Lifelong-RL: Lifelong Relaxation Labeling for Separating Entities and Aspects in Opinion Targets

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Sentiment Analysis on Customer Reviews
(Liu, 2012)

• Sentiment analysis:
  • identify opinions (sentiment polarities) from a piece of text;
  • multiple levels of sentiment analysis: document-level, sentence-level, aspect-level sentiment analysis.

• Aspect-level sentiment analysis on customer reviews:
  • identify opinion targets (targets for short) and classify the opinions on those targets.
Opinion Target

• An opinion target can be
  • an entity (general aspect):
    • I like this car.
  • or an aspect (part or attribute) of an entity:
    • The engine of this car is great.

• Why to separate entities and aspects?
  • Opinion on an entity is an opinion as a whole;
  • Opinion on an aspect is just for that aspect.
  • Example:
    • although the engine is lightly weak, this car is great.
What is an Entity?

- In this paper, an entity can be:
  - named entity ("Apple", "iPhone");
  - product category ("Phone");
  - abstract product ("machine", "product").
What is an Aspect?

• In this paper, an aspect can be:
  • a part;
  • or an attribute of an entity.

• Examples:
  • The *camera* of this phone is great.
  • The phone’s *price* is great.
Our Goal

• Assign each target a **target label** as entity, aspect or NIL in an unsupervised manner.

• Aspects are shared in many products, we can utilize lifelong machine learning to improve the classification.

• Note that we only focus on classifying entity and aspect after the opinion targets have been extracted.

The picture is from AAAI 2013 Spring Symposium
Roadmap

• Framework Overview
• Relaxation Labeling
• Lifelong Relaxation Labeling
• Experiment
• Conclusion
Labeling Pipeline

- We use an unsupervised opinion target extraction method **Double Propagation (DP)** (Qiu et. al, 2011) to get a list of targets;
- We use targets and modifiers (text clues) from reviews to perform graph construction and use **Relaxation Labeling (RL)** (Hummel et. al, 1986) to classify targets as entity, aspect or NIL.
Lifelong Machine Learning (LML) (Thrun, 1996; Silver et. al, 2013; Chen and Liu, 2014)

• LML works as how human learn:
  • Assume the learner has performed a number of learning tasks $d_1, \ldots, d_u$ in the past domains (products) and has retained the knowledge in a Knowledge Base gained so far;
  • In the new/current task (product) $d_{u+1}$, it makes use of past knowledge to help current learning and problem solving.

• The approach is effective because there is a significant amount of sharing of targets and target relations across products.
Lifelong Relaxation Labeling Framework
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Relaxation Labeling (RL)

- An unsupervised graph-based label propagation algorithm;
- A node is a target and an edge indicates how two targets influence each other;
- The graph is constructed from targets and modifiers.
Modifiers (Text Clues) as Features

• Use **type modifiers** to determine the initial label distribution of nodes:
  • entity modifiers: “this”, “these” e.g., “this camera is great” indicates that “camera” is probably an entity;
  • aspect modifiers: implicitly assumed when the appearance of entity modifiers is inadequate.

• Use **relation modifiers** to determine the structure (existence of an edge) of the graph:
  • conjunction modifier: “price and service” (if price is an aspect service is an aspect and vice versa);
  • entity-aspect modifier: “camera’s price”;
  • aspect-entity modifier: “camera’s price”.


Initial Distribution for Nodes and Edges

• Each node in the graph is associated with a distribution on labels \{entity, aspect, NIL\} that is updated during iteration;

\[ P(L(\downarrow i)) = [\square \cdots \@ \cdots \@ \cdots ] \]

• Each edge is associated with a fixed 3x3 matrix representing conditional probabilities of how the label distribution of one target affects the other’s.

\[ P(L(\downarrow i) | L(\downarrow j)) = [\square \cdots & \cdots & \@ \cdots & \cdots & \cdots ] \]

• Distribution on labels are iteratively updated until convergence.
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Lifelong Relaxation Labeling (Lifelong-RL)

• RL on a single domain data may not be sufficient
  • Insufficient edges: relation modifiers for constructing edges;
  • Unreliable initial probabilities: type modifiers for setting up “seed” nodes.

