Is "Naturalness" a result of deliberate choice?

Kevin Lee and <u>Casey Casalnuovo</u>
Adviser: Prem Devanbu
University of California, Davis





Programs are written to be read

"Instead of imagining that our main task is to instruct a computer what to do, let us concentrate rather on **explaining to human beings what we want a computer to do**." [Don Knuth]





```
public static void main (String[] args) {
   int val;
   System.cout.princh@ ("Inside main");
   Auto.id();
   Auto.id();
   Auto.id();
   Auto.id();
   System.cout.princh@ ("About to call functa");
   System.cout.princh@ ("About to call functa");
   System.cout.princh@ ("About to call functa");
   val = functa(-a);
   System.cout.princh@ ("About to call functa") asinify;
   val = functa(-a);
   System.cout.princh@ ("About to call functa(a) asinify;
   val = functa(-a);
   System.cout.princh@ ("About to call functa(a) asinify;
   System.cout.princh@ ("About to call functa(a) asinify;
   public static int functa( (int param) {
        System.cout.princh@ ("About to call functa(a) asinify;
        return param * 2;
   }
}
```



















Operational Semantics meaning=OS(code)









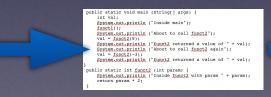


Operational
Semantics
meaning=OS(code)











Identifiers, structural patterns, program style....





Operational
Semantics
meaning=OS(code)







```
ublic static void main (String() args) (
int val;

SYXEMS.OUL.DELINIAL ("Inside main");

AURCAL();

SYXEMS.OUL.DELINIAL ("ADDUT to call famcta");

val " AURCAL(s);

SYXEMS.OUL.DELINIAL ("ADDUT to call famcta");

Val " AURCAL(s);

SYXEMS.OUL.DELINIAL ("ADDUT to call famcta avalue of " + val);

SYXEMS.OUL.DELINIAL ("ADDUT to call famcta avalue of " + val);

SYXEMS.OUL.DELINIAL ("ADDUT cetured a value of " + val);

public static int famcta (int param) (
SYXEMS.OUL.DELINIAL ("Inside famcta vith param " + param);

return param " 2;
```







m = meaningc = code

 $argmax_m P(m \mid c)$

Bayes Rule

For a given c

Informed by coding and domain knowledge

$$= argmax_m \frac{P(c \mid m) \ P(m)}{P(c)}$$

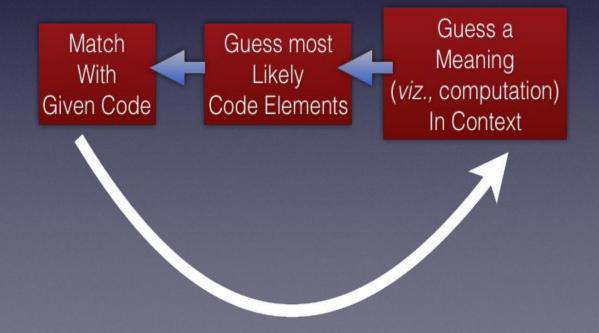
$$\approx argmax_m P(c \mid m) P(m)$$

$$\approx argmax_m P(c \mid m) P(m \mid context)$$



 $argmax_{meaning}P(meaning | code)$

 $\approx argmax_{meaning}P(code | meaning) P(meaning | context)$





Guess a
Meaning
(viz., computation)
In Context

 $argmax_{m}P(m \mid c)$

 $\approx argmax_m P(c \mid m) P(m \mid context)$



m = meaningc = code



Guess a
Meaning
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In Context

 $argmax_{m}P(m \mid c)$

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m = meaningc = code



1

Guess most
Likely
Code Elements



 $argmax_m P(m \mid c)$

 $\approx argmax_m P(c \mid m) P(m \mid context)$

m = meaningc = code



Guess a
Meaning
(viz., computation)
In Context



Guess most
Likely
Code Elements



Match With Given Code



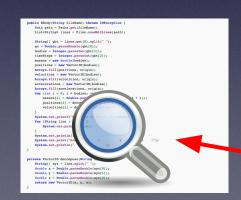


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Guess most Likely Code Elements



Match With Given Code





Guess a
Meaning
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In Context

 $argmax_m P(m \mid c)$

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m = meanic = code

This 'guessing' will be more effective if p(c|m) is 'skewed'.

