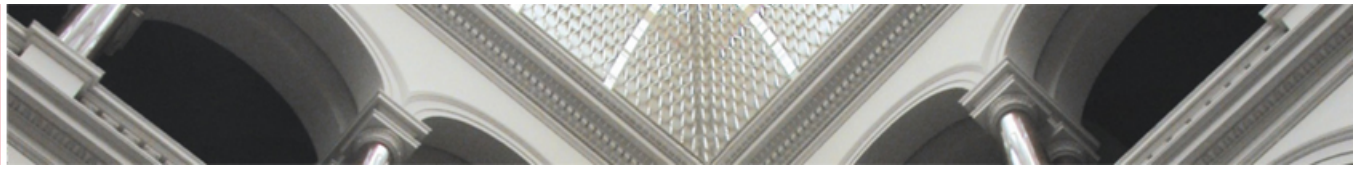

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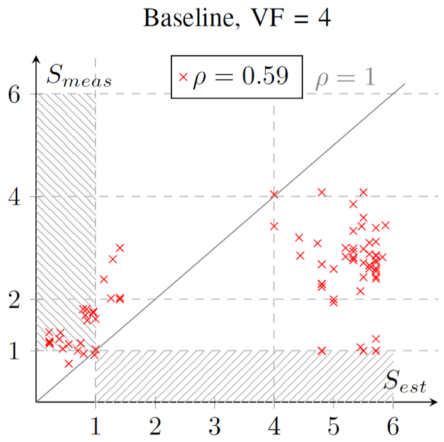

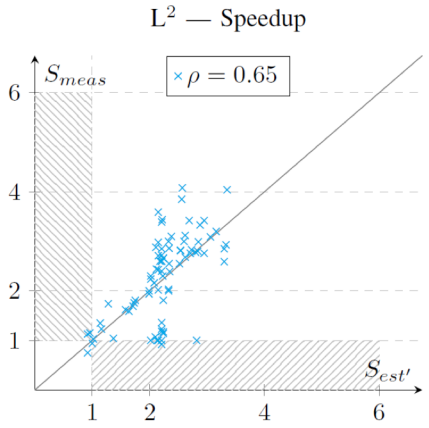

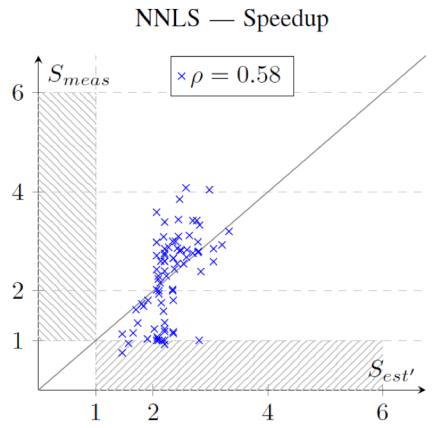

THANK YOU

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BACKUP

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Why a More Accurate Cost Model?

1. Improve classification results to decide whether code should be vectorized or not.

2. Enable comparison of different transformations with each other, not just to baseline.

```
for (int i = 0; i < LEN/2; i++){
      k = j + 1;
      a[i] = b[k] – d[i];
      j = k + 1
      b[k] = a[i] + c[k];
}
```

	LLV	SLP
Predicted Speedup	0.96	1.00
Measured Speedup	1.13	1.20

Example code run on Intel i5

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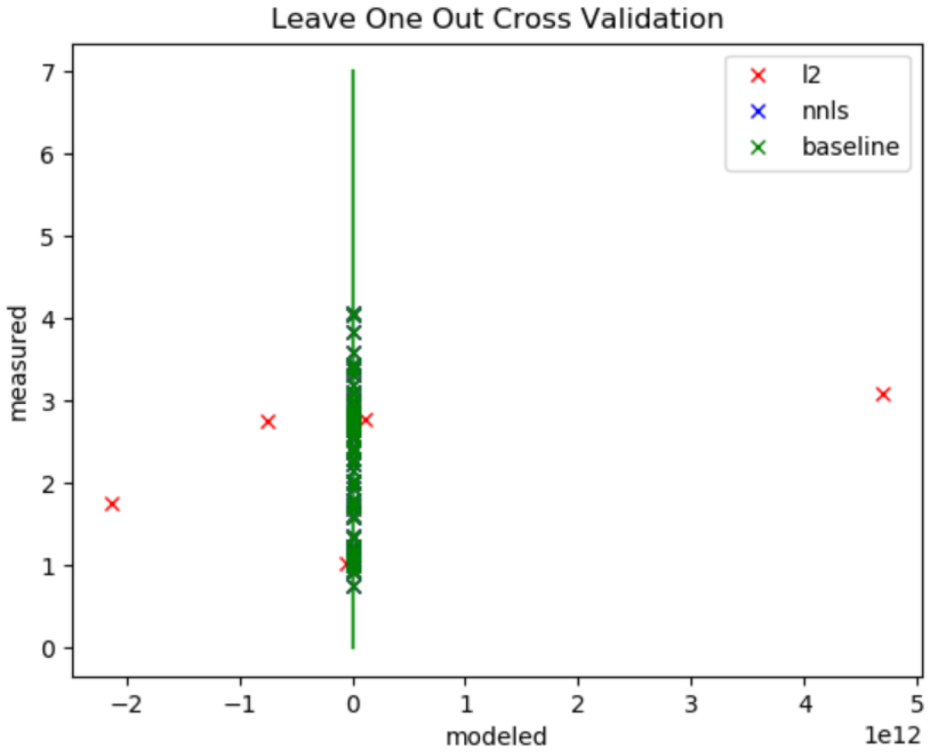
L2- LOOCV Validation Results



