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

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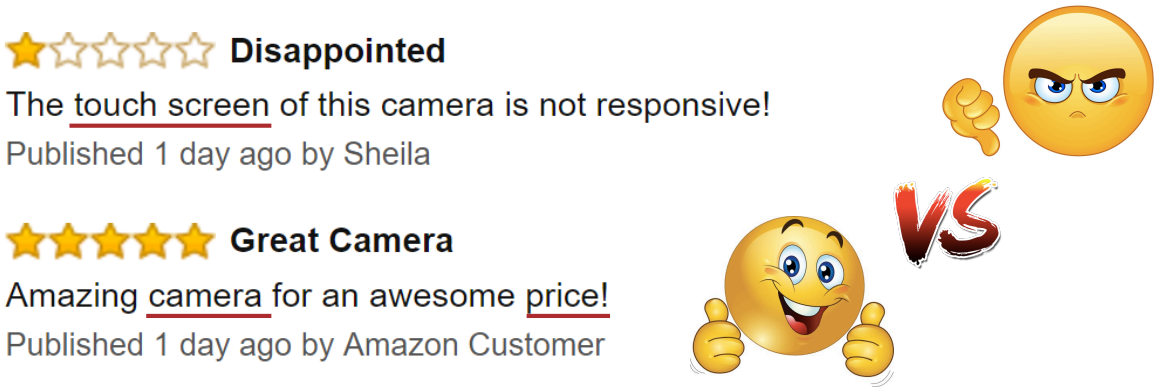
EMNLP, 2016

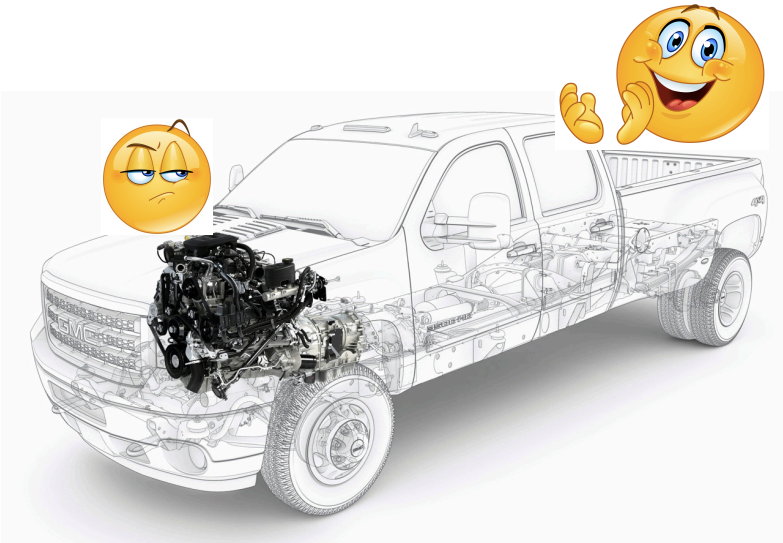
Sentiment Analysis on Customer Reviews
(Liu, 2012)

- 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.



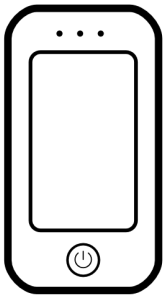
Opinion Target

- 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.

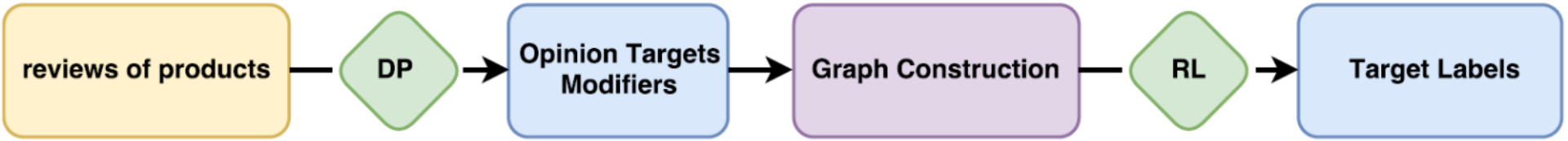
The picture is from AAAI 2013 Spring Symposium

Roadmap

- **Framework Overview**
- Relaxation Labeling
- Lifelong Relaxation Labeling
- Experiment
- Conclusion