Guess most Likely Code Elements

Match With ven Code

So what?

Given a computation to implement:

Programmers tend to favor one implementation over others.

So if $C_1, C_2, ... C_n$ are different, equivalent implementations of

the same computation M, usually:

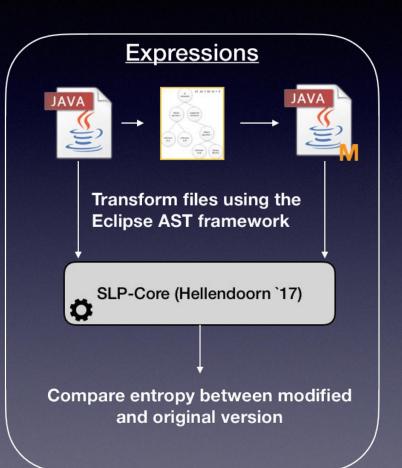
$$\exists j : p(C_i|M) \gg p(C_i|M) \quad \forall i = 1...n, i \neq j$$

General Scheme

- Estimate a language model LM over a large corpus
- Using LM, Measure the entropy of "natural" program S (not in training set)
- Apply meaningpreservingdransform to S yielding
- Using LM, measure entropy of S and
- Null hypothesis: there is no difference.
 Alternative hypothesis: S is lower in entropy, than programmers have a definite preference.

since

How to test?



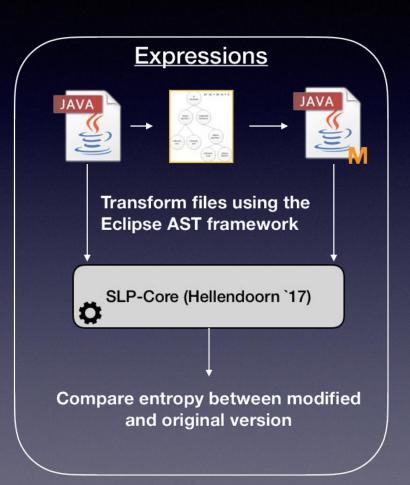
Estimate language model *LM* over a corpus (12 Java projects/~16-17 million tokens)

Using *LM*, Measure the entropy of "natural" program *S* (not in training set)

Apply meaning preserving transforms to S to create $\hat{S}_1, \hat{S}_2, \hat{S}_3, \dots$

Using *LM*, measure entropy of S and $\hat{S}_1, \hat{S}_2, \hat{S}_3, \dots$

How to test?



Null hypothesis: There is no difference in entropy between S and $\hat{S}_1, \hat{S}_2, \hat{S}_3, \dots$

Alternative hypothesis: S is lower in entropy, than $\hat{S}_1, \hat{S}_2, \hat{S}_3, \ldots$ since programmers have a definite preference.

Meaning Preserving Transform?

Focus on Expressions

Operator Commutation

$$A + B \rightarrow B + A$$

$$A * B \rightarrow B * A$$

Variable Name Swap

Limit to operations without side effects to avoid changing meaning.

<u>Future direction:</u> statement level transformations (line, if block shuffling, etc)

Adding Parenthesis

Removing Parentheses

Meaning Preserving Transform?

