Deep Generation of Coq Lemma Names Using Elaborated Terms

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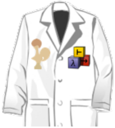

[1] The University of Texas at Austin

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Motivation: Verification Projects Growing in Size

- Proof assistants are increasingly used to formalize results in advanced mathematics and develop large trustworthy software systems

Project	**Domain**	**Assistant**	**LOC**
CompCert	compiler	Coq	120k+
MathComp	math	Coq	85k+
Verdi Raft	k/v store	Coq	50k+
seL4	kernel	Isabelle/HOL	200k+
BilbyFS	file system	Isabelle/HOL	14k+

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- Verification projects face challenges similar to those in large software projects: maintenance and enforcement of coding conventions
- **How to name lemmas?**

Motivation: Hard-coded Naming Conventions

CONTRIBUTIONS.md in MathComp, 50+ entries

Naming conventions for lemmas (non exhaustive)

Names in the library usually obey one of the following conventions

- `(condition_)?mainSymbol_suffixes`
- `mainSymbol_suffixes(_condition)?` Or in the presence of a property denoted by an n-ary or unary predicate:
- `naryPredicate_mainSymbol+`
- `mainSymbol_unaryPredicate`

Where:

- `mainSymbol` is the most meaningful part of the lemma. It generally is the head symbol of the right-hand side of an equation or the head symbol of a theorem. It can also simply be the main object of study, head symbol or not. It is usually either
  - one of the main symbols of the theory at hand. For example, it will be `opp`, `add`, `mul`, etc., or
  - a special "canonical" operation, such as a ring morphism or a subtype predicate. e.g. `linear`, `raddf`, `rmorph`, `rpred`, etc.
- "condition" is used when the lemma applies under some hypothesis.
- "suffixes" are there to refine what shape and/or what other symbols the lemma has. It can either be the name of a symbol ("add", "mul", etc.), or the (short) name of a predicate ("`inj`" for "`injectivity`", "`id`" for "identity", etc.) or an abbreviation. Abbreviations are in the header of the file which introduces them. We list here the main abbreviations.
- `A` -- associativity, as in `andbA : associative andb.`
- `AC` -- right commutativity.
- `ACA` -- self-interchange (inner commutativity), e.g., `orbACA : (a || b) || (c || d) = (a || c) || (b || d).`
- `b` -- a boolean argument, as in `andbb : idempotent andb.`
- `C` -- commutativity, as in `andbC : commutative andb.` -- alternatively, predicate or set complement, as in `predC.`

Motivation: Many Inconsistencies in Large Projects

math-comp / **math-comp**

Code | Issues 69 | Pull requests 29 | Actions | Projects | Wiki | Security | Insights

mem_imset mem_map naming/statement inconsistency #508

Open **chdoc** opened this issue on 14 May · 9 comments

chdoc commented on 14 May — Contributor

while cleaning, I noticed the following oddity:

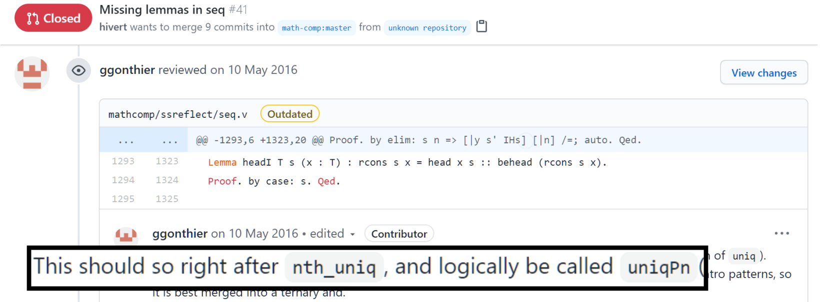
```
Lemma mem_imset (aT rT : finType) (f : aT -> rT) (D : {pred aT}) (x : aT) :
  x \in D -> f x \in [set f x | x in D]

Lemma map_f (T1 T2 : eqType) (f : T1 -> T2) (s : seq T1) (x : T1) :
   x \in s -> f x \in [seq f i | i <- s]
Lemma mem_map (T1 T2 : eqType) (f : T1 -> T2),
  injective f -> forall (s : seq T1) (x : T1), (f x \in [seq f i | i <- s]) = (x \in s)
```

