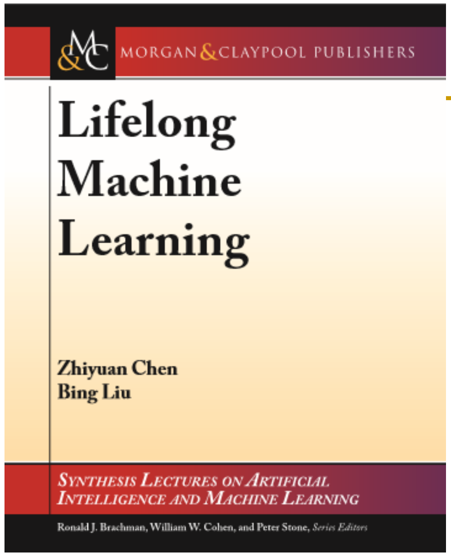
EMNLP-2016 Tutorial, Nov 1, 2016, Austin, Texas, USA

Lifelong Machine Learning for Natural Language Processing


MORGAN & CLAYPOOL PUBLISHERS
Lifelong Machine Learning
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Synthesis Lectures on Artificial Intelligence and Machine Learning
Ronald J. Brachman, William W. Cohen, and Peter Stone, Series Editors

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Introduction

(Chen and Liu, 2016-book)

- Classic Machine Learning (ML) paradigm: isolated single-task learning
  - Given a dataset, run an ML algo. to build a model
  - Without considering the past learned knowledge
- Existing ML algorithms such as
  - SVM, NB, DT, Deep NN, CRF, and topic models
  - Have been very successful in practice
- Let's call this: Machine Learning (ML) 1.0

Introduction: ML 1.0

- Weaknesses of “isolated learning”
  - Knowledge learned is not retained or accumulated
    - Needs a large number of training examples
    - Suitable for well-defined & narrow tasks in restricted env.
- Human beings never learn in isolation
  - We retain knowledge & use it to learn more knowlg.
  - Learn effectively from a few or no examples
    - Our knowledge learned and accumulated in the past
      - which allows us to learn with little data or effort

Introduction: An Example

- Nobody has ever given me 1000 positive and 1000 negative online reviews and ask me
  - to build a classifier to classify Camera reviews
    - In fact, I don’t need any training data
- I have accumulated so much knowledge
    - about how people praise and criticize things
- If I don’t have the accumulated knowledge, NO
  - E.g., I don’t know Arabic and if someone gives me 2000 training reviews in Arabic, I cannot do it.

Introduction: ML 2.0

Thrun, 1996b; Silver et al 2013; Chen and Liu, 2014a, 2016-book

- Statistical ML is getting increasingly mature
- It's time for *Lifelong Machine Learning* (LML)
  - Retain/accumulate learned knowledge in the past & use it to help future learning
    - become more knowledgeable & better at learning
  - Learn by mimicking "human learning"

- Let us call this paradigm Machine Learning 2.0
  - Without LML, it is unlikely we can build a truly intelligent system.

Outline

- A motivating example
- What is lifelong machine learning?
- Related learning paradigms
- Lifelong supervised learning
- Lifelong unsupervised learning
- Semi-supervised never-ending learning
- Lifelong reinforcement learning
- Summary

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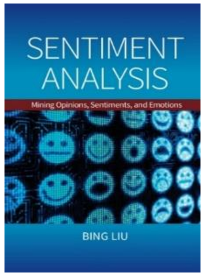
A Motivating Example
(Liu, 2012, 2015)



- My interest in LML stemmed from extensive experiences on *sentiment analysis* in a startup company many years ago.
- Sentiment analysis (SA)
  - Sentiment and target aspect: "*The screen is great, but the voice quality is poor.*"
    - Positive about screen but negative about voice quality
  - Extensive knowledge sharing across tasks/domains
    - Sentiment expressions & aspects

Knowledge Shared Across Domains

- After working on many SA projects for clients, I realized
  - a lot of concept sharing across domains
  - as we see more and more domains, fewer and fewer things are new.
- Easy to see sharing of sentiment words,
  - e.g., *good, bad, poor, terrible*, etc.
- There is also a great deal of aspect sharing
  - product feature sharing

Sharing of Product Features

- Observation: A great deal of product features (or aspects) overlapping across domains
  - Every product review domain has the aspect *price*
  - Most electronic products share the aspect *battery*
  - Many also share the aspect of *screen*.
  - Many also share sound quality
  - ….
- It is rather “silly” not to exploit such sharing in learning or extraction.

What does that Mean for Learning?

- How to systematically exploit such sharing?
  - Retain/accumulate knowledge learned in the past.
  - Leverage the knowledge for new task learning
- I.e., *lifelong machine learning* (LML)
- This leads to our own work
  - Lifelong topic modeling (Chen and Liu 2014a, b)
  - Lifelong sentiment classification (Chen et al 2015)
  - Several others

LML is Suitable for NLP

- Knowledge, easily shared across domains
  - Words and phrases almost have the same meaning in different domains or tasks.
  - Sentences in all domains follow the same syntax
- Knowledge, useful in different types of tasks.
  - NLP problems are closely related to each other
    - POS tagging, coreference resolution, entity recognition, …
- Big data provides a great opportunity for LML
  - Learn a large amount of knowledge to become
    - More and more knowledgeable & better at learning

LML is Useful in General

- LML is suitable for all learning
- It is hard to imagine:
  - We have to learn everything from scratch whenever we encounter a new problem or environment.
- If that were the case,
  - Intelligence is unlikely

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Definition of LML

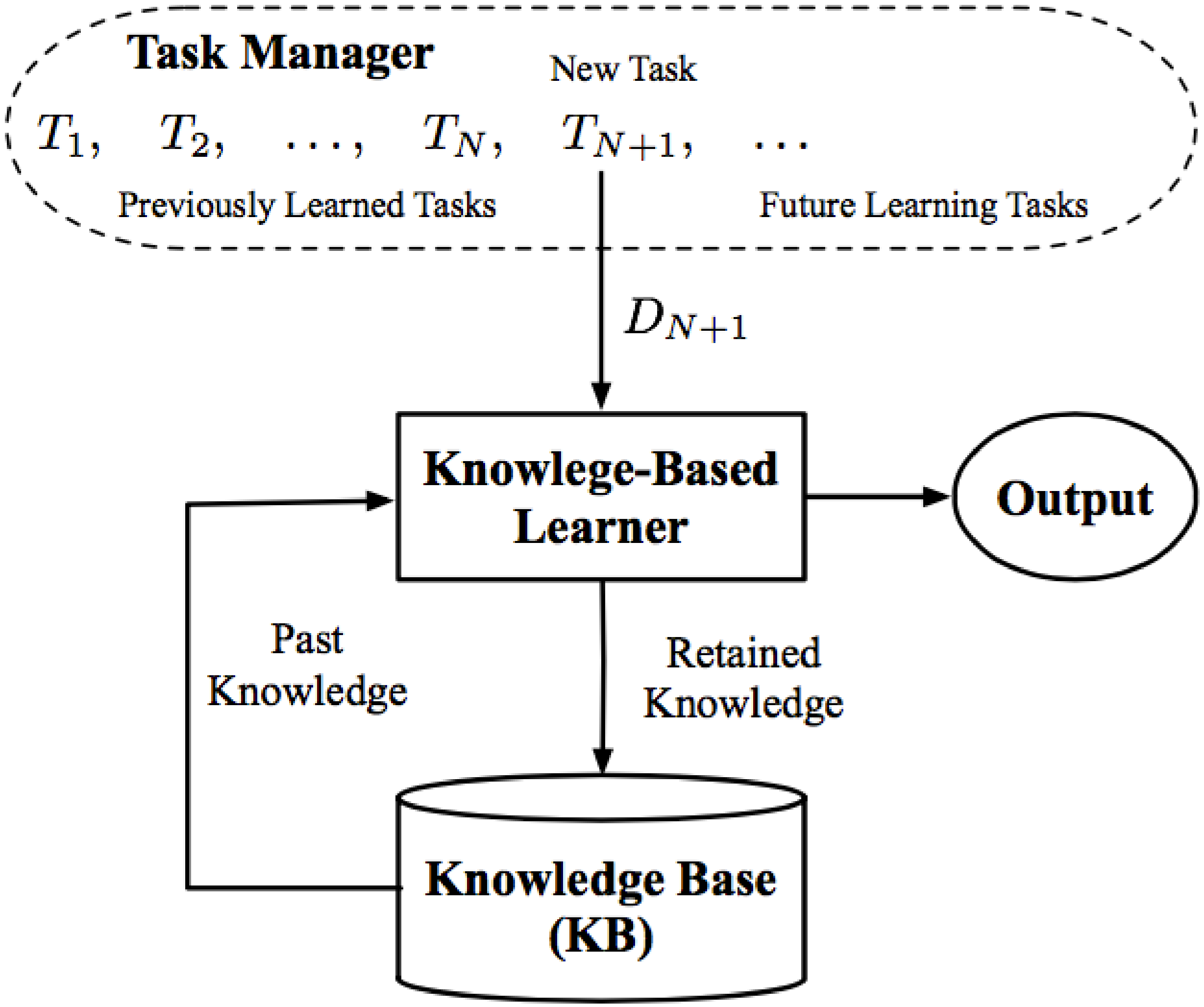
(Thrun 1995, Chen and Liu, 2016 – new book)

- The learner has performed learning on a sequence of tasks, from 1 to *N*.
- When faced with the (*N*+1)th task, it uses the relevant knowledge in its *knowledge base* (KB) to help learning for the (*N*+1)th task.
- After learning (*N*+1)th task, KB is updated with learned results from (*N*+1)th task.

