

Made of Steel?

Learning Plausible Materials for Components in the Vehicle Repair Domain

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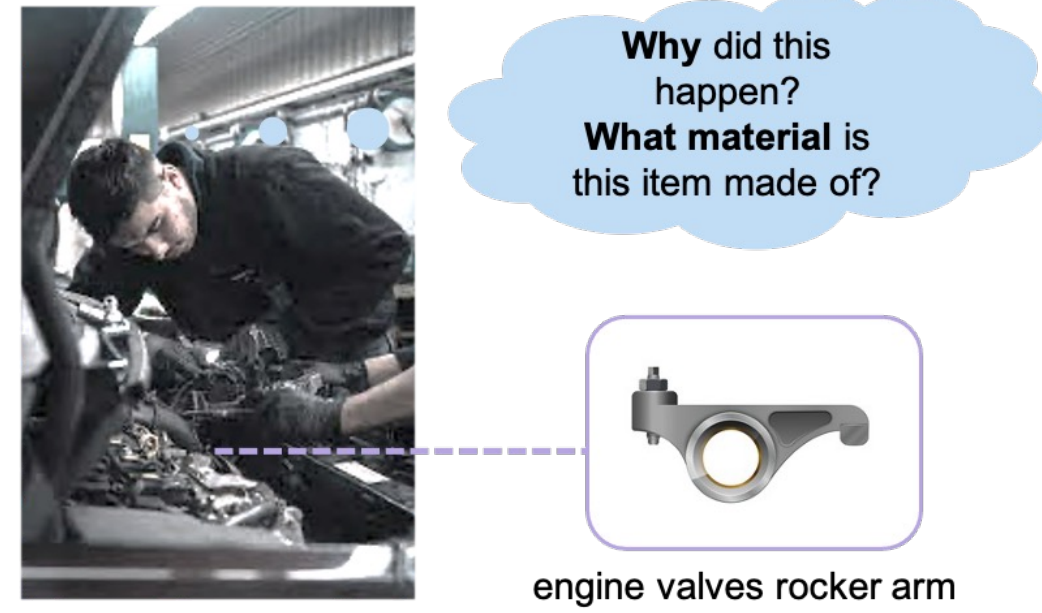
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INTRODUCTION

As a standard approach, mechanics in vehicle repair shops often exploit the link between
- a component and
- a component's material



Crucial information for vehicle repair shops:
- Mechanics are faced with constantly growing vehicle complexity
- Plausible domain-specific material information typically not directly available

RESEARCH TASK: Automatically learn plausible materials in highly domain-specific contexts such as the vehicle repair domain.

DATA

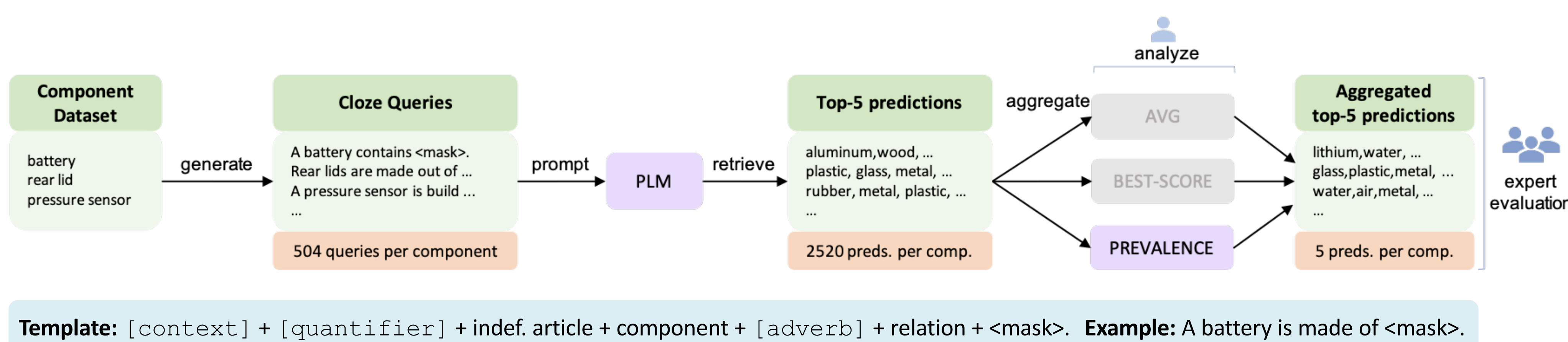
VEHICLE COMPONENT DATASET

- 7,069 expert-curated component names
 - Tangible physical components, e.g., *battery*, *cooling blower*
 - Intangible and functional components, e.g., *road test*
- 155 one-word components, 6,914 multi-word components with 725 right-most constituents as heads, e.g., *switch led* → *led*

DOMAIN-SPECIFIC CORPORA

- DOMAIN: high-quality vehicle repair manual by domain experts
- WIKI: portion of English Wikipedia customized to the domain