Wouldn't it be more consistent to rename `mem_imset` to `imset_f`

```
Lemma mem_imset (aT rT : finType) (f : aT -> rT) (A : {set aT}) (x : aT) :
  injective f -> (f x \in f @: A) = (x \in A).
```

👍 1

Motivation: Manually Checking and Enforcing



Our Contributions

- **Roosterize**: toolchain for learning and suggesting lemma names
  - Code review process
  - Interactive development
  - Batch mode

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- A qualitative **case study** on a project outside corpus

Running Example: A Lemma from reglang Project

- A lemma from a project on the theory of regular languages
- **M**ost **g**eneral classifiers can be casted to **eq**uivalent languages

```
Lemma mg_eq_proof L1 L2 (N1 : mgClassifier L1) : L1 =i L2 -> nerode L2 N1.
Proof.
move=> eq_L u v.
split=> [/nerodeP eq_in w|eq_in].
- by rewrite -!eq_L.
- apply/nerodeP=> w.
  by rewrite !eq_L.
Qed.
```

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Proof script

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Roosterize Toolchain

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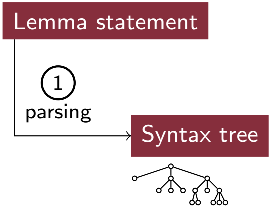

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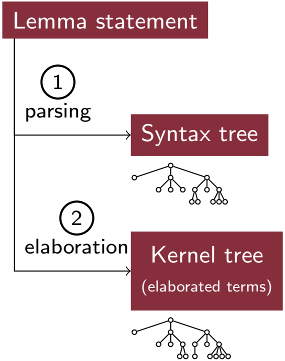

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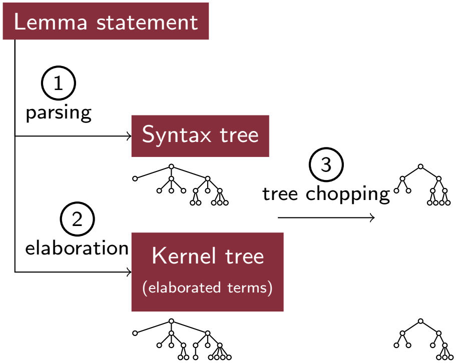

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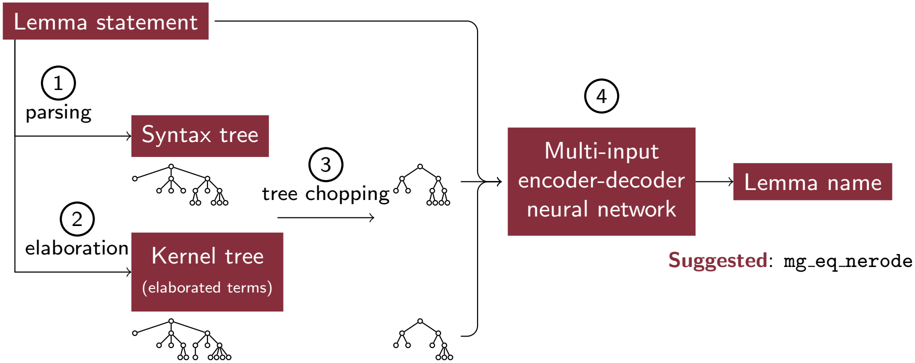
`Lemma mg_eq_proof L1 L2 (N1 : mgClassifier L1) : L1 =i L2 -> nerode L2 N1.`



Model Input: Lemma Statement

```
Lemma mg_eq_proof L1 L2 (N1 : mgClassifier L1) : L1 =i L2 -> nerode L2 N1.
```

```
(Sentence((IDENT Lemma)(IDENT mg_eq_proof)(IDENT L1)(IDENT L2)
  (KEYWORD"(")(IDENT N1)(KEYWORD :)(IDENT mgClassifier)
  (IDENT L1)(KEYWORD")")(KEYWORD :)(IDENT L1)(KEYWORD =i)(IDENT L2)
  (KEYWORD ->)(IDENT nerode)(IDENT L2)(IDENT N1)(KEYWORD .)))
```