Key Characteristics of LML
(Chen and Liu, 2016 – new book)

- Continuous learning process
- Knowledge accumulation in KB
- Use of past knowledge to help future learning

Lifelong Machine Learning System



Components of LML

- Knowledge Base (KB)
  - Past Information Store (PIS)
    - Data, intermediate and final results
  - Meta-Knowledge Miner (MKM)
    - Meta-mining of PIS and MKS
  - Meta-Knowledge Store (MKS)
    - mined knowledge
  - Knowledge Reasoner (KR)
    - Make inference to generate more knowledge
- Most current systems don't have all these

Components of LML (Contd)

- Knowledge-Based Learner (KBL)
  - Leverage past knowledge in KB in new learning
    - Task Knowledge Miner (TKM): identify/mine knowledge suitable for the task
  - Learner
- Task Manager
  - Receives and manages arriving tasks
- Output
  - Model for the current task

Two Types of Knowledge

- *Global knowledge*: Many existing LML methods assume that there is a *global latent structure* among tasks that are shared by all (Bou Ammar et al., 2014, Ruvolo and Eaton, 2013b, Tanaka and Yamamura, 1997, Thrun, 1996b, Wilson et al., 2007)
  - This global structure can be learned and leveraged in the new task learning.
  - These methods grew out of multi-task learning.

Two Types of Knowledge (Contd)

- *Local knowledge:* Many other methods do not assume such a *global latent structure* among tasks (Chen and Liu, 2014a,b, Chen et al., 2015, Fei et al., 2016, Liu et al., 2016, Shu et al., 2016)
- During the learning of a new task,
  - they select the pieces of prior knowledge to use based on the need of the new task.
- Called *local knowledge* because they are not assumed to form a coherent global structure.

Two Kinds of Tasks

- Independent tasks: each task is independent of other tasks
  - Each task can be learned independently, although using knowledge gained in other tasks may help this task learning
  - Much of the current research assume this.
- Dependent tasks: each task has some dependency on some other tasks, e.g.,
  - Cumulative learning (Fei et al 2016)

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Transfer learning

- Source domain(s): With labeled training data
- Target domain: With little/no labeled training data
- Goal: leverage the information from the source domain(s) to help learning in the target domain
    - Only optimize the target domain/task learning

A Large Body of Literature

- Transfer learning has been a popular research topic and researched in many fields, e.g.,
  - Machine learning
  - Data mining
  - Natural language processing
  - Computer vision
- (Taylor and Stone, 2009, Pan & Yang, 2010). presented excellent surveys with extensive references.

One Transfer Learning Technique

- Structural correspondence learning (SCL) (Blitzer et al., 2006)
- Pivot features
  - Have the same characteristics or behaviors in both domains
  - Non-pivot features which are correlated with many of the same pivot features are assumed to correspond

Choosing Pivot Features

- For different applications, pivot features may be chosen differently, for example,
  - For part-of-speech tagging, frequently-occurring words in both domains are good choices (Blitzer et al., 2006)
  - For sentiment classification, pivot features are words that frequently-occur in both domains and also have high mutual information with the source label (Blitzer et al., 2007).

Finding Feature Correspondence

- Compute the correlations of each pivot feature with non-pivot features in both domains by building binary pivot predictors

$$f_\ell(\mathbf{x}) = \mathrm{sgn}(\hat{\mathbf{w}}_\ell \cdot \mathbf{x}), \quad \ell = 1 \ldots m$$

  - Using unlabeled data (predicting whether the pivot feature *l* occurs in the instance)
  - The weight vector $\hat{\mathbf{w}}_\ell$ encodes the covariance of the non-pivot features with the pivot feature

Finding Feature Correspondence

- Positive values in $\hat{\mathbf{w}}_\ell$:
  - Indicate that those non-pivot features are positively correlated with the pivot feature *l* in the source or the target
- Produce a correlation matrix W

$$W = [\hat{\mathbf{w}}_1 | \ldots | \hat{\mathbf{w}}_m]$$

Computing Low Dim. Approximation

- SVD is employed to compute a low-dimensional linear approximation θ

$$W = UDV^T \quad \theta = U^T_{[1:h,:]}$$

- θ : mapping from original space to new space

- The final set of features used for training and for testing: original features **x** + θ**x**

Multi-Task Learning

- Problem statement: Co-learn multiple related tasks simultaneously:
  - All tasks have labeled data and are treated equally
  - Goal: optimize learning/performance across all tasks through shared knowledge
- Rationale: introduce inductive bias in the joint hypothesis space of all tasks (Caruana, 1997)
  - By exploiting the task relatedness structure, or shared knowledge

One Multi-Task Model: GO-MTL
(Kumar et al., ICML 2012)

- GO-MTL: Grouping and Overlap in Multi-Task Learning
- Does not assume that all tasks are related
- Applicable to classification and regression

GO-MTL Assumptions

- All task models share latent basic model components
- Each task model is a linear combination of shared latent components
- The linear weight is sparse, to use a small number of latent components

Notations

- N tasks in total
- k (< N) latent basis model components
- Each basis task is represented by $\boldsymbol{l}$ (a vector of size d)
- For all latent tasks, $\boldsymbol{L} = (\boldsymbol{l}_{1}, \boldsymbol{l}_{2}, \ldots, \boldsymbol{l}_{k})$
- $\boldsymbol{L}$ is learned from N individual tasks.
  - E.g., weights/parameters of logistic regression or linear regression

The Approach

- $\mathbf{s}^t$ is a linear weight vector and is assumed to be sparse.

$$\boldsymbol{\theta}^t = \mathbf{L}\mathbf{s}^t$$

- Stacking $\mathbf{s}^t$ ($\boldsymbol{\theta}^t$) for all tasks, we get **S** ($\boldsymbol{\Theta}$). **S** captures the task grouping structure.

$$\underset{d \times N}{\boldsymbol{\Theta}} = \underset{d \times k}{\mathbf{L}} \times \underset{k \times N}{\mathbf{S}}$$

Objective Function in GO-MTL

$$\sum_{t=1}^{N}\sum_{i=1}^{n_t}\mathcal{L}\left(f(\mathbf{x}_i^t;\mathbf{L}\mathbf{s}^t),y_i^t\right)+\mu\left\|\mathbf{S}\right\|_1+\lambda\left\|\mathbf{L}\right\|_F^2$$

Optimization Strategy

- Alternating optimization strategy to reach a local minimum.
- For a fixed ***L***, optimize *s*$_t$:

$$\mathbf{s}^t = \underset{\mathbf{s}^t}{\operatorname{argmin}} \sum_{i=1}^{n_t} \mathcal{L}\left(f(\mathbf{x}_i^t; \mathbf{L}\mathbf{s}^t), y_i^t\right) + \mu \left\|\mathbf{s}^t\right\|_1$$

- For a fixed ***S***, optimize ***L***:

$$\underset{\mathbf{L}}{\operatorname{argmin}} \sum_{t=1}^{N} \sum_{i=1}^{n_t} \mathcal{L}\left(f(\mathbf{x}_i^t; \mathbf{L}\mathbf{s}^t), y_i^t\right) + \lambda \left\|\mathbf{L}\right\|_F^2$$

A Large Body of Literature

- Two tutorials on MTL
  - Multi-Task Learning: Theory, Algorithms, and Applications. SDM-2012, by Jiayu Zhou, Jianhui Chen, Jieping Ye
  - Multi-Task Learning Primer. IJCNN'15, by Cong Li and Georgios C. Anagnostopoulos

Transfer, Multitask → Lifelong

- Transfer learning vs. LML
  - Transfer learning is not continuous
  - No retention or accumulation of knowledge
  - Only one directional: help target domain

Transfer, Multitask → Lifelong

- Transfer learning vs. LML
  - Transfer learning is not continuous
  - No retention or accumulation of knowledge
  - Only one directional: help target domain
- Multitask learning vs. LML
  - Multitask learning retains no knowledge except data
  - Hard to re-learn all when tasks are numerous

- Online (incremental) multi-task learning is LML

Online Learning

- The training data points come in a sequential order (online setting)
  - Computationally infeasible to train over the entire dataset
- Different from LML
  - Still performs the same learning task over time
  - LML aims to learn from a sequence of different tasks, retain and accumulate knowledge

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Lifelong Supervised Learning (LSL)

- The learner has performed learning on a sequence of supervised learning tasks, from 1 to *N*.

- When faced with the (*N*+1)th task, it uses the relevant knowledge and labeled training data of the (*N*+1)th task to help learning for the (*N*+1)th task.

Early Work on Lifelong Learning
(Thrun, 1996b)

- Concept learning tasks: The functions are learned over the lifetime of the learner, f_1, f_2, f_3, … $\in F$.
- Each task: learn the function $f: I \rightarrow \{0, 1\}$. $f(x)=1$ means x is a particular concept.
  - For example, $f_{dog}(x)=1$ means x is a dog.
- For *n*th task, we have its training data X
  - Also the training data X_k of k =1 , 2, …, n-1 tasks.

Intuition

- The paper proposed a few approaches based on two learning algorithms,
  - Memory-based, e.g., kNN or shepard's method
  - Neural networks
- Intuition: when we learn $f_{dog}(x)$, we can use functions or knowledge learned from previous tasks, such as $f_{cat}(x)$, $f_{bird}(x)$, $f_{tree}(x)$, etc.
  - Data for $f_{cat}(X)$, $f_{bird}(X)$, $f_{tree}(X)$… are support sets.