- Operator Commutation
- Superfluous parentheses removal
- Superfluous parentheses insertion
- Operator associativity (Pending)
- Renaming Variables within and across types
- Independent statement reordering (Pending)

Training/Testing

- Training:
 - 12 popular (Most Starred) Github projects
 - Manually selected to cover a diverse set of domains
- Testing (Projects with large number of numeric expressions)
 - Apache Commons Math Library Biojava Spring Framework by Pivotal









Language Models

- 6-gram with Jelinek-Mercer smoothing ('global')
- 6-gram-cache
- Above models with types from Pygments syntax highlighter
- Implemented using SLP-Core framework

Language Models

Ordinary Ngram Models

```
return this . objectDepth = = 0 & & ( ( token = = JsonToken . START_ARRAY ... ) );
```

Identifiers Replaced with Types

Implemented in SLP-Core (Hellendoorn)

 Fast and easy to quickly update

Used Pygments to generate types for variables.

Uncover structural patterns separate from identifiers.

Language Models

Ordinary Ngram Models

6-gram model

6-gram model + cache

Identifiers Replaced with Types

6-gram model

6-gram model + cache

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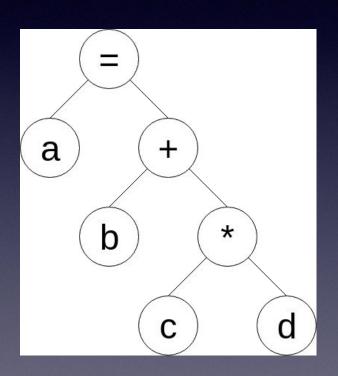
AST Transformations

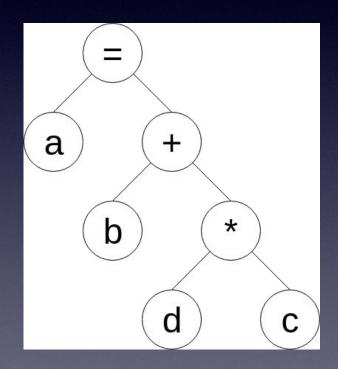
Abstract Syntax Tree

 Parser from Eclipse Foundation's Java Development Tools (JDT) API

Commutation

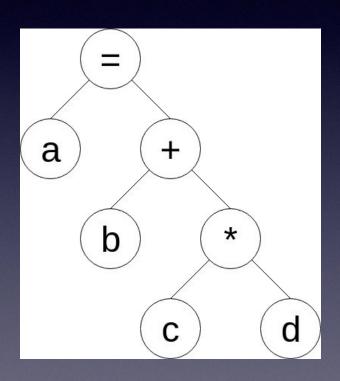
a = b + c * d -> a = b + d * c

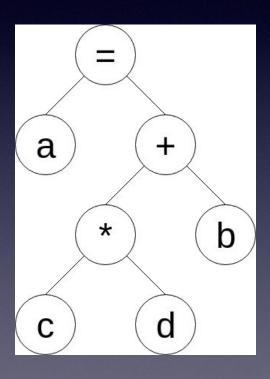




Commutation

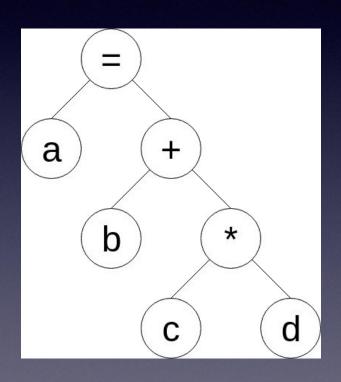
a = b + c * d -> a = d * c + b

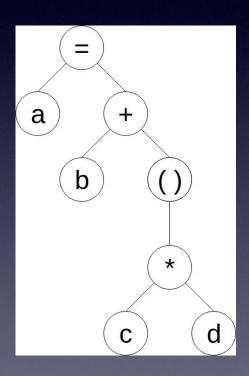




Parentheses Addition

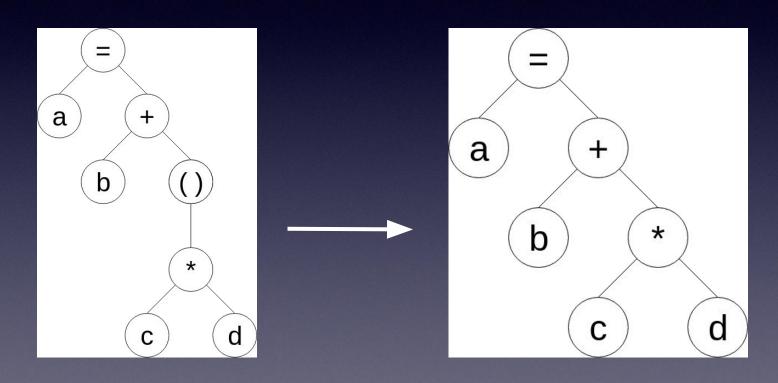
a = b + c * d -> a = b + (c * d)