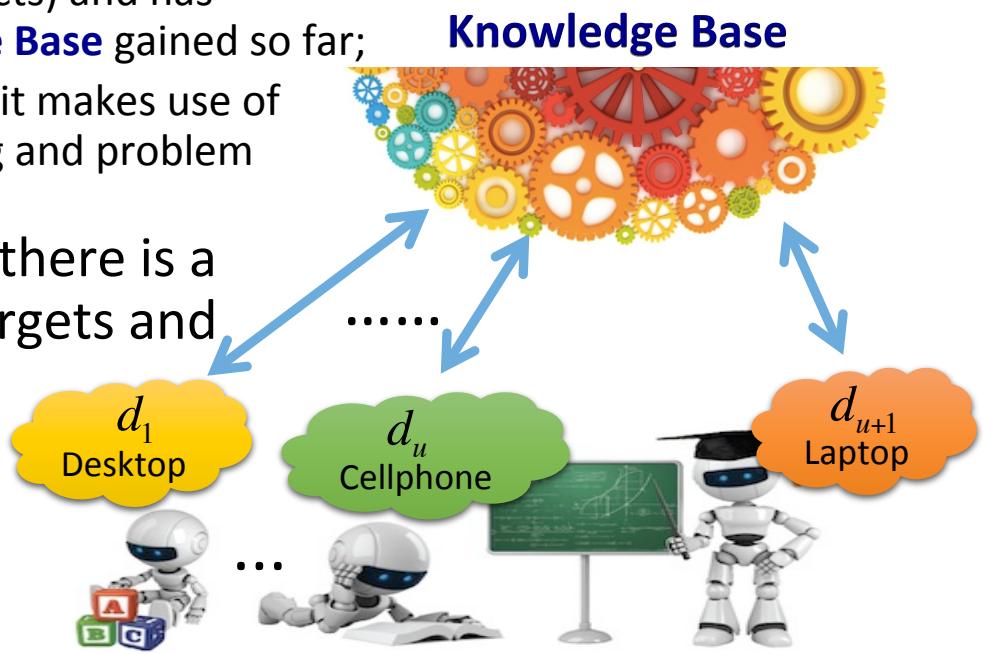
Labeling Pipeline

- 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.