PRETRAINED LANGUAGE MODEL (PLM) EXPERIMENTS



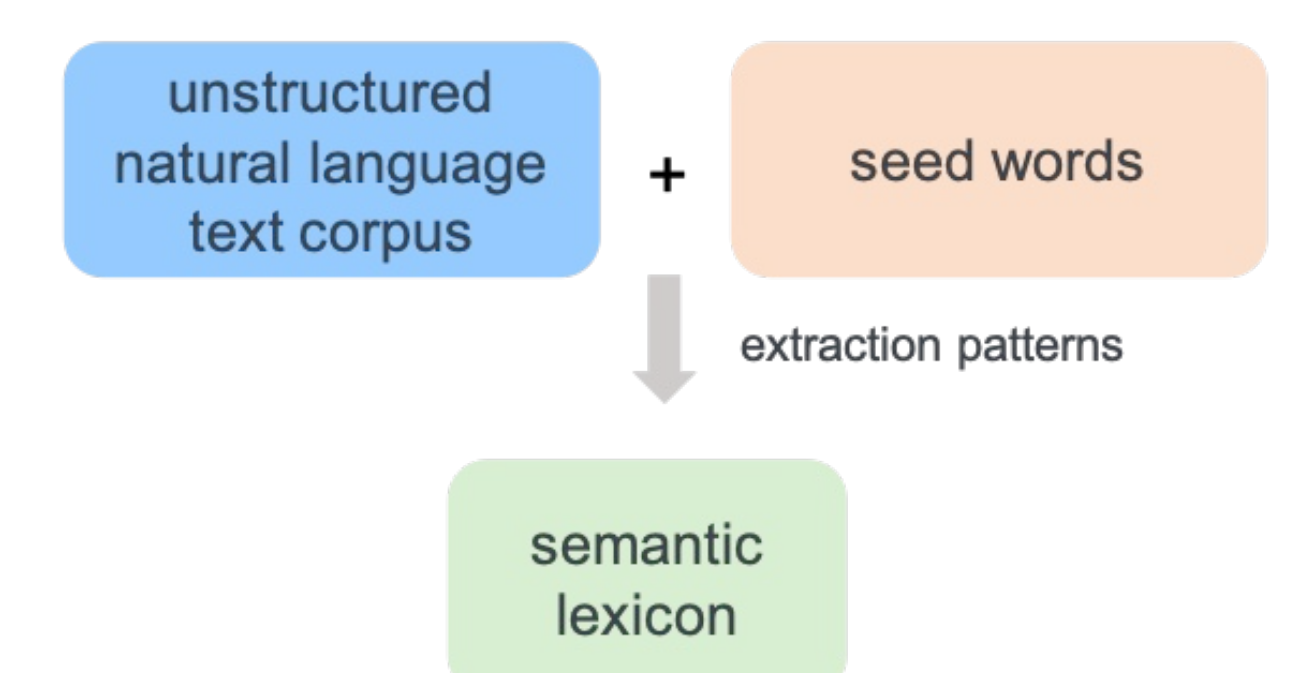
AGGREGATION METHOD development using Vanilla RoBERTa

- BEST-SCORE:** aggregate most probable PLM-predicted material types from 2,520 top-5 predictions across all queries
- AVG:** sum probabilities for each query variant on material type level and average by number of queries that predicted that material
- PREVALENCE:** rank by how often material was predicted across all top-5 suggestions of all query variants

DOMAIN ADAPTATION

- Domain-adaptation of RoBERTa using Masked Language Modeling (DOMAIN-RB, WIKI-RB)
- Resource-leaner alternative: Train domain-adapted of DistilRoBERTa (DOMAIN DISTILRB)

A CLASSIC: BASILISK EXPERIMENTS



- Determine seed nouns from semantic class material, e.g., *steel*, *metal*, ...
- Construct 396,887 domain-specific syntactic contextual patterns using dependency parsing on DOMAIN.
- Apply Basilisk as bootstrapping algorithm to select best-performing patterns and fill candidate pool with extracted words.
- Connect and generate up to 200 material candidates to components.

RESULTS

EVALUATION

- Evaluation task with 3 domain experts as no annotated datasets are available
- Experts rate plausibility of top-5 material predictions for 100 vehicle components for four PLMs and the Basilisk algorithm
- Substantial pairwise Inter-Annotator Agreement is achieved (avg. 0.81)