• Lifelong learning comes to rescue:
  • Assume the learner has “relax labeled” u domains (products);
  • The learner can borrow some useful prior/past knowledge (e.g., nodes and edges etc.) in the Knowledge Base (KB) to help RL in the new/current domain $d_{u+1}$
  • The learner can further add the results of the new/current domain $d_{u+1}$ to the KB for future use.
Knowledge Base (KB)

- The results of RL for each domain is stored in a KB.
- There are two types of knowledge:
  - prior edges:
    - relation modifiers;
    - used in *Lifelong-RL-1* and *Lifelong-RL*;
  - prior labels:
    - target labels;
    - used in *Lifelong-RL*.
Lifelong-RL-1: Exploiting Relation Modifiers

• Idea: relation modifiers from past domains can help to link targets in the current domain.

• Example:
  • Relation modifiers can be shared across domains;
  • Example: a Cellphone domain can borrow the edge “camera and battery” from Laptop.
Consistency Check

- Knowledge may contain noise:
  - (1) target labels may be wrong since Double Propagation and RL may be inaccurate;
  - (2) target labels in one domain may not be the same as the other;
- Example: a new/current Cellphone domain cannot borrow the relation modifier “camera's battery” from Camera domain.

Is camera an entity or an aspect?
Consistency Check

• Lifelong learner further performs a **consistency check**.

• Two types of consistency check:
  • **Label Consistency Check** (for noise (1)): ensure that a relation modifier from a domain in the KB are consistent with target labels of those two targets associated with that relation modifier in that past domain;
  • **Type Consistency Check** (for noise (2)): the type modifier for a target in new/current domain must match the type modifiers of that target in the past domains.
Lifelong-RL: Further Exploiting Target Labels

• Idea: target labels from past domains can give a better idea about the initial label distributions of targets in the current domain.

• Example:
  • after labeling domains like Laptop, Tablet and E-reader, it is likely that “camera" is an aspect in the new domain.
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Experiment: Dataset & Evaluation

• Datasets:
  • Test Datasets: reviews on 8 products labeled with entities and aspects;
  • Unlabeled review datasets for LML: 100 diverse domains (products) (Chen and Liu 2014); Each domain has 1000 reviews.

• Evaluation Method:
  • precision, recall, F1-score and accuracy as evaluation measures.
  • We only evaluate entities and aspects.
Experiment: Compared Methods

• **NER+TM**
  - Use Named Entity Recognition (NER) (UIUC NER) to find entities;
  - Use type modifier(TM) to recognize more product category or abstract product as entities;
  - Regard those entities as predicted entities and the rest of the targets as aspects.

• **NER+TM+DICT**
  - Run NER+TM on the 100 datasets for LML to get a list of entities;
  - For a new task, treat targets in the list as an entity; the rest are aspects.

• **RL**
  - the base method that performs RL without the help of LML.

• **Lifelong-RL-1**
  - perform LML with RL but the current task only uses the prior edges in the KB.

• **Lifelong-RL**
  - improve Lifelong-RL-1 by further incorporating prior labels in the KB.
## Results

For entity label, Lifelong-RL improves RL 23.3% on Recall 10.9% on Precision.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Entity F1-score</th>
<th>Aspect F1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>NER+TM</td>
<td>61.3</td>
<td>78</td>
</tr>
<tr>
<td>RL</td>
<td>61.2</td>
<td>77.2</td>
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<td>Lifelong-RL-1</td>
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<td>79.7</td>
</tr>
<tr>
<td>Lifelong-RL</td>
<td>79.9</td>
<td>80.2</td>
</tr>
</tbody>
</table>
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Conclusion

• Propose the problem of classifying opinion targets into entities and aspects for sentiment analysis on reviews;
• Propose a novel method based on relaxation labeling and the paradigm of lifelong machine learning to solve the problem.
• Experimental results show the effectiveness of the proposed method and lifelong machine learning.
Question and Answer [?]