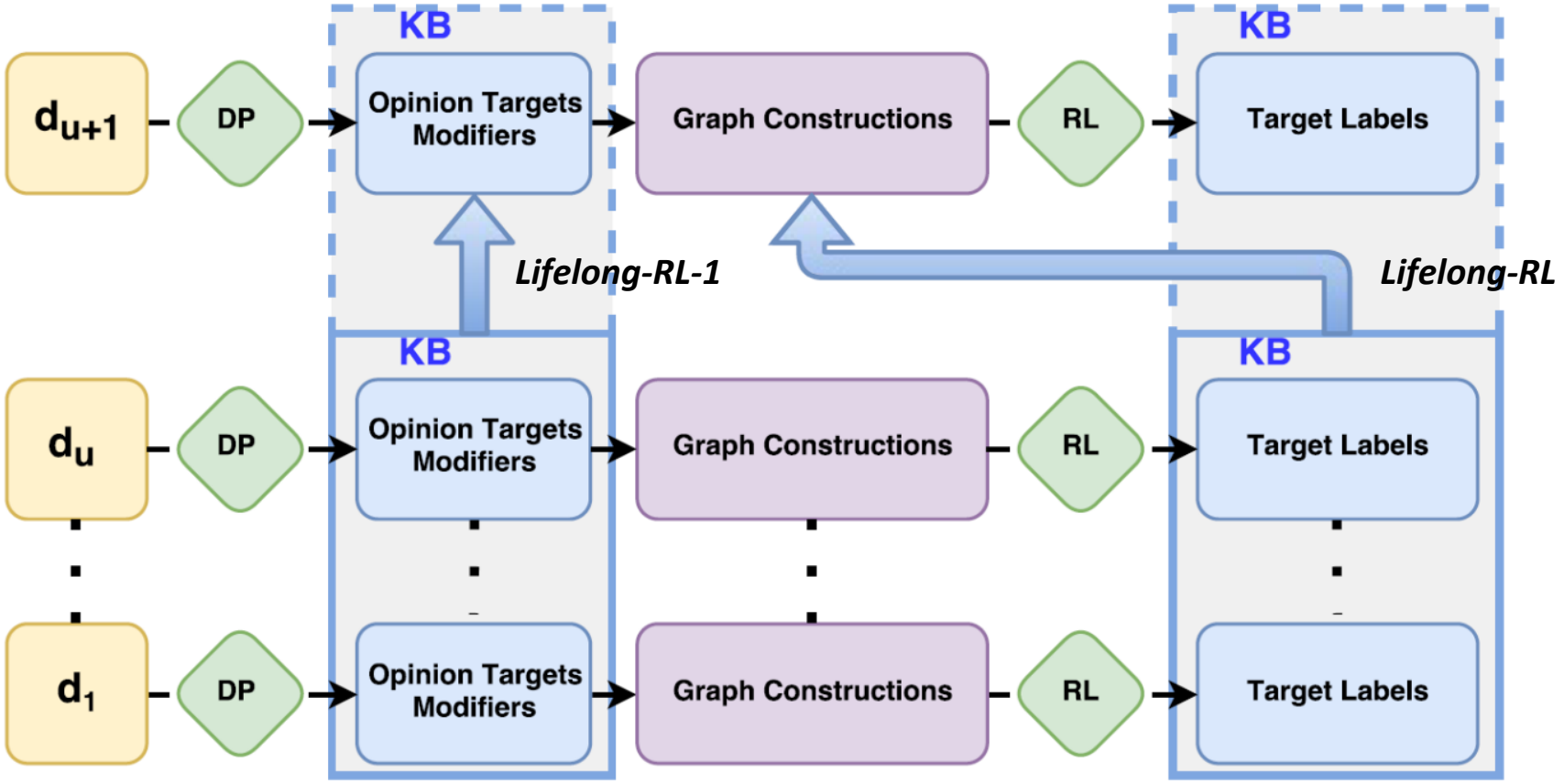


Lifelong Machine Learning (LML) (Thrun, 1996; Silver et. al, 2013; Chen and Liu, 2014)

- 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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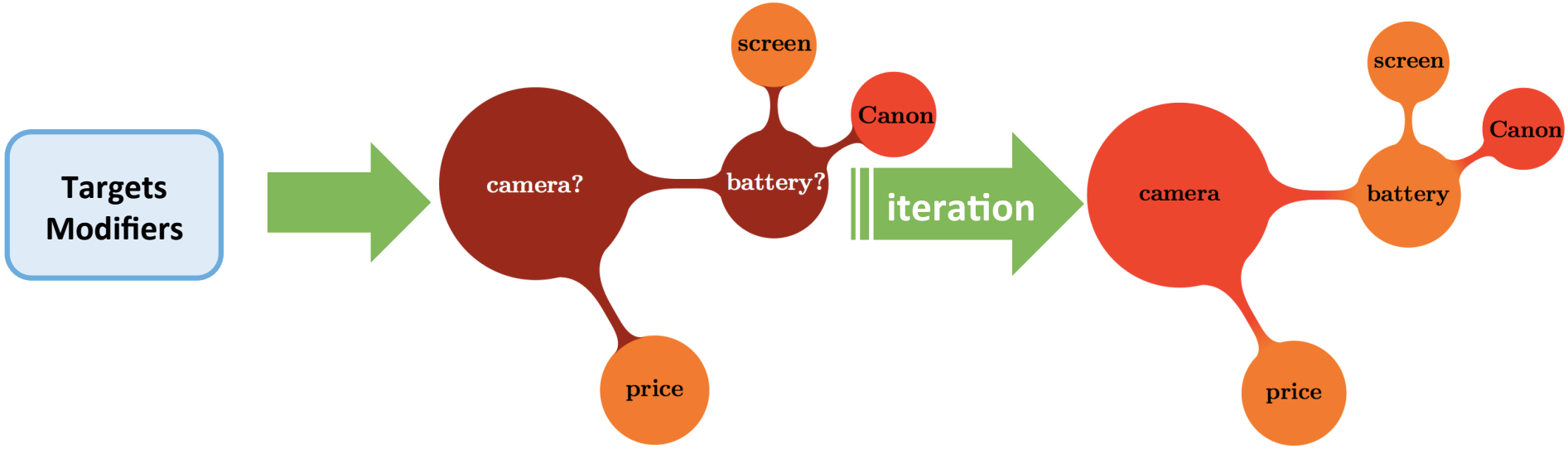
Relaxation Labeling (RL)

- 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;
- $P(L(t{\downarrow}i))=[\blacksquare\cdots@\cdots@\cdots]$
- Each edge is associated with a fixed 3x3 matrix representing conditional probabilities of how the label distribution of one target affects the other's.
- $P(L(t{\downarrow}i)|L(t{\downarrow}j))=[\blacksquare\cdots\&\cdots\&\cdots@\cdots\&\cdots\&\cdots@\cdots\&\cdots\&\cdots]$
- Distribution on labels are iteratively updated until convergence.