S-expression

- In lexing phase
- **Surface syntax** level information

Model Input: Syntax Tree

```
Lemma mg_eq_proof L1 L2 (N1 : mgClassifier L1) : L1 =i L2 -> nerode L2 N1.
```

```
(VernacExpr()(VernacStartTheoremProof Lemma (Id mg_eq_proof)
 (((CLocalAssum(Name(Id L1))(CLocalAssum(Name(Id L2)))
   (CLocalAssum(Name(Id N1))(CApp(CRef(Ser_Qualid(DirPath())(Id mgClassifier)))
    (CRef(Ser_Qualid(DirPath())(Id L1))))))
  (CNotation(InConstrEntrySomeLevel"_ -> _")
   (CNotation(InConstrEntrySomeLevel"_ =i _")
    (CRef(Ser_Qualid(DirPath())(Id L1)))(CRef(Ser_Qualid(DirPath())(Id L2))))
   (CApp(CRef(Ser_Qualid(DirPath())(Id nerode)))
    (CRef(Ser_Qualid(DirPath())(Id L2)))(CRef(Ser_Qualid(DirPath())(Id N1))))))))
```

- In parsing phase
- **Surface syntax** level information

Model Input: Kernel Tree

```
Lemma mg_eq_proof L1 L2 (N1 : mgClassifier L1) : L1 =i L2 -> nerode L2 N1.
```

```
(Prod (Name (Id char)) ... (Prod (Name (Id L1)) ...
  (Prod (Name (Id L2)) ... (Prod (Name (Id N1)) ...
   (Prod Anonymous (App (Ref (DirPath ((Id ssrbool) (Id ssr) (Id Coq))) (Id eq_mem)) ...
     (Var (Id L1)) ... (Var (Id L2)))
    (App (Ref (DirPath ((Id myhill_nerode) (Id RegLang))) (Id nerode)) ...
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```

- In elaboration phase
- **Semantic** level information