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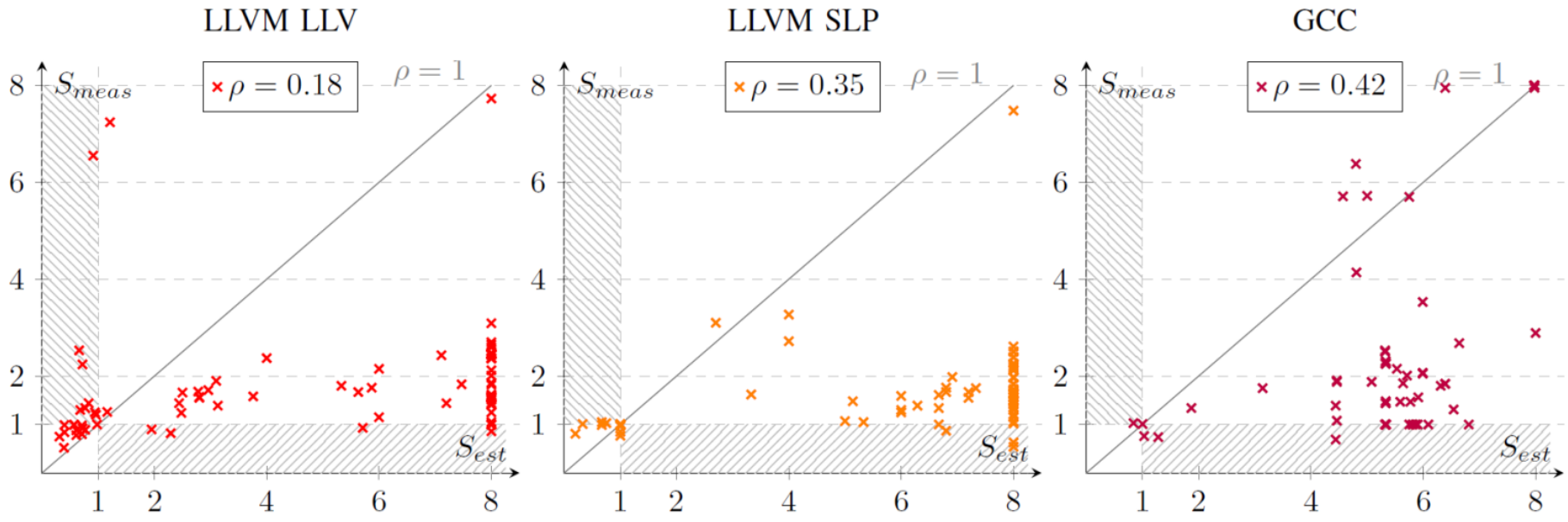
State of the Art Analysis – x86



- TSVC benchmark: 151 basic loop patterns
- SLP vectorization applied after loop unrolling
- Results shown for Intel Xeon E5 with AVX2

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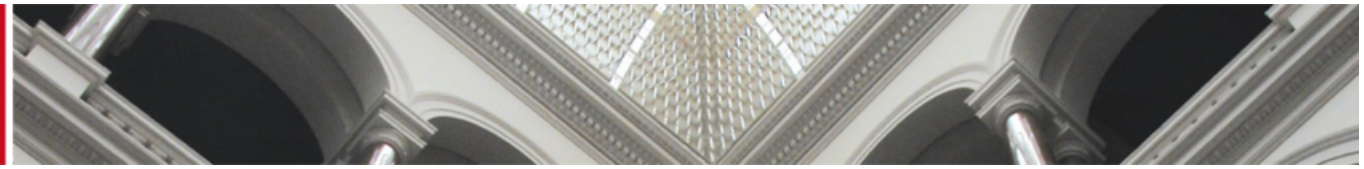