Memory based Lifelong Learning

- First method: use the support sets to learn a new representation, or function

  g: *I* → *I'*

  - which maps input vectors to a new space. The new space is the input space for the final *k*NN
  - Adjust *g* to minimize the energy function

$$E := \sum_{k=1}^{n-1} \sum_{\langle x, y=1 \rangle \in X_k} \left(\sum_{\langle x', y'=1 \rangle \in X_k} ||g(x) - g(x')|| - \sum_{\langle x', y'=0 \rangle \in X_k} ||g(x) - g(x')|| \right)$$

  - g is a neural network, trained with Back-Prop. kNN is then applied for the *n*th (new) task

Second Method

- It learns a distance function using support sets

  d: $I \times I \rightarrow [0, 1]$

  - It takes two input vectors x and x' from a pair of examples <x, y>, <x', y'> of the same support set X_k (k = 1, 2, , …, n-1)
  - d is trained with neural network using back-prop, and used as a general distance function
  - Training examples are:

$$\langle (x, x'), 1 \rangle \quad \text{if } y{=}y'{=}1$$
$$\langle (x, x'), 0 \rangle \quad \text{if } (y{=}1 \wedge y'{=}0) \text{ or } (y{=}0 \wedge y'{=}1)$$

Making Decision

- Given the new task training set X_n and a test vector x, for each +ve example, (x', y'=1)$\in X_n$,
  - d(x, x') is the probability that x is a member of the target concept.
- Decision is made by using votes from positive examples, <x_1, 1>, <x_2, 1>, … $\in X_n$ combined with Bayes' rule

$$P(f_n(x)=1) = 1 - \left(1 + \prod_{\langle x', y'=1\rangle \in X_n} \frac{d(x,x')}{1-d(x,x')}\right)^{-1}$$

LML Components in this Case

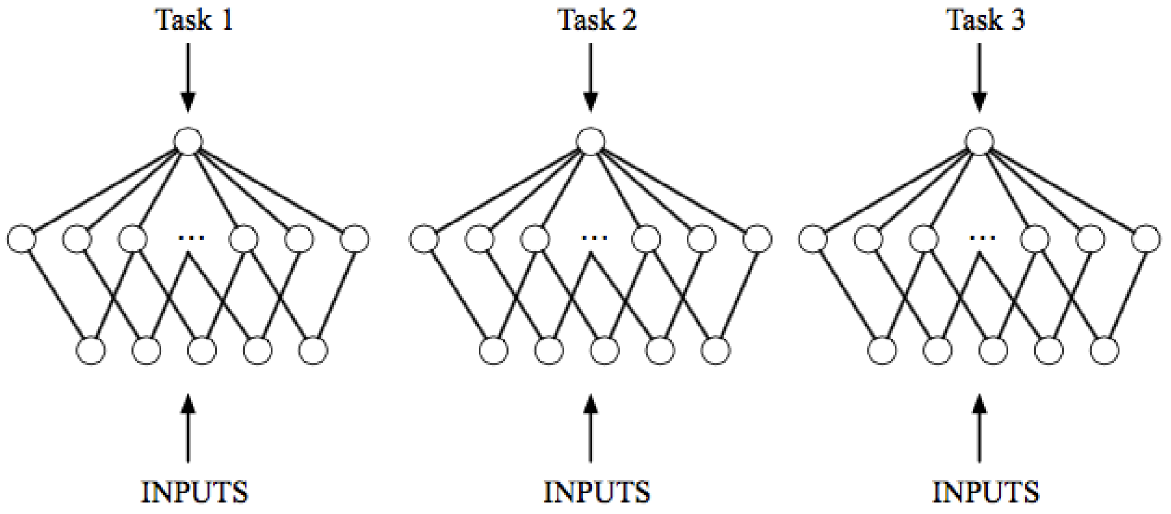
- **KB**
  - Store all the support sets.
  - Distance function *d*(x, x’): the probability of example x and x’ being the same concept.
- **KBL**
  - Voting with Bayes’ rule.

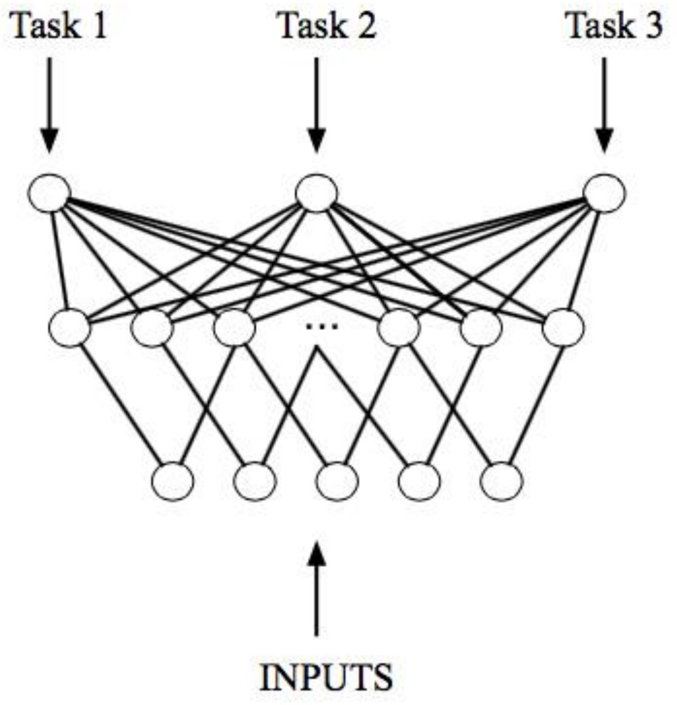
Neural Network approaches

- Approach 1: based on that in (Caruana, 1993, 1997), which is actually a batch multitask learning approach.
  - Simultaneously minimize the error on both the support sets $\{X_k\}$ and the training set X_n

- Approach 2: an *explanation-based neural network (EBNN)*

Neural Network approaches





Task Clustering (TC)
(Thrun and O'Sullivan, 1996)

- In general, not all previous *N*-1 tasks are similar to the *N*th (new) task
- Based on a similar idea to the lifelong memory-based methods in (Thrun, 1996b)
  - It clusters previous tasks into groups or clusters
- When the (new) *N*th task arrives, it first
  - selects the most similar cluster and then
  - uses the distance function of the cluster for classification in the *N*th task

Some Other Early works on LML

- Constructive inductive learning to deal with learning problem when the original representation space is inadequate for the problem at hand (Michalski, 1993)
- Incremental learning primed on a small, incomplete set of primitive concepts (Solomonoff, 1989)
- Explanation-based neural networks MTL (Thrun, 1996a)
- MTL method of functional (parallel) transfer (Silver & Mercer, 1996)
- Lifelong reinforcement learning (Tanaka & Yamamura, 1997)
- Collaborative interface agents (Metral & Maes, 1998)

ELLA

(Ruvolo & Eaton, 2013a)

- ELLA: Efficient Lifelong Learning Algorithm
- It is based on GO-MTL (Kumar et al., 2012)
  - A batch multitask learning method
- ELLA is online multitask learning method
  - ELLA is more efficient and can handle a large number of tasks
  - Becomes a lifelong learning method
    - The model for a new task can be added efficiently.
    - The model for each past task can be updated rapidly.

Inefficiency of GO-MTL

- Since GO-MTL is a batch multitask learning method, the optimization goes through all tasks and their training instances (Kumar et al., 2012).

$$\sum_{t=1}^{T}\sum_{i=1}^{n_t}\mathcal{L}\left(f(\boldsymbol{x}_i^{(t)};\boldsymbol{L}\boldsymbol{s}^{(t)}), y_i^{(t)}\right)+\mu\|\boldsymbol{S}\|_1+\lambda\|\boldsymbol{L}\|_F^2$$

- Very inefficient and impractical for a large number of tasks.
  - It cannot incrementally add a new task efficiently

Initial Objective Function of ELLA

- Objective Function (Average rather than sum)

$$e_T(\mathbf{L}) = \frac{1}{T}\sum_{t=1}^{T}\min_{\mathbf{s}^{(t)}}\left\{\frac{1}{n_t}\sum_{i=1}^{n_t}\mathcal{L}\left(f\left(\mathbf{x}_i^{(t)};\mathbf{L}\mathbf{s}^{(t)}\right),y_i^{(t)}\right) + \mu\|\mathbf{s}^{(t)}\|_1\right\} + \lambda\|\mathbf{L}\|_{\mathsf{F}}^2\ , \qquad (1)$$

Approximate Equation (1)

- Eliminate the dependence on all of the past training data through inner summation
  - By using the second-order Taylor expansion of around $\theta = \theta^{(t)}$ where
  - $\theta^{(t)}$ is an optimal predictor learned on only the training data on task *t*.