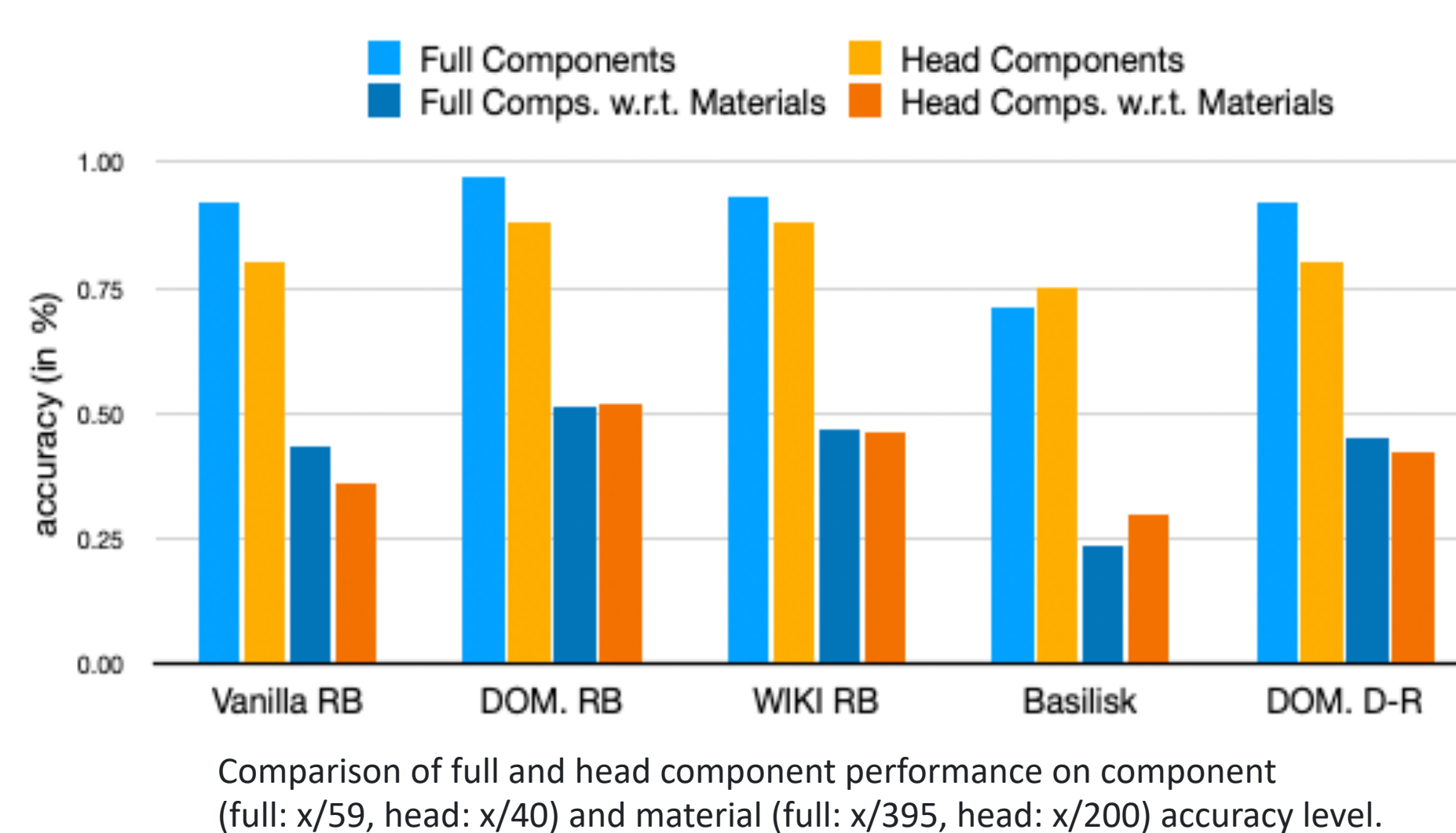
Model	Components		Materials	
	≥ 1A	3A	≥ 1A	3A
VANILLA RB	0.87	0.68	0.49	0.24
DOMAIN RB	0.93	0.73	0.62	0.28
WIKI RB	0.91	0.66	0.56	0.24
BASILISK	0.73	0.40	0.45	0.14
DOMAIN DISTILRB	0.87	0.69	0.53	0.23



Vanilla RB	[wood, metal, steel, bones, legs]
WIKI RB	[wood, metal, steel, joints, aluminium]
DOMAIN RB	[steel, metal, parts, aluminium, plastic]
Basilisk	[structures, glass, core, steel, plating]
DOMAIN DistilRB	[steel, metal, parts, plastic, aluminium]

FINDINGS

- Domain adaptation boosts performance
- Small PLMs viable resource-lean option
- Domain-specific MWEs assumed to be largely compositional
- Comprehensive, domain-specific, and syntactically diverse cloze query set crucial for optimal results



ABLATION EXPERIMENT

- Create cloze queries using 5 frequent non-related full verbs (make, say, go, use, take)
- Results: only 9 correct materials are predicted; small number of sometimes semantically related types predicted for many components, for example:
fuel tank: [sense, noise, hydrogen, oil, cold]

ACKNOWLEDGEMENTS



CONCLUSIONS

- Tackled a **challenging task from material sciences** that are under-investigated from an NLP perspective
- Developed **novel approach to learn domain-specific plausible materials** by harnessing (i) standard PLMs and (ii) semi-automatically created cloze prompts combined with (iii) a suitable aggregation method
- Showed that **domain adaptation** using high-quality / customized Wikipedia corpora **boosts performance**