Opinion-based Relational Pivoting for Cross-domain Aspect Term Extraction

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Abstract

Domain adaptation methods often exploit domain-transferable input features, a.k.a. pivots. The task of Aspect and Opinion Term Extraction presents a special challenge for domain transfer: while opinion terms largely transfer across domains, aspects change drastically from one domain to another (e.g. from restaurants to laptops). In this paper, we investigate and establish empirically a prior conjecture, which suggests that the linguistic relations connecting opinion terms to their aspects transfer well across domains and therefore can be leveraged for cross-domain aspect term extraction.

We present several analyses supporting this conjecture, via experiments with four linguistic dependency formalisms to represent relation patterns. Subsequently, we present an aspect term extraction method that drives models to consider opinion–aspect relations via explicit multitask objectives. This method provides significant performance gains, even on top of a prior state-of-the-art linguistically-informed model, which are shown in analysis to stem from the relational pivoting signal.

1 Introduction

Sentiment Analysis is one of the most widely used applications of natural language processing. A common fine grained formulation of the task, termed Aspect Based Sentiment Analysis, matches the terms in the text expressing opinions to corresponding aspects. For example, in the restaurant review in Figure 1, great, calm and quiet are opinion terms (OTs) referring to the aspect term (AT) ambience.

Following the SemEval shared tasks (Pontiki et al., 2014, 2015), the preliminary task of AT and OT extraction has attracted significant research attention (Wang and Pan, 2020; Pereg et al., 2020, inter alia), especially for its domain adaptation setup, where a model trained on one domain is tested on another, unseen domain. Considering each product or service as a "domain", domain adaptation is crucial for making models of this task widely applicable. Yet performance on cross-domain aspect term extraction is still low, reflecting that it poses a special challenge to common domain adaptation paradigms.

In most domain adaptation settings, some features of the input are domain specific, while others — also known as pivot features (Blitzer et al., 2006) — do transfer into unseen domains. Hence, cross-domain generalization concerns focusing the model’s learning on the latter. However, aspect terms across domains share little direct commonalities. Essentially, their common denominator is being the target topic referred to by opinion terms. For this reason, prior works suggested using hand-crafted syntactic rules (Hu and Liu, 2004; Ding et al., 2017), or alternatively, injecting a full syntactic analysis into the model (Wang and Pan, 2018; Pereg et al., 2020), aiming to capture the transferable relation-based properties of aspects.

Our first contribution is establishing the relational pivoting approach for cross-domain AT extraction on quantitative, data driven analysis (§3). We utilize four different linguistic formalisms (i.e.,...
syntactic and semantic dependencies) to characterize OT–AT relations, and empirically confirm their domain transferability and importance for the task. Following, we propose an auxiliary multi-task learning method with specialized relation-focused tasks, designed to teach the model to focally capture these relations during OT and AT extraction training (§4). Our method improves cross-domain AT extraction performance when applied over both vanilla BERT (Devlin et al., 2019) and the state-of-the-art SA-EXAL (Pereg et al., 2020) models. We conclude with a quantitative analysis of model predictions, ascribing observed performance gains to enhanced relational pivoting.1

2 Background

Following the SemEval Aspect Based Sentiment Analysis shared tasks (Pontiki et al., 2014, 2015), recent works have formulated the OT and AT extraction task: given an opinionated text, identify the spans denoting OTs and ATs. We adopt the benchmark dataset that was used by recent works (Wang and Pan, 2020; Pereg et al., 2020), which consists of three customer-review domains — (R)estaurants, (L)aptops and digital (D)evices — and was aggregated from the SemEval tasks jointly with several published resources (Hu and Liu, 2004; Wang et al., 2016). While promising AT extraction performance has been demonstrated for in-domain settings (Li et al., 2018; Augustyniak et al., 2019), it does not scale to unseen domains, where state-of-the-art models exhibited small incremental improvements and struggle to surpass F1 scores of 40–55 (for the different domain pairs).