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- In elaboration phase
- **Semantic** level information
  - Add implicit terms

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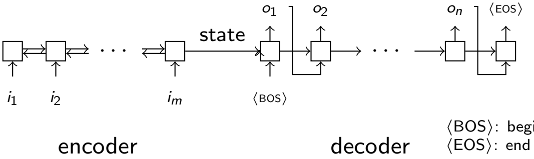
- In elaboration phase
- **Semantic** level information
  - Add implicit terms
  - Translate operators to their kernel names

Lemma Naming as a Transduction Task

- **Encoder-decoder neural network**: specifically designed for **transduction tasks** (e.g., machine translation, summarization, question answering)

input
lemma statement
syntax tree
kernel tree



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⟨BOS⟩: begin of sequence
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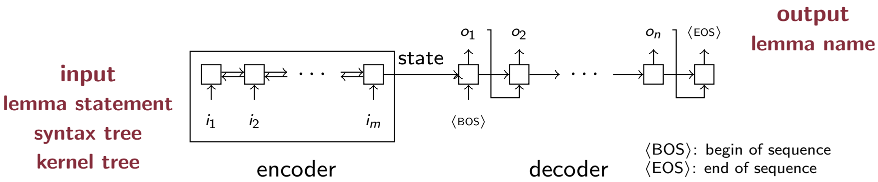

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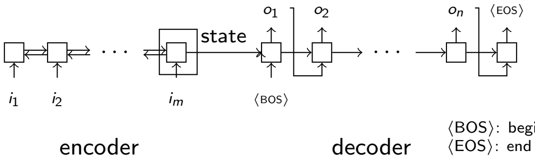

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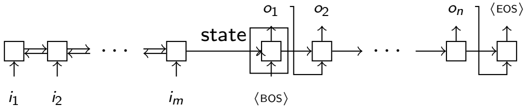

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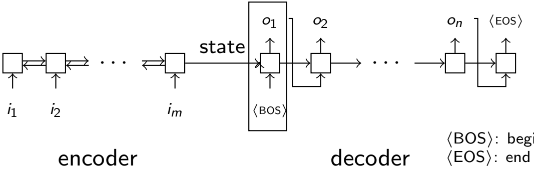

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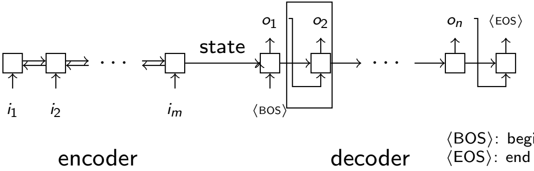

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Lemma Naming as a Transduction Task

- **Encoder-decoder neural network**: specifically designed for **transduction tasks** (e.g., machine translation, summarization, question answering)