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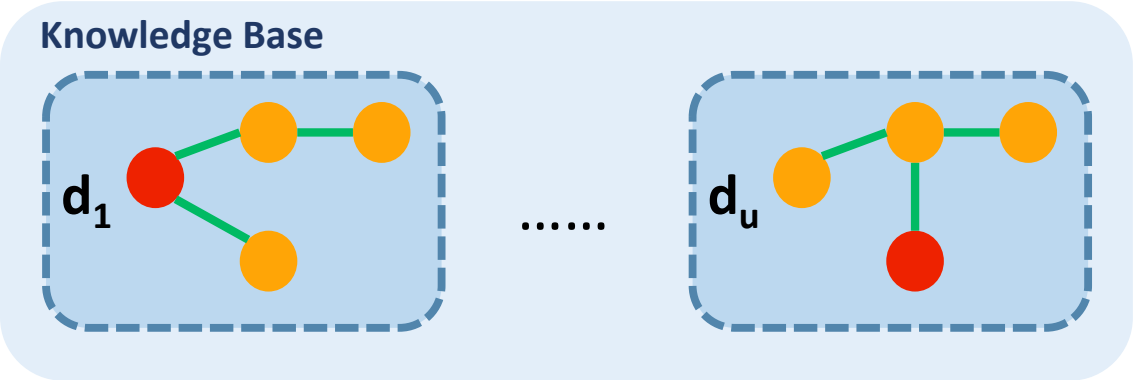
Lifelong Relaxation Labeling (Lifelong-RL)

- 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)

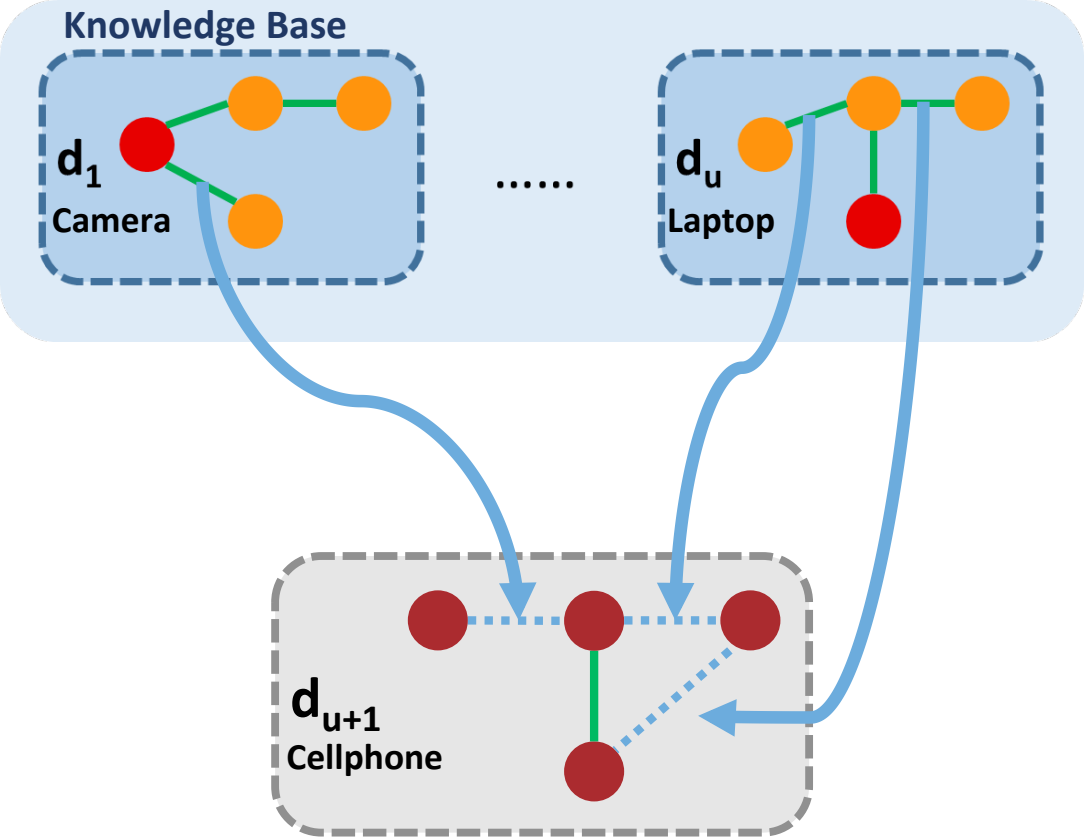
- The results of RL for each domain is stored in a KB
- There are two types of knowledge:
  - prior edges:
    - relation modifiers;
    - used in **Lifelong-RL-1** and **Lifelong-RL**;
  - prior labels:
    - target labels;
    - used in **Lifelong-RL**.