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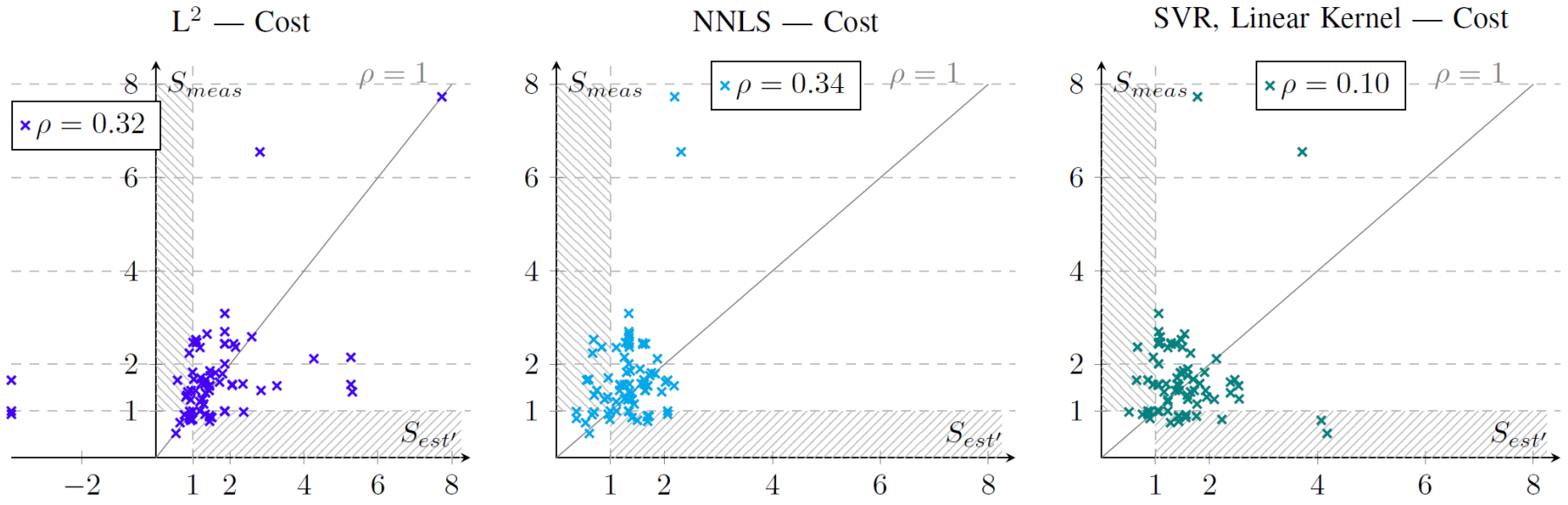
Results: Fitted for Cost – x86



- Correlation between estimated and measured speedup in LLVM‘s LLV pass after fitting
- L2: Least Squares (minimizes Euclidian L2 Norm)
- NNLS: Non-Negative Least Squares (all coefficients > 0)
- SVR: Support Vector Regression

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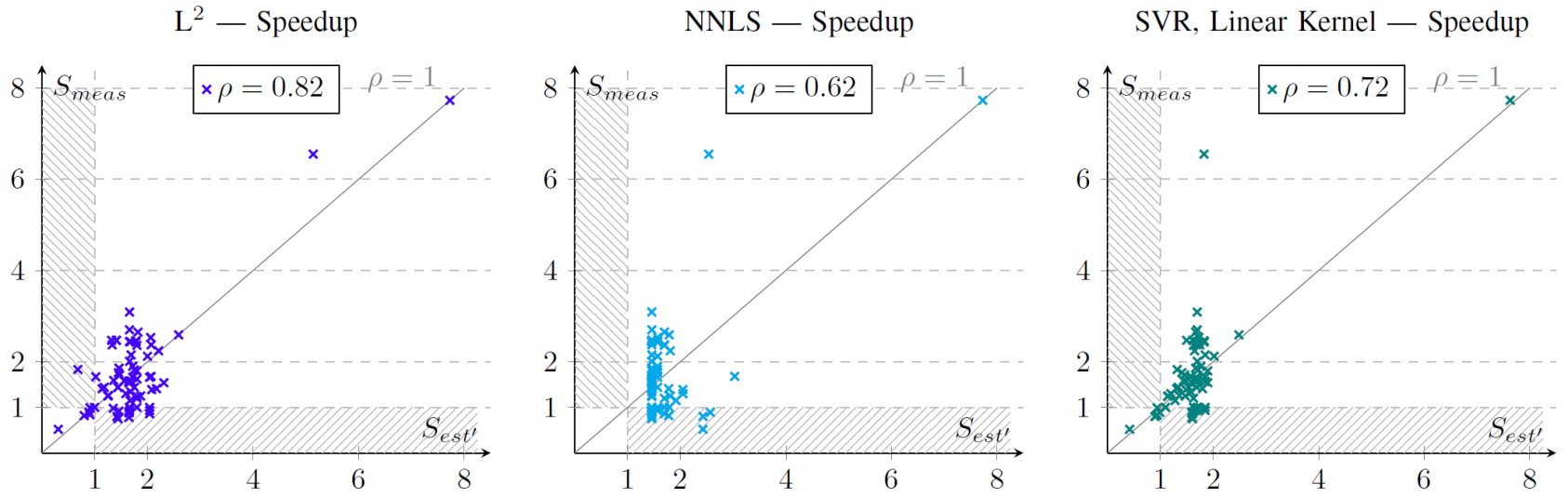
Results: Fitted for Speedup – x86



- All three approaches improve correlation further
- False negatives reduced (L2) or eliminated (NNLS, SVR)
- But: small increase in false positives

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