Removing inner summation

$$\frac{1}{N}\sum_{t=1}^{N}\min_{\mathbf{s}^t}\left\{\|\hat{\boldsymbol{\theta}}^t-\mathbf{L}\mathbf{s}^t\|^2_{\boldsymbol{H}^t}+\mu\|\mathbf{s}^t\|_1\right\}+\lambda\|\mathbf{L}\|_F^2$$

$$\boldsymbol{H}^t=\frac{1}{2}\nabla^2_{\boldsymbol{\theta}^t,\boldsymbol{\theta}^t}\frac{1}{n_t}\sum_{i=1}^{n_t}\mathcal{L}\left(f(\boldsymbol{x}_i^t;\boldsymbol{\theta}^t),y_i^t\right)\Big|_{\boldsymbol{\theta}^t=\hat{\boldsymbol{\theta}}^t}$$

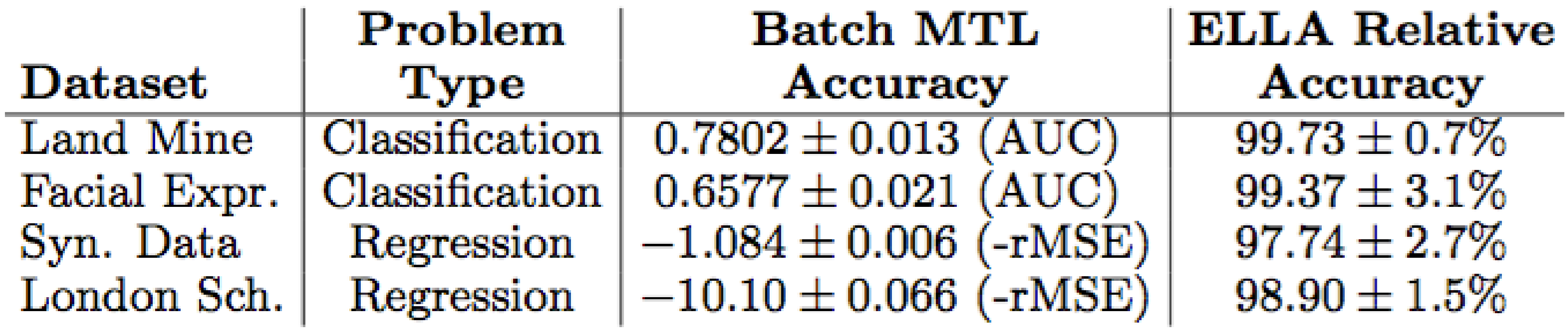
$$\hat{\boldsymbol{\theta}}^t=\underset{\boldsymbol{\theta}^t}{\operatorname{argmin}}\frac{1}{n_t}\sum_{i=1}^{n_t}\mathcal{L}\left(f(\boldsymbol{x}_i^t;\boldsymbol{\theta}^t),y_i^t\right)$$

Simplify optimization

- GO-MTL: when computing a single candidate ***L***, an optimization problem must be solved to re-compute the value of each $s^{(t)}$.
- ELLA: after $s^{(t)}$ is computed given the training data for task *t*, it will not be updated when training on other tasks. Only ***L*** will be changed.
- Note: (Ruvolo and Eaton, 2013b) added the mechanism to actively select the next task to learn.

ELLA Accuracy Result

- ELLA vs. GO-MTL

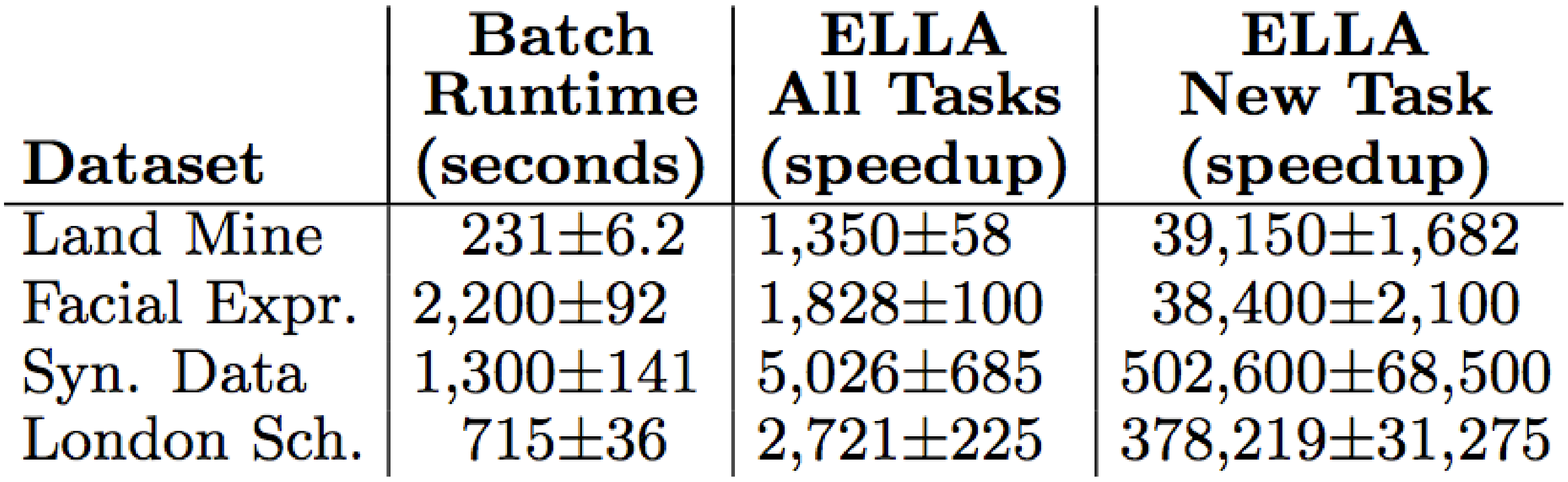


Dataset	Problem Type	Batch MTL Accuracy	ELLA Relative Accuracy
Land Mine	Classification	0.7802 ± 0.013 (AUC)	$99.73 \pm 0.7\%$
Facial Expr.	Classification	0.6577 ± 0.021 (AUC)	$99.37 \pm 3.1\%$
Syn. Data	Regression	-1.084 ± 0.006 (-rMSE)	$97.74 \pm 2.7\%$
London Sch.	Regression	-10.10 ± 0.066 (-rMSE)	$98.90 \pm 1.5\%$

Batch MTL is GO-MTL

ELLA Speed Result

- ELLA vs. GO-MTL



Dataset	Batch Runtime (seconds)	ELLA All Tasks (speedup)	ELLA New Task (speedup)
Land Mine	231±6.2	1,350±58	39,150±1,682
Facial Expr.	2,200±92	1,828±100	38,400±2,100
Syn. Data	1,300±141	5,026±685	502,600±68,500
London Sch.	715±36	2,721±225	378,219±31,275

ELLA is 1K times faster than GO-MTL on all tasks, 30K times on a new task

LML Components of ELLA

- **KB**
  - Stores all the task data
  - Matrix ***L*** for *K* basis tasks and *S*
- **KBL**
  - Each task parameter vector is a linear combination of **KS**, i.e., $\boldsymbol{\theta}^{(t)} = \boldsymbol{L}s^{(t)}$
  - Alternating optimization solving

Lifelong Sentiment Classification
(Chen, Ma, and Liu 2015)

- "*I bought a cellphone a few days ago. It is such a nice phone. The touch screen is really cool. The voice quality is great too. ....*"
- Goal: classify docs or sentences as + or -.
  - Need to manually label a lot of training data for each domain, which is highly labor-intensive
- Can we not label for every domain or at least not label so many docs/sentences?

A Simple Lifelong Learning Method

Assuming we have worked on a *large number of past domains* with all their training data *D*

- Build a classifier using *D*, test on new domain
  - Note - using only one past/source domain as in ***transfer learning*** is not good.
- In many cases – improve accuracy by as much as 19% (= 80%-61%). Why?
- In some others cases – not so good, e.g., it works poorly for toy reviews. Why? “toy”

Lifelong Sentiment Classification
(Chen, Ma and Liu, 2015)

- It adopts a Bayesian optimization framework for LML using stochastic gradient decent

- Lifelong learning uses
  - Word counts from the past data as priors.
  - Penalty terms to deal with domain dependent sentiment words and reliability of knowledge.

Naïve Bayesian Text Classification

- Key parameter

$$P(w|c_j) = \frac{\lambda + N_{c_j,w}}{\lambda|V| + \sum_{v=1}^{|V|} N_{c_j,v}}$$

- Only depends on the count of words in each class

Stored Information

- Probabilities of a word appearing in positive or negative

  $P^{\hat{t}}(w|+)$ and $P^{\hat{t}}(w|-)$

- Word counts
  - Number of times that a word appears in positive class: $N^{\hat{t}}_{+,w}$
  - Number of times that a word appears in negative class: $N^{\hat{t}}_{-,w}$