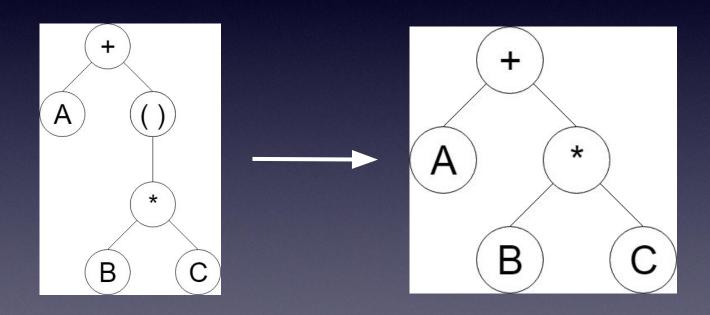
Parentheses Removal

$$a = b + (c * d) -> a = b + (c * d)$$



Parentheses Removal

$$A + (B * C) \rightarrow A + B * C$$



Data Collected

- File Path
- Line Number
- Number of Tokens (Java and Pygments Type)
- Number of Transformations
- Average depth of transformed AST nodes
- Entropies
- Common Parent of Transformed Nodes
- Most and Least common operator involved

Number of Data Points

- 8,611 commutations
- 20,844 parentheses additions
- 2,670 parentheses removals

Results

What do we want to convey?

These transformations generally make code harder to predict (matching our theory) (Show Cohens D table?

Transformations relationship to the original entropy of the expression.

Certain 'odd' data out (add global model) + interesting interpretations of combined models.

Some ideas for future directions/gather feedback/ideas from audience.

A Note on Results

- Present results focusing on the change in average expression entropy.
 - Looked at line entropy as well (similar)

 Include tokens that only appear in both the original and the changed lines (e.g. parenthesis) in average.

Do the models prefer the original?

- Paired T-tests comparing line before and after the change (all significant p<.001)
- Directed paired Cohen's D effect size.

	Global	Cache	Global Type	Cache Type
Operator Swap	0.313	0.859	0.360	0.706
Addition	-0.858	0.142	0.366	0.869
Removal	1.034	0.940	0.087	0.361

Summary

- When employing cache models, the negative impact on entropy is usually stronger...
- Interpretation: Local style tends to add additional restrictions?

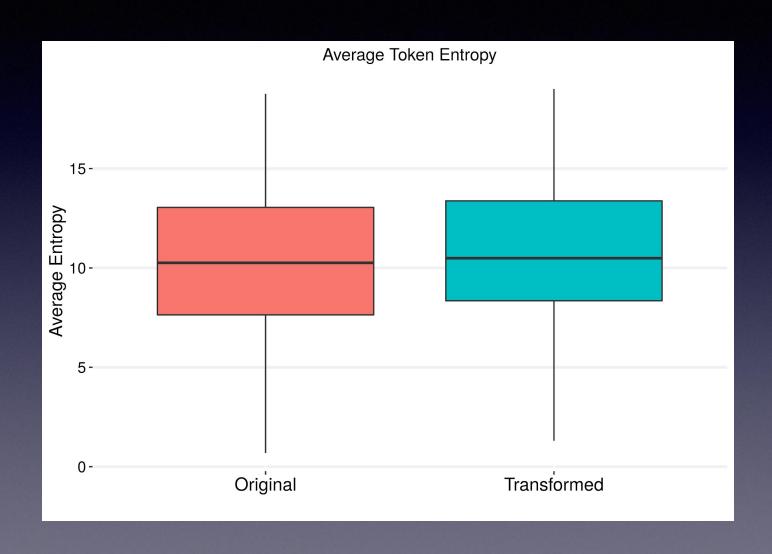
	Global	Cache	Global	Cache
			Type	Type
Operator Swap	0.313	0.65 9	0.300	0.700
Addition	-0.858	0.142	0.366	0.869
Removal	1.034	0.940	0.087	0.361