Previous works have conjectured that aspect and opinion terms maintain frequent syntactic relations between them. Subsequently, Hu and Liu (2004), followed by Qiu et al. (2011), crafted a handful of simple syntactic patterns for in-domain AT extraction based on OTs. Motivated by the hypothesized domain transferability of syntactic OT–AT relations, Ding et al. (2017) employed pseudo labeling of AT based on the aforementioned patterns, which was used as auxiliary supervision for domain adaptation setup. We, however, extract our patterns from the data rather than manually crafting them.

In a related line of work, syntax was leveraged more broadly for the same relational pivoting mo-

Table 1: Cross-Domain lexical term overlap — how many term instances from target domain occur at least once in source domain (percentage).

| Domain | Aspects | Opinions |
|--------|---------|----------|
| D → R  | 5.3     | 78.6     |
| D → L  | 42.3    | 83.2     |
| R → D  | 12.2    | 59.1     |
| R → L  | 11.0    | 61.4     |
| L → D  | 41.3    | 65.4     |
| L → R  | 9.1     | 68.3     |
| Mean   | 20.5    | 69.3     |

1Our code for all experiments and analyses can be found here: https://github.com/IntelLabs/nlp-architect/tree/libert-path-amtl/nlp_architect/models/libert
cross-domain AT extraction, from lower 70s in-domain to around 45 F1, while exhibiting a “reasonable” drop in OT extraction, from lower 80s to around 70 F1.

### 3.2 OT–AT Path Patterns

Next, we measure the degree to which linguistic relations connecting OT–AT pairs are shared across domains. To this end, we capture OT–AT linguistic relations using their path pattern in a dependency graph, i.e., the ordered list of the dependency relation labels occurring throughout the shortest (undirected) path between the terms (Figure 1).^2^ We investigate and compare four linguistic formalisms: SpaCy’s syntactic dependencies^3^, Universal Dependencies (UD), and two formalisms from Semantic Dependency Parsing (Oepen et al., 2015) — DELPH-IN MRS (DM) and Prague Semantic Dependencies (PSD).^4^ We parsed all the sentences in the benchmark dataset with state-of-the-art parsers — SpaCy 2.0, UDPipe^5^, and HIT-SCIR (Che et al., 2019) for DM and PSD. Importantly, since correspondences between ATs and OTs are not annotated in the benchmark dataset, we first heuristically define which (OT, AT) pairs would be considered related. Following a preliminary analysis, we selected for each formalism all pairs whose shortest path length is ≤ 2. This yields 9K–10K pairs which cover 60%–70% of the ATs across the different formalisms. These pairs and their path patterns constitute the data for the analyses below, as well as for training relation-focused auxiliary tasks (§4).

We find that between 94%–97% of the patterns in one domain are covered by another domain (More details in Appendix A). This confirm the variability across different domain transfer settings. In section 3.4 we further analyze the variability across different domain transfer settings.

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^2^We maintain edge direction by appending a directionality marker to each edge label. In case of multi-word terms, we take the token pair across the terms having the shortest path.

^3^https://spacy.io/

^4^We also experimented with three application-oriented UD extensions: Enhanced UD, Enhanced UD++ (Schuster and Manning, 2016), and pyBART (Tiktinsky et al., 2020). These formalisms introduced more label variability compared with UD, but also shortened OT–AT paths and performed slightly better in the multitask experiments. However, we omit these for presentation convenience.

^5^https://ufal.mff.cuni.cz/udpipe

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### 3.3 Deterministic Relational Pivoting

To quantify the estimated potential of relation-based pivoting, we analyze a deterministic method for extracting ATs via gold OTs based on path patterns, similar to prior rule-based methods (Hu and Liu, 2004; Qiu et al., 2011), and assess how well such an approach transfer across domains. Given predicted linguistic parses, we select the top k common OT-to-AT path patterns and apply them on every OT, where traversal destination tokens are selected as ATs. To illustrate, given the UD pattern OT → AT, the OTs quiet and calm would both yield ambience as an AT (Figure 1, bottom). Notably, this analysis is only a rough upper-bound estimate; it is limited to identifying single-word ATs (70% of all ATs) which furthermore relates to an OT in a strictly known pattern, whereas models may generalize over some of these limitations.