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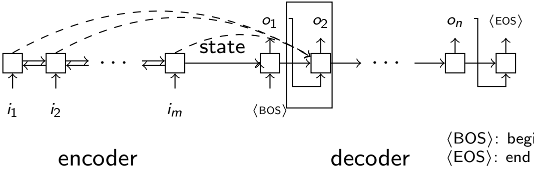

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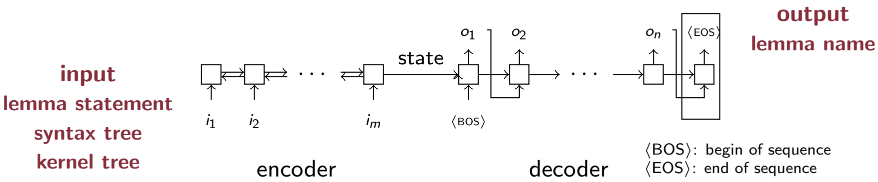
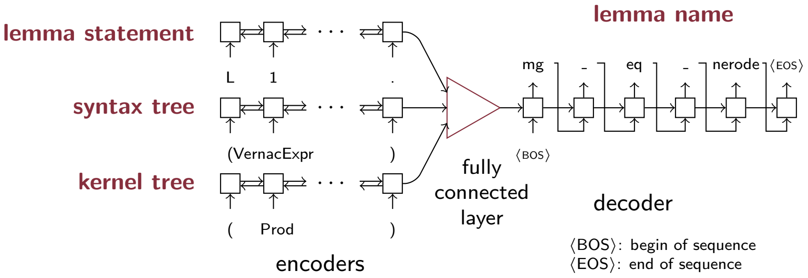


Multi-input Encoder-decoder Neural Network Architecture



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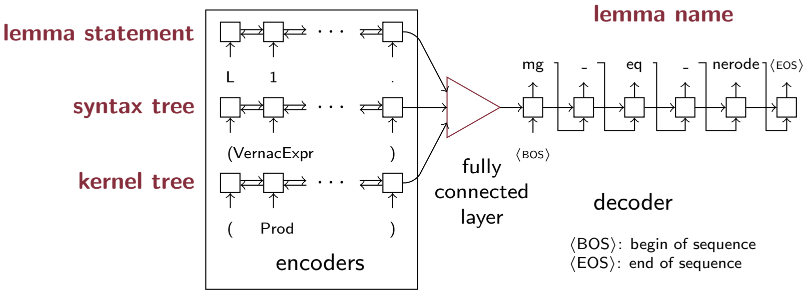

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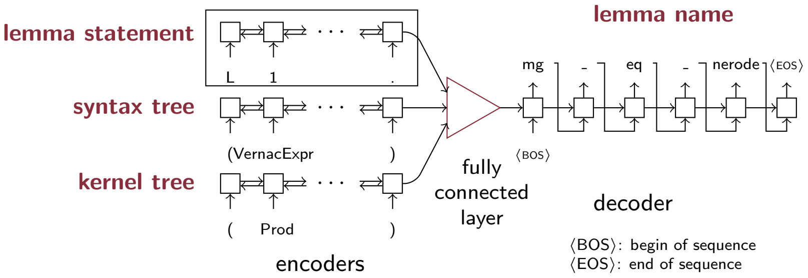

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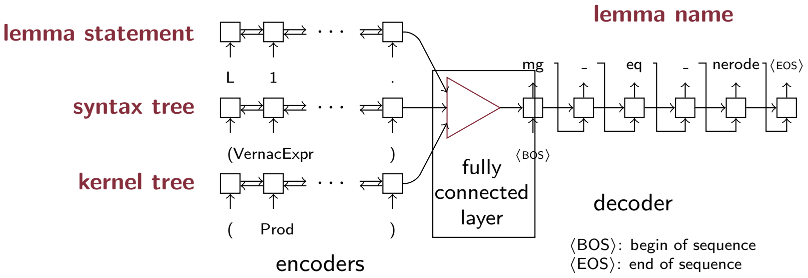

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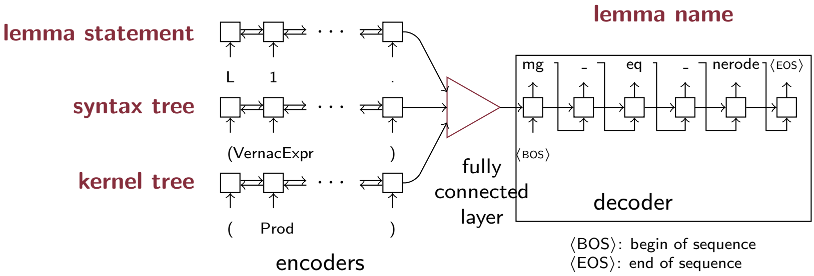
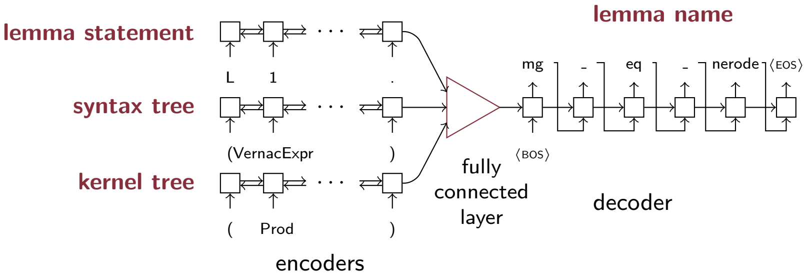


Tree Chopping



- Syntax and kernel trees can be large, which prevents the neural networks to learn effectively
- Some parts are irrelevant for naming and can be “chopped”

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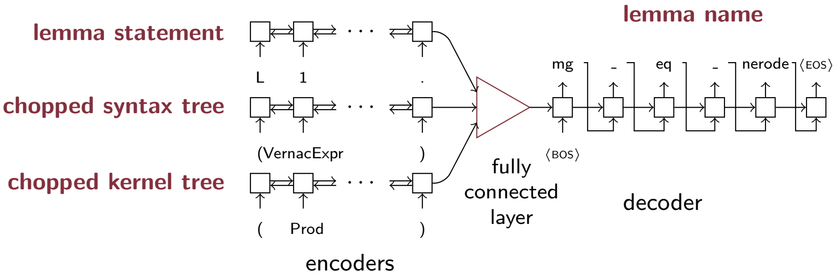

- Syntax and kernel trees can be large, which prevents the neural networks to learn effectively
- Some parts are irrelevant for naming and can be "chopped"
- Tree chopping heuristics:
  1. Replace the fully qualified name sub-trees with only the last component of the name
  2. Remove the location information
  3. Extract the singletons

Example Tree Chopping

- Before chopping