Local Style Stronger

- When employing cache models, the negative impact on entropy is usually stronger...
- => Local style tends to be even more consistent.

	Global	Cache	Global Type	Cache Type
Operator Swap	0.313	0.859	0.360	0.706
Addition	-0.858	0.142	0.366	0.869
Removal	1.034	0.940	0.087	0.361

Operand Swapping (Global)



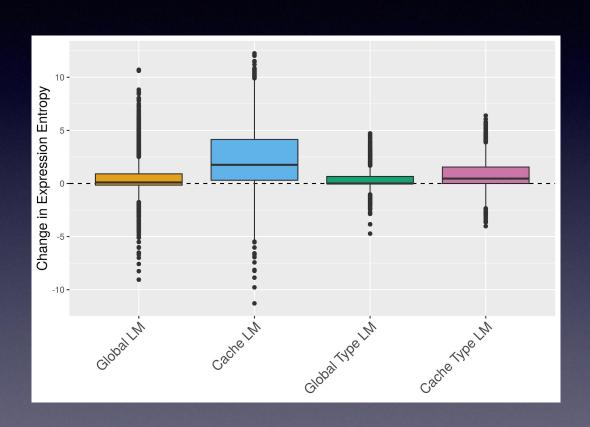
Parentheses Removal (Global)



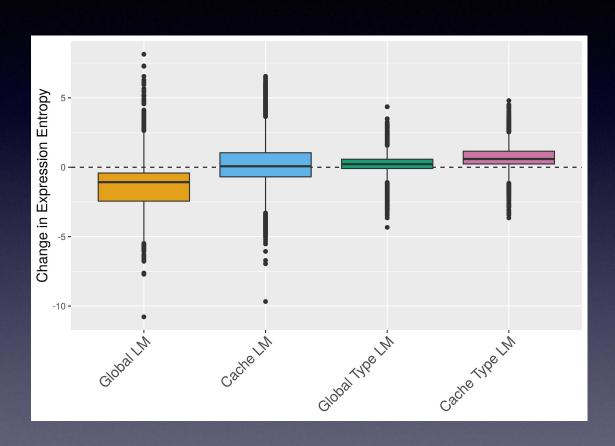
Parentheses Addition (Global)