Averaged results (across domain settings) are shown in Table 2 for varying k sizes (see Appendix B for a breakdown by domain pairs). Overall, pattern-based AT extraction can bring averaged F1 score up to 39 (DM), and recall up to 54 (UD). Crucially, there is hardly any drop in cross-domain settings relative to in-domain, affirming that patterns from a different source domain are as informative as in-domain patterns for opinion based AT extraction, consistent with observed pattern stability (§3.2). These findings suggest that driving a model to encode OT–AT relations should enhance domain adaptation.
3.4 Analysis of Domain Differences

It is illuminating to examine the differences between domains with respect to the path-pattern variability and transferability. In order to assess the linguistic diversity of OT–AT relations within each domain, we plot the relative cumulative pattern distribution for each linguistic formalism, visualizing how many OT–AT pairs (%) are covered by how many different patterns (See Figure 2 for a representative, and Appendix Figure 3 for the complete set of figures). The general picture is that the vast majority of OT–AT pairs exhibit a few dozens of path patterns, albeit most pairs are covered by a few high-frequency patterns.

Specifically, we observe that the Laptops domain is the most diverse and slowly-accumulating, while the opposite is true for the Restaurants domain. We conjecture that the linguistic variability of OT–AT relations inside a domain affects its transferability. High variability makes the domain harder to transfer to, as many relation patterns were not seen during training on the source domain. At the same time, it might make it a good choice for the source domain, acquainting the model with a rich set of relational linguistic constructions to generalize from.

Obviously, the within-domain variability is not the most prominent factor affecting domain transfer; rather, it interacts with the similarity of the domain pairs, both on the pivot features (here: OT–AT relations) and on the non-pivot features (here: the lexical and semantic profile of ATs and OTs). To have a better handle on cross-domain similarity of OT–AT relations that accounts for pattern frequency in each domain, we compute the Jensen-Shannon Distance between path-pattern probability distributions (Table 6 in Appendix A), where smaller distance indicates greater similarity. While the Devices and Laptops domains are the most similar to each other, the Restaurants and Laptops domains are least similar.

By and large, this is inline both with results of the deterministic pivoting analysis (Section 3.3) broken down by domain pairs (Table 7 in Appendix B), and, to a smaller degree, with performance gains of our relation-focused multitask learning experiments (Section 5).

4 Multi-task Learning Method

To propagate the relational pivoting signal into an OT and AT extraction model, we apply auxiliary multitask learning (AMTL). We experimented with two auxiliary tasks for steering the model to encode OT–AT relationship information during training. Given an OT from an OT–AT pair of the collected auxiliary training data (§3.2), the model learns to: (1) predict its counterpart AT (ASP); and (2) predict the path-pattern connecting them on the dependency graph (PATT). The ASP task should foreground the implicit representation of OT–AT relations, whereas PATT injects explicit, linguistically-oriented relation information.

Prior multitask learning approaches for enriching models with syntax (Strubell et al., 2018; Wang and Pan, 2018, 2020) have pushed them to encode a full syntactic analysis, possibly including irrelevant information. In contrast, our auxiliary tasks form a “partial parsing” objective, specialized in the relevant terms and their multifarious relations. We use both vanilla BERT (Devlin et al., 2019) and state-of-the-art SA-EXAL (Pereg et al., 2020) as base models, where the latter may imply whether our relation-focused signal is subsumed by SA-EXAL’s awareness to the full syntactic parse (§2).