```
(Prod Anonymous (App (Ref (DirPath ((Id ssrbool) (Id ssr) (Id Coq))) (Id eq_mem))
  ... ((App (Ref ... ))) ... ))
```

Example Tree Chopping

- Before chopping

#1 prefixes in a fully-qualified name:
usually related to directory paths and likely not relevant

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#3 singleton: unnecessarily increase tree size

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```
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```
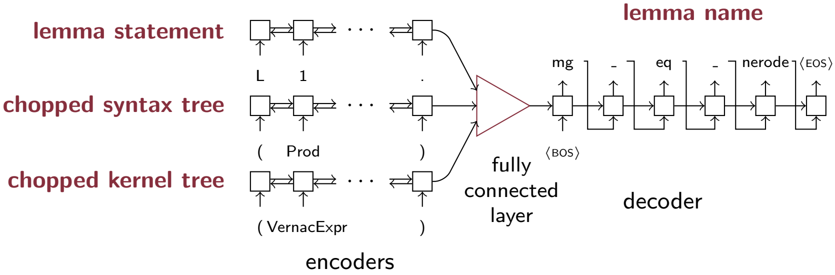

Sub-tokenization



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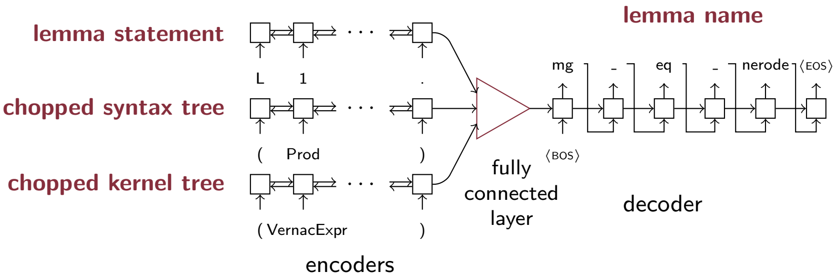

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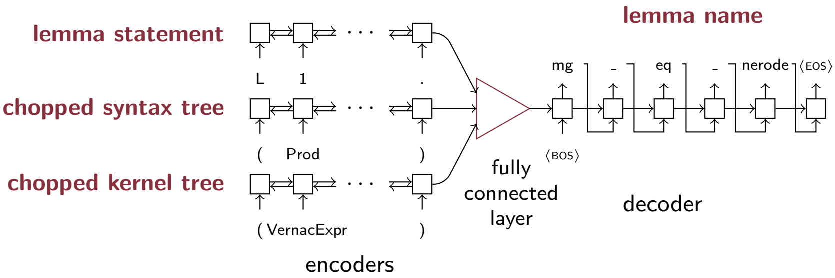

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- All inputs and outputs are **sub-tokenized** (e.g., `extprod_mulgA` → `extprod`, `_`, `mul`, `g`, and `A`)
- Reduces the sparsity of the vocabulary and improves the performance of the model

Corpus: MathComp Family of Projects

- We constructed a corpus of four large Coq projects from the MathComp family, totaling **164k lines of code**
- High quality and stringent adherence to coding conventions

Project	SHA	#Files	#Lemmas	#Toks	LOC Spec.	LOC Proof
finmap	27642a8	4	940	78,449	4,260	2,191
fourcolor	0851d49	60	1,157	560,682	9,175	27,963
math-comp	748d716	89	8,802	1,076,096	38,243	46,470
odd-order	ca602a4	34	367	519,855	11,882	24,243
Avg.	N/A	46.75	2,816.50	558,770.50	15,890.00	25,216.75
Σ	N/A	187	**11,266**	2,235,082	63,560	100,867

Evaluation: Setup

- Randomly split corpus files into training, validation and testing sets which contain 80%, 10%, 10% of the files, respectively

	#Files	#Lemmas	Name		Lemma Statement	
			#Char	#SubToks	#Char	#SubToks
training	152	**8,861**	10.14	4.22	44.16	19.59
validation	18	**1,085**	9.20	4.20	38.28	17.30
testing	17	**1,320**	9.76	4.34	48.49	23.20

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- Train ROOSTERIZE using training and validation sets
- Apply ROOSTERIZE on testing set, and evaluate generated lemma names against the reference lemma names (as written by developers)

Evaluation: Automated Metrics

- **BLEU**
- **Fragment accuracy**
- **Top-1 accuracy**
- **Top-5 accuracy**

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- **BLEU**: range 0–100, percentage of 1–4-grams overlap between the characters of the generated name and the reference name
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$$\begin{aligned}
&\mathrm{BLEU}(\texttt{card_Syl_dvd}, \texttt{card_Syl_dvd}) = 100\\
&\mathrm{BLEU}(\texttt{card_Syl_dvd}, \texttt{card_dvd_Syl}) = 81.9\\
&\mathrm{BLEU}(\texttt{card_Syl_dvd}, \texttt{card_dvd}) = 52.7\\
&\mathrm{BLEU}(\texttt{card_Syl_dvd}, \texttt{Frattini_arg}) = 14.7
\end{aligned}$$

Evaluation: Automated Metrics

- **BLEU**: range 0–100, percentage of 1–4-grams overlap between the characters of the generated name and the reference name
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Evaluation: Results

- Key results: ROOSTERIZE significantly outperforms baselines
- Ablation studies:
  - **Tree chopping** effectively improves performance
  - ROOSTERIZE's tree chopping is better than variants
  - Using **kernel trees** in inputs effectively improves performance (i.e., **semantics** information helps naming)

Evaluation: Key Results

Model	BLEU	Frag.Acc.	Top-1	Top-5
ROOSTERIZE	**47.2**	**24.9%**	**9.6%**	**18.0%**
Baseline neural network based model	20.0	4.7%	0.1%	0.3%
Baseline retrieval-based model	28.3	10.0%	0.2%	0.3%

- Baseline neural network based model: using only lemma statement as input, w/o attention mechanism
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- Baseline neural network based model: using only lemma statement as input, w/o attention mechanism
- Baseline retrieval-based model: *details in the paper*
- Roosterize, using **lemma statement and chopped kernel tree** as inputs, obtained the best performance
  - 20+ points in BLEU better than baselines
  - statistically significantly better than all other model variants

Ablation Study: Tree Chopping

Model	BLEU	Frag.Acc.	Top-1	Top-5
ChopKnlTree+attn+copy	42.9	19.8%	5.0%	11.7%
KnlTree+attn+copy	37.0	14.2%	2.2%	8.4%
ChopSynTree+attn+copy	39.8	18.3%	6.8%	12.2%
SynTree+attn+copy	31.0	10.8%	2.8%	6.1%