Knowledge Base

- Two types of knowledge
  - Document-level knowledge
  - Domain-level knowledge

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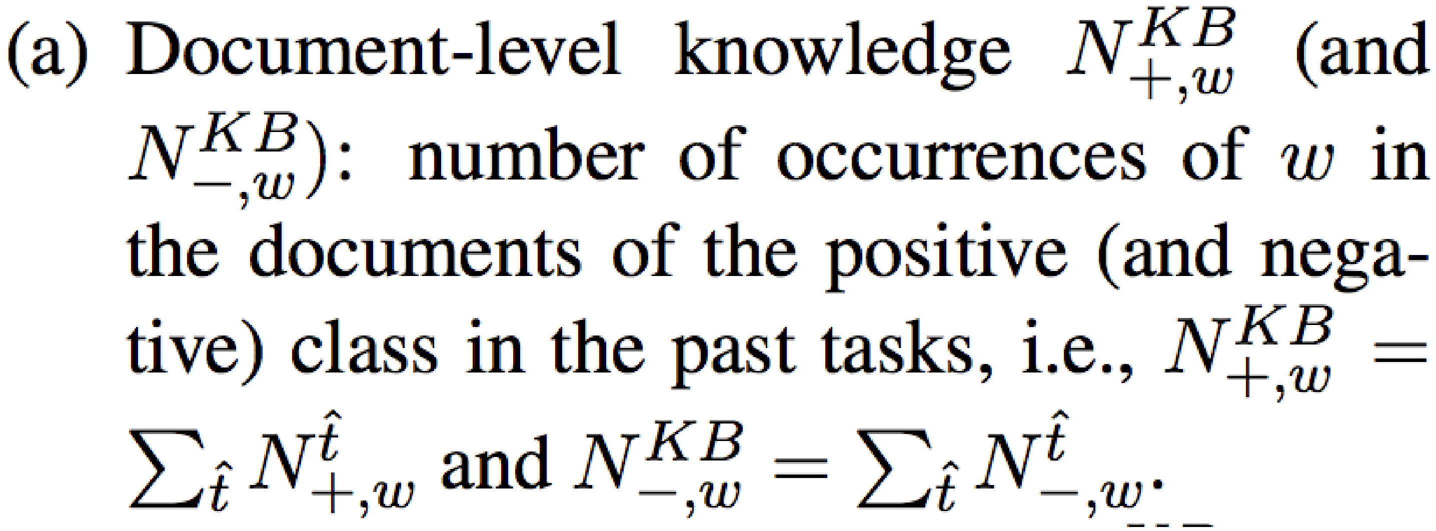
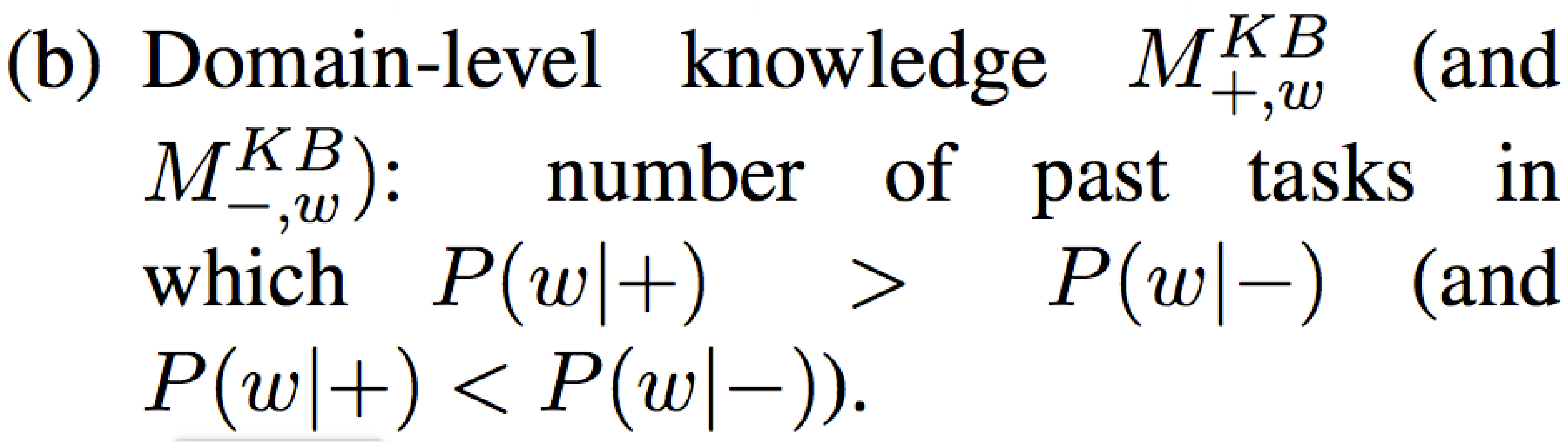


(a) Document-level knowledge $N^{KB}_{+,w}$ (and $N^{KB}_{-,w}$): number of occurrences of w in the documents of the positive (and negative) class in the past tasks, i.e., $N^{KB}_{+,w} = \sum_{\hat{t}} N^{\hat{t}}_{+,w}$ and $N^{KB}_{-,w} = \sum_{\hat{t}} N^{\hat{t}}_{-,w}$.

Knowledge Base

- Two types of knowledge
  - Document-level knowledge
  - Domain-level knowledge



(b) Domain-level knowledge $M^{KB}_{+,w}$ (and $M^{KB}_{-,w}$): number of past tasks in which $P(w|+) > P(w|-)$ (and $P(w|+) < P(w|-)$).

Objective Function

- Maximize the probably difference

$$\sum_{i=1}^{|D^t|} \left(P\left(c_j|d_i\right) - P\left(c_f|d_i\right)\right)$$

- c_j: labeled class in groundtruth
- c_f: all classes other than c_j

Exploiting Knowledge via Penalties

- Penalty terms for two types of knowledge
  - Document-level knowledge
  - Domain-level knowledge

Exploiting Knowledge via Penalties

- Penalty terms for two types of knowledge
  - Document-level knowledge
  - Domain-level knowledge

$$\frac{1}{2}\alpha \sum_{w \in V_T} \left(\left(X_{+,w} - N^t_{+,w} \right)^2 + \left(X_{-,w} - N^t_{-,w} \right)^2 \right)$$

  - *t* is the new task

Exploiting Knowledge via Penalties

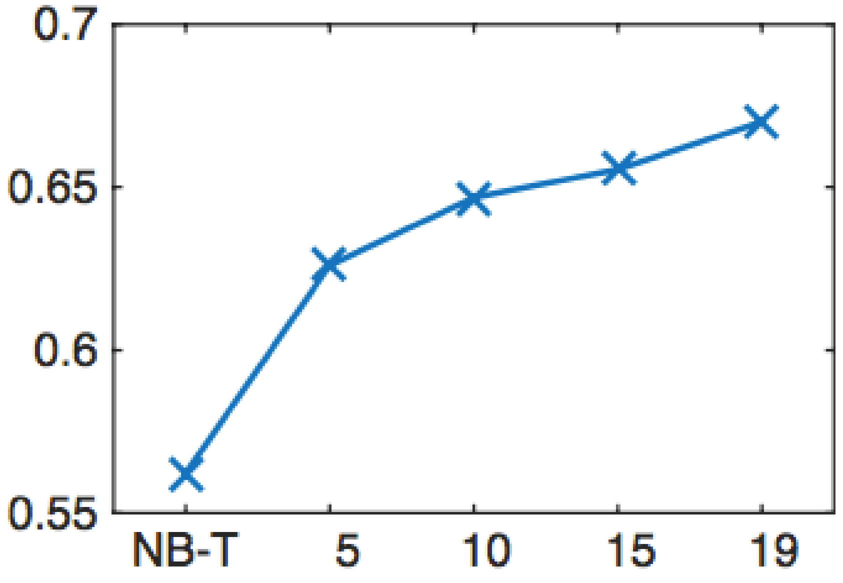
- Penalty terms for two types of knowledge
  - Document-level knowledge
  - Domain-level knowledge

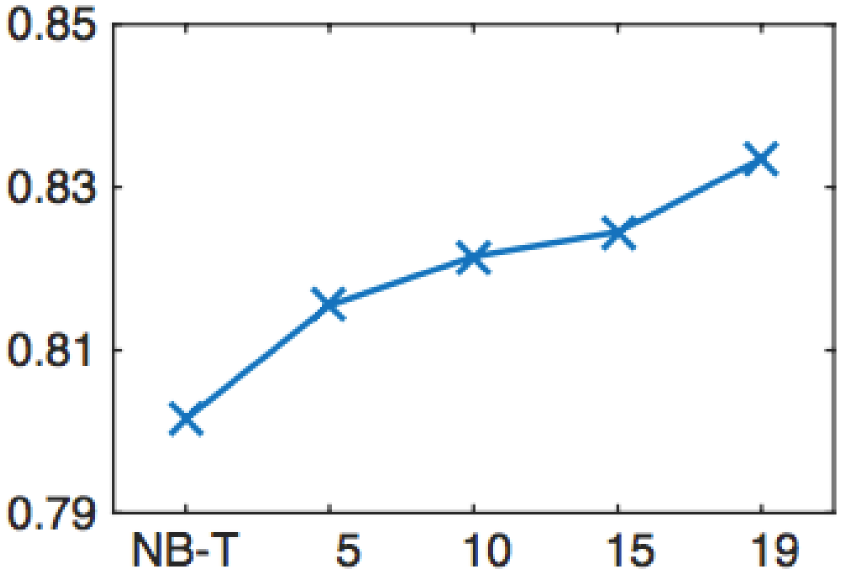
$$\frac{1}{2}\alpha \sum_{w \in V_S} \left(X_{+,w} - R_w \times X^0_{+,w}\right)^2 + \frac{1}{2}\alpha \sum_{w \in V_S} \left(X_{-,w} - (1 - R_w) \times X^0_{-,w}\right)^2$$

  - R_W: ratio of #tasks where *w* is positive / #all tasks
  - $X^0_{+,w} = N^t_{+,w} + N^{KB}_{+,w}$ and $X^0_{-,w} = N^t_{-,w} + N^{KB}_{-,w}$

One Result of LSC model

- Better F1-score (left) and accuracy (right) with more past tasks





LML Components of LSC

- **KB**
  - Word counts from previous tasks
  - Document-level knowledge
  - Domain-level knowledge
- **KBL**
  - LSC algorithm with regularization

Cumulative Learning

(Fei et al., 2016)

- Cumulative learning
  - Incrementally adding a new class without re-training the whole model from scratch
    - Learner becomes more knowledgeable
  - Detecting unseen classes in test data
    - Traditional supervised learning cannot do this
    - It needs *open classification*

- Self-learning: detect unseen/new things and learn them.