Implementation details We follow the experimental setup of (Pereg et al., 2020) and formulate OT and AT extraction as a single BIO-tagging task. One-layer classifiers are applied on top of either bert-base-uncased or SA-EXAL encoders, both for the main task and for the auxiliary tasks. Let \( Z = \{z_1, z_2, \ldots, z_n\} \) be the contextualized representations of the input sequence produced by the encoder, and \( op \) be the OT index from an extracted OT–AT pair. The auxiliary classifiers are defined as follows:

\[
\text{PATT}(Z, op) = \text{softmax}(z_{op}W^P + U^P)
\]

\[
\text{ASP}(Z, op) = \text{softmax}(o_1, \ldots, o_n)
\]

\[
\alpha_i = (z_{op}W^A + U^A) \cdot z_i
\]

where \( W^P \in \mathbb{R}^{d \times m}, U^P \in \mathbb{R}^m, W^A \in \mathbb{R}^{d \times d} \).

Table 3: Jensen-Shannon Distances between pattern probabilities in different domains. Lower distance indicates similarity between the frequency signature of patterns in a domain pair.

|       | R ↔ L | R ↔ D | L ↔ D | Mean  |
|-------|-------|-------|-------|-------|
| Spacy | 0.62  | 0.60  | 0.58  | 0.60  |
| UD    | 0.60  | 0.59  | 0.56  | 0.58  |
| DM    | 0.50  | 0.50  | 0.50  | 0.50  |
| PSD   | 0.60  | 0.56  | 0.58  | 0.58  |
| Mean  | 0.38  | 0.56  | 0.35  | 0.37  |

\text{The SA-EXAL model was amended to generalize over the graph structures (rather than trees) produced by semantic formalisms (Appendix E).}
Model (+ AMTL task — Formalism) & L → R & D → R & R → L & D → L & R → D & L → D & Mean

BERT & 47.2 (4.0) & 51.6 (2.1) & 44.5 (3.1) & 46.7 (1.7) & 38.3 (2.4) & 42.6 (0.6) & 45.16
BERT + Asp — DM & 53.5 (3.3) & 52.0 (2.1) & 45.7 (2.4) & 45.9 (2.3) & 38.8 (1.5) & 42.8 (1.0) & 46.45
BERT + Asp — Spacy & 49.8 (3.2) & 51.6 (1.5) & 46.2 (2.5) & 45.2 (2.5) & 39.4 (1.6) & 42.5 (1.0) & 45.77
BERT + Patt — DM & 46.3 (4.7) & 50.9 (2.6) & 42.9 (3.4) & 46.2 (2.4) & 38.0 (1.9) & 42.1 (1.0) & 44.40
BERT + Patt — Spacy & 50.1 (3.0) & 51.6 (2.0) & 43.1 (2.2) & 46.6 (2.5) & 37.8 (1.6) & 42.0 (0.9) & 45.20

SA-EXAL — DM & 48.7 (3.8) & 53.8 (2.8) & 46.0 (3.1) & 47.7 (1.8) & 40.7 (1.3) & 41.9 (0.6) & 46.48
SA-EXAL — Spacy & 47.9 (3.1) & 54.1 (1.9) & 45.4 (3.3) & 47.1 (1.1) & 40.7 (1.7) & 42.1 (1.4) & 46.24
SA-EXAL + Asp — DM & 54.1 (2.3) & 51.6 (2.0) & 45.6 (2.9) & 45.8 (4.1) & 39.2 (1.9) & 41.8 (0.9) & 46.37
SA-EXAL + Asp — Spacy & 54.0 (3.1) & 52.6 (1.9) & 47.1 (3.0) & 46.9 (2.4) & 39.1 (2.7) & 42.2 (0.6) & 47.00
SA-EXAL + Patt — DM & 52.8 (4.3) & 54.3 (1.8) & 47.5 (1.9) & 47.7 (2.2) & 40.3 (1.5) & 41.6 (0.8) & 47.37
SA-EXAL + Patt — Spacy & 51.2 (3.4) & 53.3 (2.3) & 46.5 (2.3) & 46.6 (1.8) & 39.5 (1.2) & 41.5 (0.9) & 46.42

Table 4: Cross-domain AT-extraction for different models and linguistic formalisms, evaluated by mean F1 score (and standard deviation). Each column (e.g. L → R) stands for a cross-domain transfer (e.g. Laptops to Restaurants), where the best BERT and SA-EXAL results are highlighted in bold.