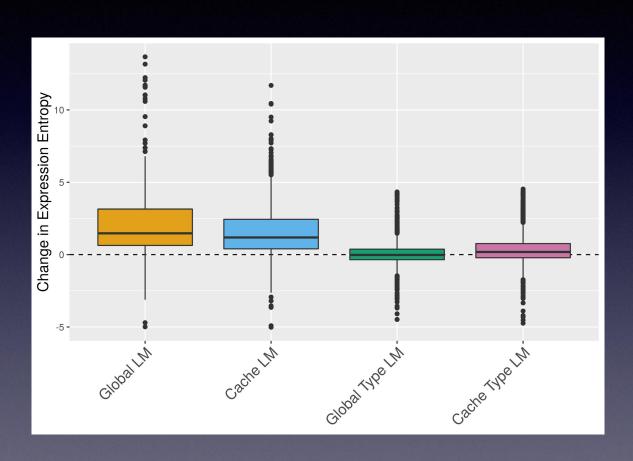
Operator Swapping



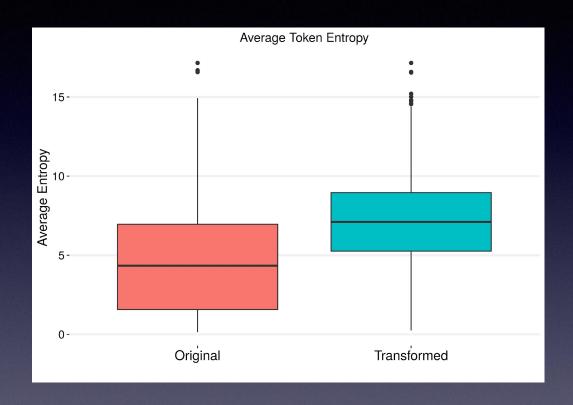
Adding Parenthesis



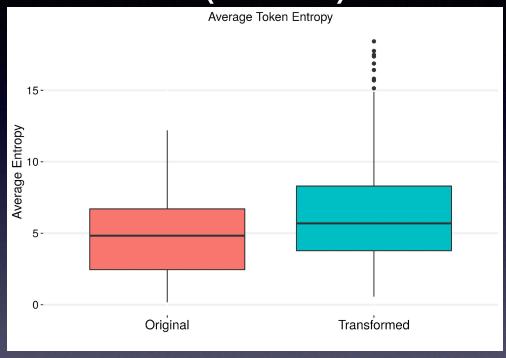
Removing Parenthesis



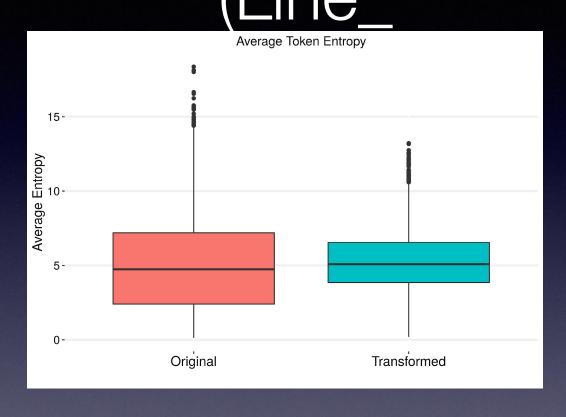
Commutation (Line)



Parentheses Removal (Line)



Parentheses Addition

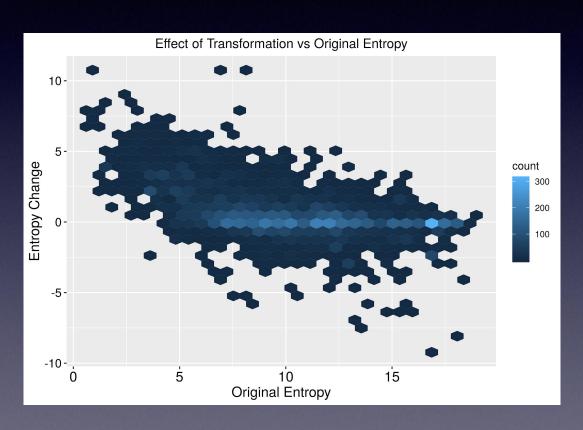


What's up with adding ()?

Code Examples	(Global) Ent Change
result = 31 * result + (int)(temp ^ (temp >>> 32));	-10.78
if (strict && (lowerBound == upperBound)) {	-7.62
Num = (floor*den) + num;	-6.78
final int minIndex = (binIndex * numRows) / numComponents;	-6.59
if (k > (n / 2)) {	-6.58

Effects Vs Original Entropy

Operand Swap (Global Model)



Higher Original Entropy = Greater Potential to reduce entropy

True for most, but not all of the transformations.

Exception: Global models on () remove transformation.

 Models capturing preference for including () in complex expressions?

Summary

- Programmers do generally show preference in choice of computations over the same meaning.
- But, not always true...
 - Opportunity for transforming code?
 - How well can LMs (and entropy measures)
 correspond with human understanding of code?

Future Directions

- Larger transformations (line swapping)
 - May move to C#/Roslyn
- Human evaluation of entropy score vs understanding/readability metrics
- Variation in human written programs (student code/multiple solutions to Rosetta Code)