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- **Tree chopping** improves performance by 6 points in BLEU for kernel tree and 9 points in BLEU for syntax tree
- The size of the original trees and a lot of irrelevant data in those trees hurt the performance

Ablation Study: Tree Chopping Variants

Model	BLEU	Frag.Acc.	Top-1	Top-5
Roosterize Chopping	47.2	24.9%	9.6%	18.0%
Keep-category Chopping	46.8	25.3%	9.5%	19.0%
Rule-based Chopping	37.0	17.7%	5.9%	10.5%
Random Chopping	37.7	19.2%	6.7%	10.9%

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- **Random chopping** chops random 91.4% nodes from the kernel tree to match the average number of nodes of Roosterize chopped trees, as the "dumb" baseline

Ablation Study: Inputs

Inputs Combinations	BLEU	Frag.Acc.	Top-1	Top-5
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- The inputs combination of **lemma statement and chopped kernel tree** works the best
- Lemma statement and syntax tree do not work well together because the two representations contain mostly the same information
- Multiple inputs $\geq$ single input most of the times

Case Study: Setup

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- Apply ROOSTERIZE to a project outside of our corpus: the PCM library (#Files = 12, #Lemmas = 690)
- Automated evaluation metrics: BLEU = 36.3, fragment accuracy = 17%, Top-1 accuracy = 5% (i.e., **36 lemmas** match exactly)

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- Apply Roosterize to a project outside of our corpus: the PCM library (#Files = 12, #Lemmas = 690)
- Automated evaluation metrics: BLEU = 36.3, fragment accuracy = 17%, Top-1 accuracy = 5% (i.e., **36 lemmas** match exactly)
- We asked the maintainer of the PCM library to evaluate **the remaining 654 lemma names** that do not match exactly and send us feedback

Case Study: Findings

- The maintainer provided comments on 150 suggested names
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  recall the analysis was of top-1 suggestions excluding exact matches

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- 20% were of good quality, out of which more than half were of high quality
  recall the analysis was of top-1 suggestions excluding exact matches
- Other suggested names tend to be "too generic"
- Unsuitable suggestions may contain useful parts

Case Study: Examples

Lemma statement: `g e k v f : path ord k (supp f) ->`
`foldfmap g e (ins k v f) = g (k, v) (foldfmap g e f)`
Hand-written: `foldf_ins`
Roosterize: `foldfmap_ins`
Comment: ✓ The whole function name is used in the suggested name.

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Lemma statement: `p1 p2 s : kfilter (predI p1 p2) s =`
`kfilter p1 (kfilter p2 s)`
Hand-written: `kfilter_predI`
Roosterize: `eq_kfilter`
Comment: ✕ The suggested name is too generic.

More Details in Our Paper

- Using copy mechanism to increase generalibility of models
- Using repetition prevention for decoder
- Implementation details of ROOSTERIZE toolchain
- Ablation study of more variants of ROOSTERIZE
- Expanded corpus of 21 MathComp family projects
- Generalizability case study: applying ROOSTERIZE on an out-of-corpus project with additional training

Conclusions

- **Roosterize**: toolchain for learning and suggesting Coq lemma names, based on multi-input encoder-decoder neural networks
- **Kernel trees** provides important semantics context for lemma naming
- **Tree chopping** helps our models to effectively handle long inputs
- Evaluated on a **corpus** of 164k LOC high quality Coq code
- Case study shows ROOSTERIZE can provide useful suggestions in practice for a project outside our corpus

ROOSTERIZE: `https://github.com/EngineeringSoftware/roosterize`
MathComp corpus: `https://github.com/EngineeringSoftware/math-comp-corpus`

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Backup Slides After This Point

Ablation Study: Copy Mechanism

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Stmt+ChopKnlTree+attn+copy	**47.2**	**24.9%**	**9.6%**	**18.0%**
Stmt+ChopKnlTree+attn	25.6	8.5%	0.9%	1.7%

- **Copy mechanism** improves performance by 22 points in BLEU
- Many sub-tokens are specific to the file context and do not appear in the fixed vocabulary of the training set