Cumulative Learning is LML

- At time point *t*, a *t*-class classifier F_t learned from past datasets $D^t = \{D_1, D_2, \ldots, D_t\}$ of classes $Y^t = \{l_1, l_2, \ldots, l_t\}$.
  - F_t classifies each test instance **x** to either one of the known classes in Y^t or the *unknown class* $\boldsymbol{l_0}$.
    - $y = F_t(\mathbf{x}), y \in \{l_1, l_2, \ldots, l_t, \boldsymbol{l_0}\}$
- At time point t+1, a class l_{t+1} (D_{t+1}) is added, F_t is ***updated*** to a (t+1)-class classifier F_{t+1}
    - $y = F_{t+1}(\mathbf{x}), y \in \{l_1, l_2, \ldots, l_t, l_{t+1}, \boldsymbol{l_0}\}$

Learning cumulatively

- How to incrementally add a class without retraining from scratch?
- "Human learning": uses the past knowledge F_t to help learn the new class l_{t+1}.
  - Find similar classes SC from known classes Y^t. E.g
    - Old classes: Y^t = {movie, cat, politics, soccer}.
    - New class: l_{t+1}= basketball
    - SC = {soccer}
  - Building F_{t+1} by focusing on separating l_{t+1} and SC.

Cumulative Learning Algorithm

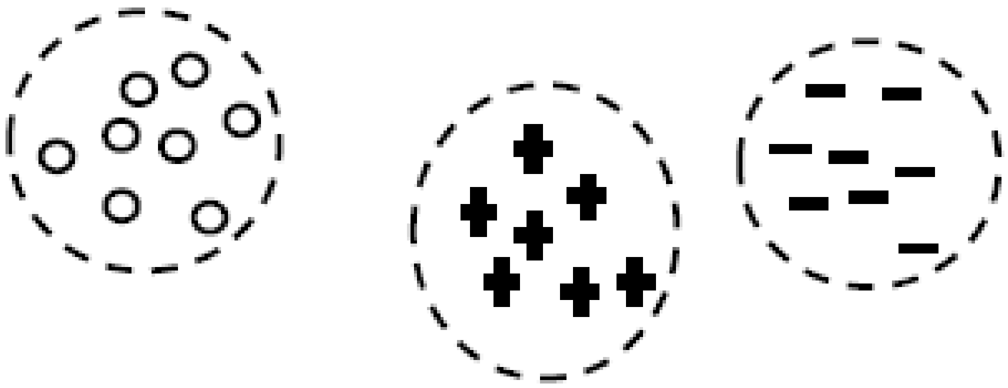
- $F_t = \{f_1, f_2, \ldots, f_t\}$, a set of binary classifiers.
- Identifying a set of similar classes ***SC*** to the new class l_{t+1} by
  - Using each f_i to classify instances in D_{t+1}.
    - SC is the set of classes that accept many from D_{t+1}
- Build f_{t+1} for l_{t+1} using classes in ***SC*** as negative data.
- Update each classifier for classes in SC by adding class l_{t+1} as an extra negative class.

Open Classification
(Fei and Liu, 2016)

- Traditional classification makes the closed world assumption:
  - Classes in testing have been seen in training
  - i.e., no new classes in the test data
- Not true in many real-life environments.
  - New data may contain unseen class documents
- We need *open (world) classification*
  - Detect the unseen class of documents

Open Classification

- *Open space risk* formulation (see Fei & Liu 2016)
  - Don't give each class too much open space
  - SVM is one half space for each class: too much
- Ideally, a "ball" to cover each class l_i
  - Each "ball" is a binary classifier f_i



Open World Learning

- Build a set of 1-vs-rest classifiers, one for each training class l_i.
- The set of 1-vs-rest classifiers $F_t = \{f_1, f_2, \ldots, f_{t+1}\}$ works together to classify
  - Each binary classifier produces a probability $P(y|\mathbf{x})$
  - $\boldsymbol{l_0}$: class of unknown

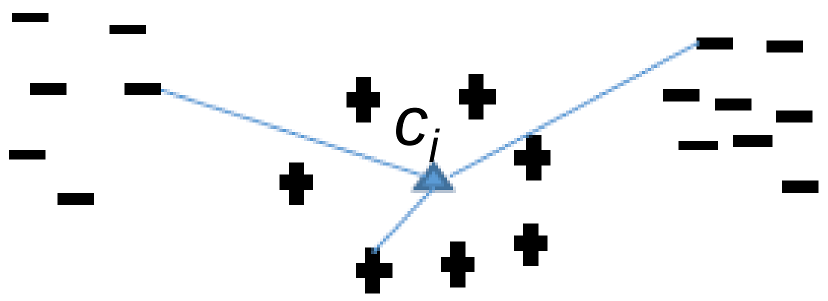
$$y^* = \begin{cases} argmax_{y \in Y^{t+1}} P(y|\mathbf{x}) & if\ P(y|\mathbf{x}) \geq \theta \\ l_0 & otherwise \end{cases}$$

CBS Learning

- To detect unseen classes, Fei and Liu (2016) proposed CBS learning:
  - Center-based similarity (CBS) space learning.
- It performs space transformation
  - Each document vector *d* is transformed to a CBS space vector
    1. Compute centers c_i for the positive class
    2. Compute similarities of each document to c_i.

    - This gives us a new data set in the CSB space.

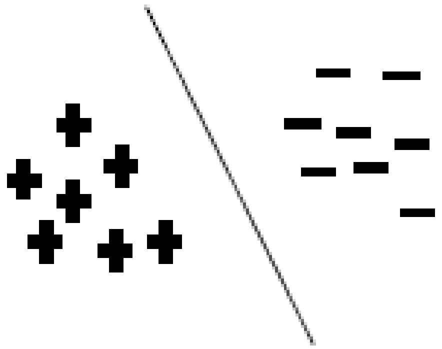
Space Transformation and Learning



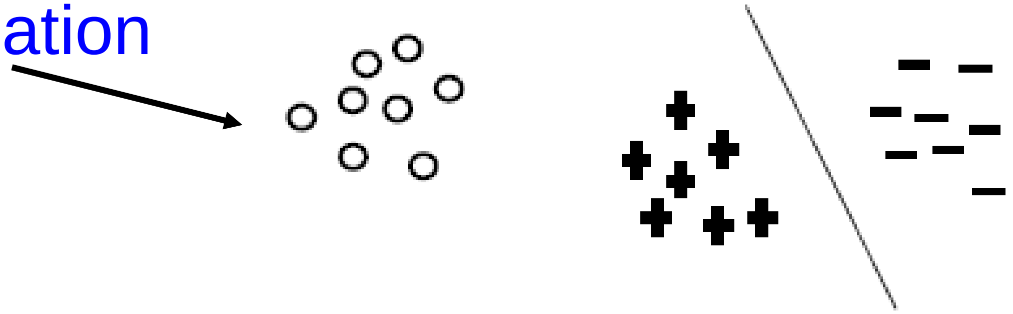
- We can use many similarity measures.
- After space transformation, we can run SVM to build a classification in the CBS space
  - CBS learning basically finds a ball for each class

Why does CBS Learning Work?

- SVM classifier

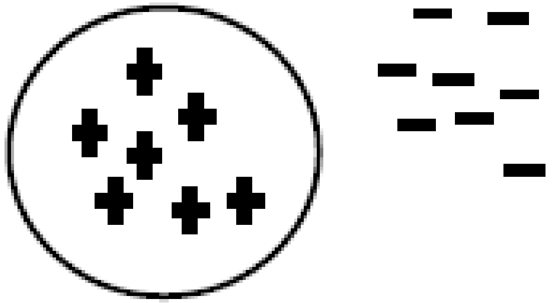


- SVM classification (test)
  - Wrong classification

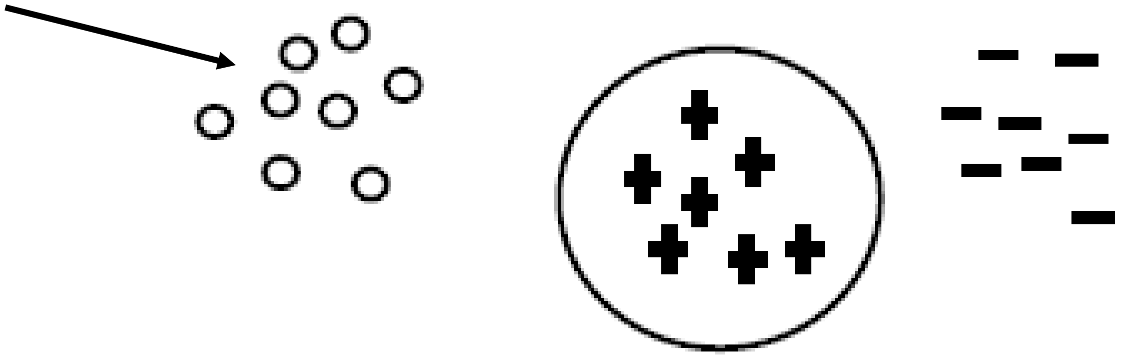


Why does CBS Learning Work?