$U^A \in \mathbb{R}^d$ are model parameters, $\cdot$ stands for dot product, $d$ is the hidden vector size and $m$ is the size of the output pattern vocabulary. $m$ is set by taking all the patterns whose frequency in training data (i.e., source domain) is $\geq 3$, while mapping other patterns to a fixed UNK symbol.

5 Results and Analysis

Following Pereg et al. (2020), we run each model on 3 random data splits and 3 different random seeds, presenting the mean F1 (and standard deviation) of the 9 runs. Detailed results are shown in Table 4, omitting the UD and PSD formalisms — which perform virtually on par with the other formalisms — for space considerations.

For BERT, training for Asp consistently improves the mean F1 score, by up to 1.3 points (DM), bringing BERT’s performance to be on par with the state-of-the-art SA-EXAL model. Improvements over the SA-EXAL baseline is generally smaller, yet some settings improve by 0.5–1 mean F1 points. Best performance is attained using SA-EXAL + Patt with semantic formalisms, indicating that pattern-focused signal is complementary to generic syntax enrichment methods.

Performance Analysis The overlap between model predictions and the deterministic relational pivoting method (§3.3) indicates to what extent the model utilizes relational pivot features. Given model predictions, we define pivot-$\Delta R$ as the recall improvement a model gains by unifying its true predicted ATs with those of the deterministic method (at $k = 10$). Greater pivot-$\Delta R$ indicates greater discrepancy from the potential scope of pattern-based coverage, hinting that the model incorporates less relational pivot features. Taking DM as the formalism, we find that for the vanilla BERT model, average pivot-$\Delta R$ across 6 domain transfers is 16.5 recall points, with 22.6 for the Laptops to Restaurants transfer (L → R). This implies that relational features have a significant potential for enhancing its cross-domain coverage, especially on L → R, where we indeed observe the most profound model improvements using our relation-focused tasks. In comparison, BERT + ASP (DM) has an averaged pivot-$\Delta R$ of 14, with 15.7 on L → R (See Appendix E for more details). This drop confirms that the AMTL objective pushes the model to cover more OT-related ATs using relational pivoting.

6 Conclusion

We establish an opinion-based cross-domain AT extraction approach, by analyzing the domain invariance of linguistic OT–AT path pattern. We consequently propose a relation-focused multitask learning method, and demonstrate that it enhances models results by utilizing relational features.

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7Our reported baseline figures are slightly different than those reported by Pereg et al. (2020), as we could not fully reproduce their hyperparameter settings, e.g. random seeds. Aiming for a controlled experiment concerning only the AMTL improvements over baselines, we have not optimized the random seeds for any condition.

8Results for models trained with both ASP and Patt were also omitted due to their lower performance.

9We average this measure as well over the 9 model runs.
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Appendices

A Cross-domain overlap in path patterns

In Table 5, we present the percentage of target domain path patterns occurring at least once in the source domain. To account for pattern frequency in each domain, we also compute the Jensen-Shannon Distance between pattern probability distributions (Table 6). Overall, DM has the best cross-domain pattern overlap, while the Devices and Laptops domains are slightly more similar to each other.
Table 5: Cross-domain pattern overlap — how many AT–OT paths in target domain share a pattern with paths in source domain (percentage).

|        | R \rightarrow L | R \rightarrow D | L \rightarrow R | L \rightarrow D | D \rightarrow R | D \rightarrow L |
|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Spacy  | 89.9            | 87.4            | 97.5            | 96.8            | 95.3            | 93.0            |
| UD     | 93.4            | 94.7            | 96.7            | 95.9            | 95.7            | 93.0            |
| DM     | 97.8            | 97.9            | 97.9            | 97.3            | 97.1            | 97.0            |
| PSD    | 93.8            | 95.5            | 95.3            | 96.8            | 93.2            | 90.4            |

Table 6: Jensen-Shannon Distances between pattern probabilities in different domains. Lower distance indicates similarity between the frequency signature of patterns in a domain pair.