Lifelong-RL-1: Exploiting Relation Modifiers

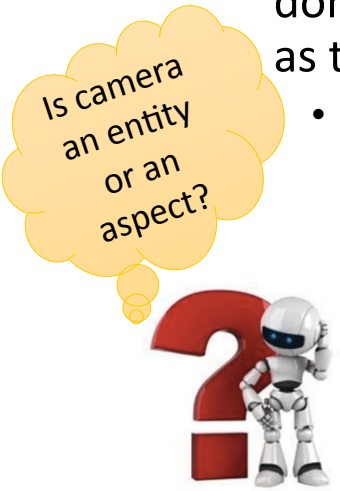
- Idea: relation modifiers from past domains can help to link targets in the current domain.

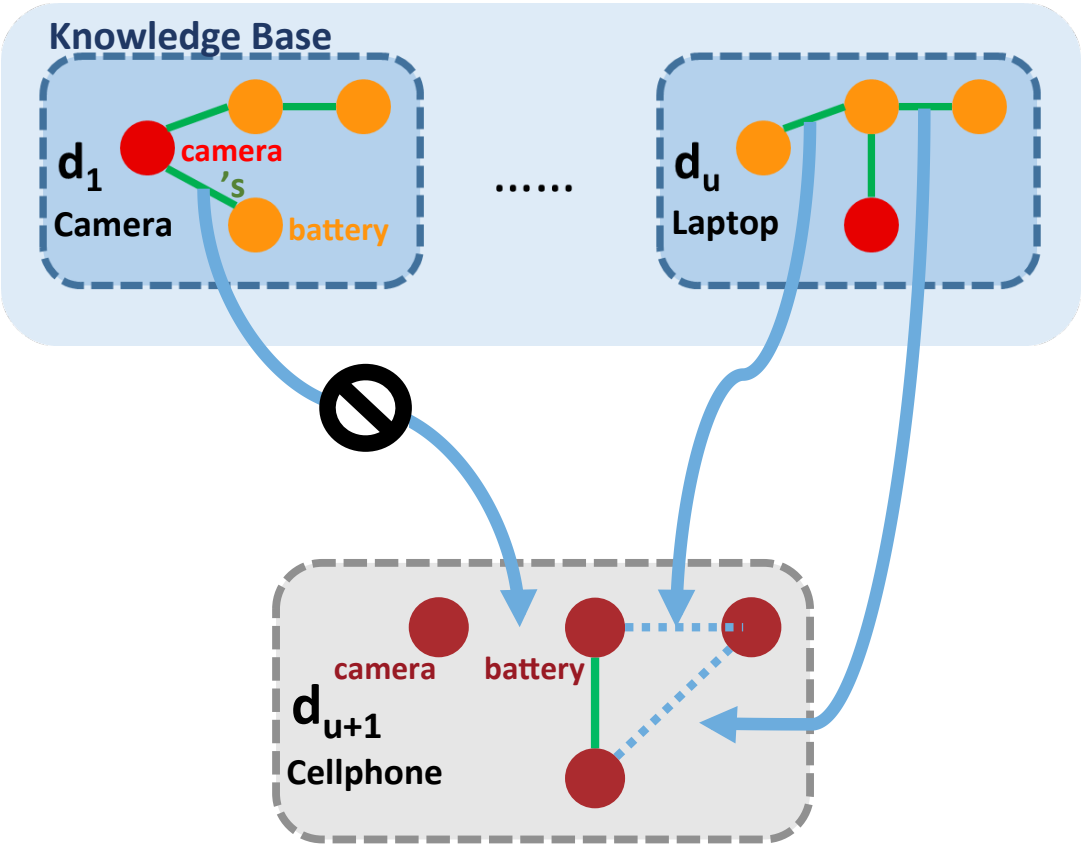
- Example:
  - Relation modifiers can be shared across domains;
  - Example: a Cellphone domain can borrow the edge "camera and battery" from Laptop.



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.





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

Algorithm	Entity F1-score	Aspect F1-score
NER+TM	61.3	78
RL	61.2	77.2
Lifelong-RL-1	**77.4**	**79.7**
Lifelong-RL	**79.9**	**80.2**

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

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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 [?]

Lei Shu, Bing Liu, Hu Xu, and Annice Kim.
2016.
Lifelong-rl: Lifelong relaxation labeling for separating entities and aspects in opinion targets.
In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 225–235, Austin, Texas, November. Association for Computational Linguistics.