- CBS classifier



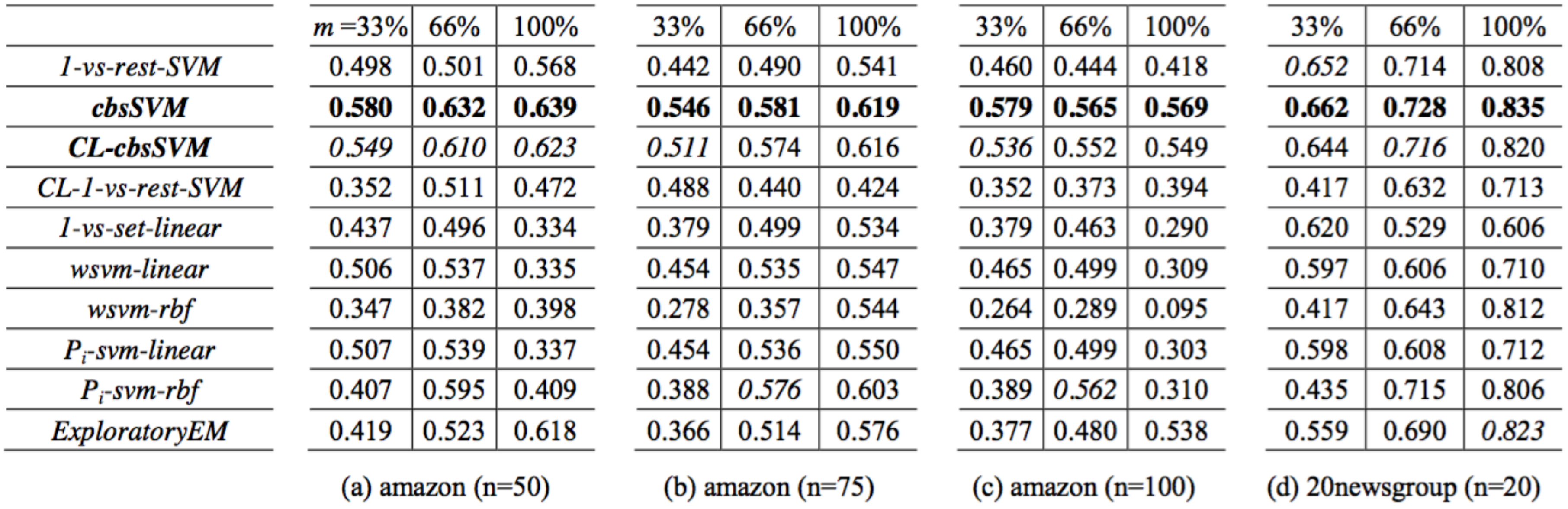
- CBS classification (test)
  - Correct now



Evaluation

Datasets

- Amazon reviews of 100 domains.
- 20 classes in 20newsgroup.



	m =33%	66%	100%	33%	66%	100%	33%	66%	100%	33%	66%	100%
1-vs-rest-SVM	0.498	0.501	0.568	0.442	0.490	0.541	0.460	0.444	0.418	*0.652*	0.714	0.808
cbsSVM	**0.580**	**0.632**	**0.639**	**0.546**	**0.581**	**0.619**	**0.579**	**0.565**	**0.569**	**0.662**	**0.728**	**0.835**
CL-cbsSVM	*0.549*	*0.610*	*0.623*	*0.511*	0.574	0.616	*0.536*	0.552	0.549	0.644	*0.716*	0.820
CL-1-vs-rest-SVM	0.352	0.511	0.472	0.488	0.440	0.424	0.352	0.373	0.394	0.417	0.632	0.713
1-vs-set-linear	0.437	0.496	0.334	0.379	0.499	0.534	0.379	0.463	0.290	0.620	0.529	0.606
wsvm-linear	0.506	0.537	0.335	0.454	0.535	0.547	0.465	0.499	0.309	0.597	0.606	0.710
wsvm-rbf	0.347	0.382	0.398	0.278	0.357	0.544	0.264	0.289	0.095	0.417	0.643	0.812
P_i-svm-linear	0.507	0.539	0.337	0.454	0.536	0.550	0.465	0.499	0.303	0.598	0.608	0.712
P_i-svm-rbf	0.407	0.595	0.409	0.388	*0.576*	0.603	0.389	*0.562*	0.310	0.435	0.715	0.806
ExploratoryEM	0.419	0.523	0.618	0.366	0.514	0.576	0.377	0.480	0.538	0.559	0.690	*0.823*
	(a) amazon (n=50)			(b) amazon (n=75)			(c) amazon (n=100)			(d) 20newsgroup (n=20)		

LML Components in this Case

- **KB**
  - Previous model $F_t = \{f_1, f_2, \ldots, f_t\}$
  - Training data from previous tasks
- **KBL**
  - Cumulative learning algorithm

20 Minutes Break

Outline

- A motivating example
- What is lifelong machine learning?
- Related learning paradigms
- Lifelong supervised learning
- Lifelong unsupervised learning
- Semi-supervised never-ending learning
- Lifelong reinforcement learning
- Summary

LTM: Lifelong Topic Modeling
(Chen and Liu, ICML-2014)

- Topic modeling (Blei et al 2003) finds topics from a collection of documents.
  - A document is a distribution over topics
  - A topic is a distribution over terms/words, e.g.,
    - {*price*, *cost*, *cheap*, *expensive*, …}

LTM: Lifelong Topic Modeling
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- Topic modeling (Blei et al 2003) finds topics from a collection of documents.
  - A document is a distribution over topics
  - A topic is a distribution over terms/words, e.g.,
    - {*price*, *cost*, *cheap*, *expensive*, …}
- **Question**: how to find good past knowledge and use it to help new topic modeling tasks?
- **Data**: product reviews in the sentiment analysis context

Sentiment Analysis (SA) Context

- "*The size is great, but pictures are poor*."
  - Aspects (product features): size, picture
- Why lifelong learning can help SA?
  - Online reviews: Excellent data with extensive sharing of aspect/concepts across domains
    - A large volume for all kinds of products
- Why big (and diverse) data?
  - Learn a broad range of reliable knowledge. More knowledge makes future learning easier.

Key Observation in Practice

- A fair amount of aspect overlapping across reviews of different products or domains
  - Every product review domain has the aspect *price*,
  - Most electronic products share the aspect *battery*
  - Many also share the aspect of *screen*.
- This sharing of concepts / knowledge across domains is true in general, not just for SA.
  - It is rather “silly” not to exploit such sharing in learning

Problem setting

- Given a large set of document collections (big data), $D = \{D_1, D_2, \ldots, D_N\}$, learn from each D_i to produce the results S_i. Let $S = \bigcup_i S_i$.
  - S is called *topic base*
- Goal: Given a test/new collection D^t, learn from D^t with the help of S (and possibly D).
  - D^t in D or D^t not in D
  - The results learned this way should be better than those without the guidance of S (and D)

What knowledge?