|        | R \leftrightarrow L | R \leftrightarrow D | L \leftrightarrow D | Mean |
|--------|---------------------|---------------------|---------------------|------|
| Spacy  | 0.62                | 0.60                | 0.58                | 0.60 |
| UD     | 0.60                | 0.59                | 0.56                | 0.58 |
| DM     | 0.50                | 0.50                | 0.50                | 0.50 |
| PSD    | 0.60                | 0.56                | 0.58                | 0.57 |
| Mean   | 0.58                | 0.56                | 0.55                | 0.57 |

As mentioned in Section 2, the SA-EXAL model augments BERT with a specialized, 13th attention head, incorporating the syntactic parse directly into the model attention mechanism. In the original paper, SA-EXAL was fed with syntactic dependency trees, where each token has a syntactic head token to which it should attend. The learned attention matrix $A \in \mathbb{R}^{n \times n}$ is multiplied element-wise by a matrix representation of the syntactic parse $P$, where each row is a one-hot vector stating the token to which to attend.

However, semantic dependency formalisms, such as PSD and DM, produce bi-lexical directed acyclic graphs, in which a word can have zero “heads” (for semantically vacuous words, e.g. copular verbs) or multiple “heads” (i.e. outgoing edges). We modify the SA-EXAL model such that instead of one-hot rows, $P$ can have all-one rows (no heads) or multiple-ones rows (multiple heads). Consequently, for tokens with no heads the network is learning the attention without external interference, whereas for tokens with multiple heads, the attention mass is distributed between the heads.

E Correlating pivot-$\Delta R$ and model improvement

In Section 5 we define the pivot-$\Delta R$ measure for model predictions, which quantifies how much can model predictions be improved with pattern-based relational pivoting. We observe that pivot-$\Delta R$ is higher for the baseline models compared to the corresponding models enhanced by our AMTL objectives (specifically the Asp objective). Nonetheless, this reduction in pivot-$\Delta R$ seem to correlate with model’s improvement along the transfer settings. In Figure 4 we illustrate this for the BERT and BERT + ASP (DM) models. Observed Spearman’s $\rho$ over
Table 7: Results of deterministic relational pivoting per DA settings (K=10).

|        | R → L | R → D | L → R | L → D | D → R | D → L |
|--------|-------|-------|-------|-------|-------|-------|
| Spacy  | P: 0.32 R: 0.22 F1: 0.26 | P: 0.61 R: 0.29 F1: 0.4 | P: 0.49 R: 0.37 F1: 0.42 | P: 0.58 R: 0.33 F1: 0.42 | P: 0.54 R: 0.37 F1: 0.44 | P: 0.3 R: 0.24 F1: 0.27 |
| UD     | P: 0.26 R: 0.23 F1: 0.24 | P: 0.46 R: 0.29 F1: 0.36 | P: 0.44 R: 0.39 F1: 0.41 | P: 0.47 R: 0.3 F1: 0.36 | P: 0.49 R: 0.37 F1: 0.43 | P: 0.26 R: 0.23 F1: 0.24 |
| PSD    | P: 0.22 R: 0.26 F1: 0.24 | P: 0.41 R: 0.34 F1: 0.37 | P: 0.35 R: 0.4 F1: 0.38 | P: 0.41 R: 0.35 F1: 0.38 | P: 0.3 R: 0.4 F1: 0.34 | P: 0.19 R: 0.27 F1: 0.22 |

Figure 3: Relative cumulative frequency distributions of path patterns for each domain in all formalisms, showing how many different patterns (X axis) cover what percentage of OT–AT pairs (Y axis).

the 6 transfer settings is 0.83 (though obviously this small sample cannot be tested for statistical significance). This examination of model predictions entails that the improvement we observe in model performance is indeed attributed to instances that exhibit a relation pattern present in the source domain.

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Figure 4: Relation between reduction in pivot-$\Delta R$ from BERT to BERT + ASP and the corresponding improvement in model performance. Results are provided for DM dependencies.