- Should be in the same aspect/topic

  => Must-Links

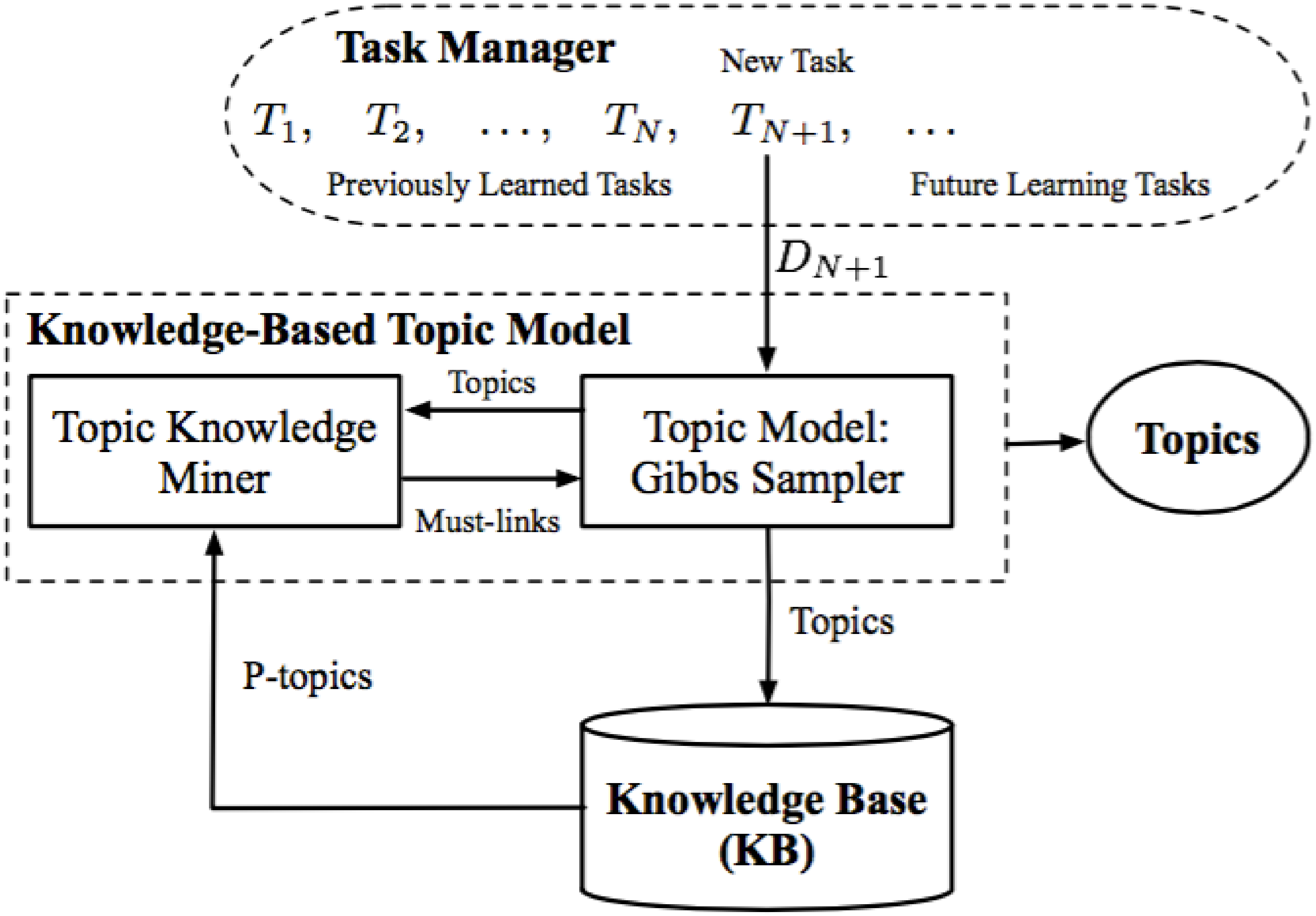
  e.g., {picture, photo}

- Should not be in the same aspect/topic

  => Cannot-Links

  e.g., {battery, picture}

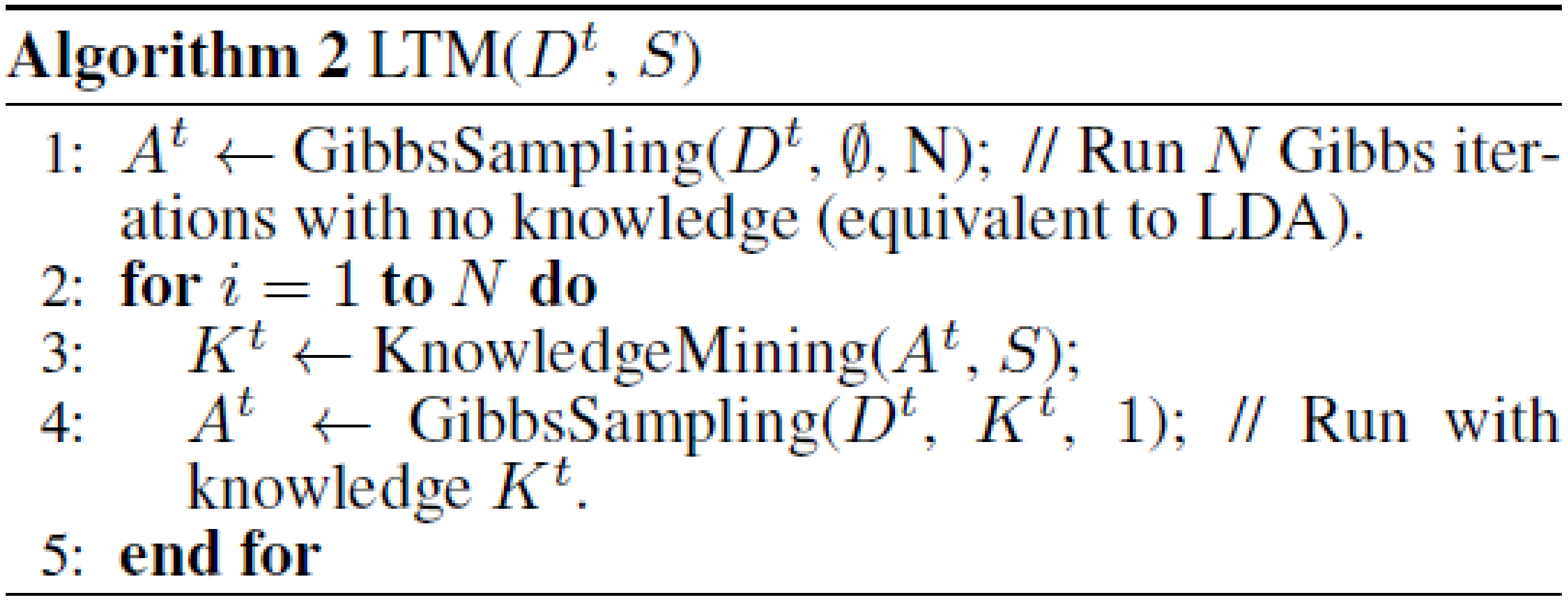
LTM System


Task Manager
New Task
T_1, T_2, …, T_N, T_{N+1}, …
Previously Learned Tasks
Future Learning Tasks
D_{N+1}
Knowledge-Based Topic Model
Topic Knowledge Miner
Topics
Must-links
Topic Model: Gibbs Sampler
Topics
Topics
P-topics
Knowledge Base (KB)

LTM Model

- Step 1: Run a topic model (e.g., LDA) on each domain D_i to produce a set of topics S_i called Topic Base
- Step 2: Mine prior knowledge (must-links) and use knowledge to guide modeling.

LTM Model



Algorithm 2 LTM(D^t, S)

```
1: $A^t \leftarrow$ GibbsSampling($D^t$, $\emptyset$, N); // Run $N$ Gibbs iterations with no knowledge (equivalent to LDA).
2: for $i = 1$ to $N$ do
3:     $K^t \leftarrow$ KnowledgeMining($A^t$, $S$);
4:     $A^t \leftarrow$ GibbsSampling($D^t$, $K^t$, 1); // Run with knowledge $K^t$.
5: end for
```

Knowledge Mining Function

- Topic matching: find similar topics from topic base for each topic in the new domain

- Pattern mining: find frequent itemsets from the matched topics

An Example

- Given a newly discovered topic:

  {*price*, *book*, *cost*, *seller, money*}

  - We find 3 matching topics from topic base *S*
    - Domain 1: {*price*, *color*, *cost*, *life, picture*}
    - Domain 2: {*cost*, *screen*, *price, expensive, voice*}
    - Domain 3: {*price*, *money*, *customer, expensive*}

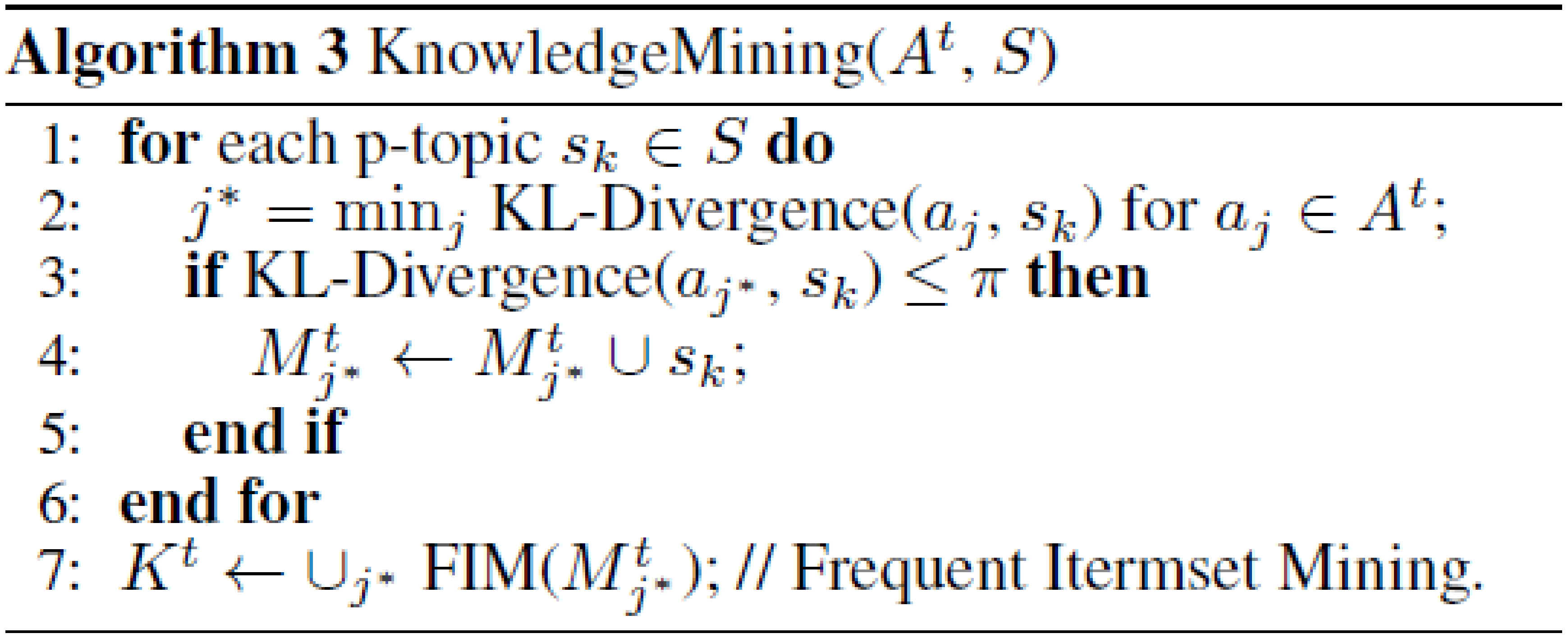
An Example

- Given a newly discovered topic:

  {*price*, *book*, *cost*, *seller, money*}

  - We find 3 matching topics from topic base *S*
    - Domain 1: {*price*, *color*, *cost*, *life, picture*}
    - Domain 2: {*cost*, *screen*, *price, expensive, voice*}
    - Domain 3: {*price*, *money*, *customer, expensive*}
- If we require words to appear in at least two domains, we get two must-links (knowledge):
  - {*price*, *cost*} and {*price*, *expensive*}.
  - Each set is likely to belong to the same aspect/topic.

Knowledge Mining Function

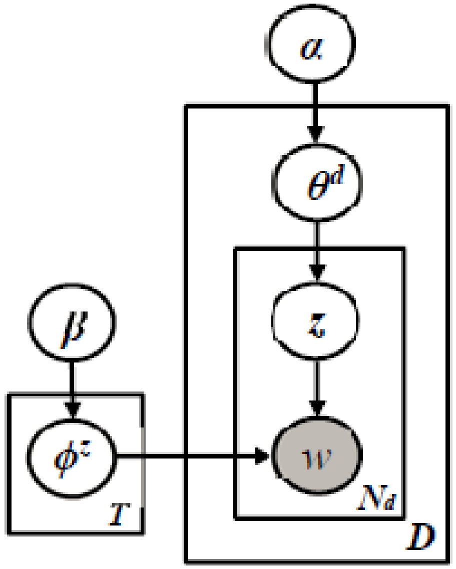


Algorithm 3 KnowledgeMining(A^t, S)

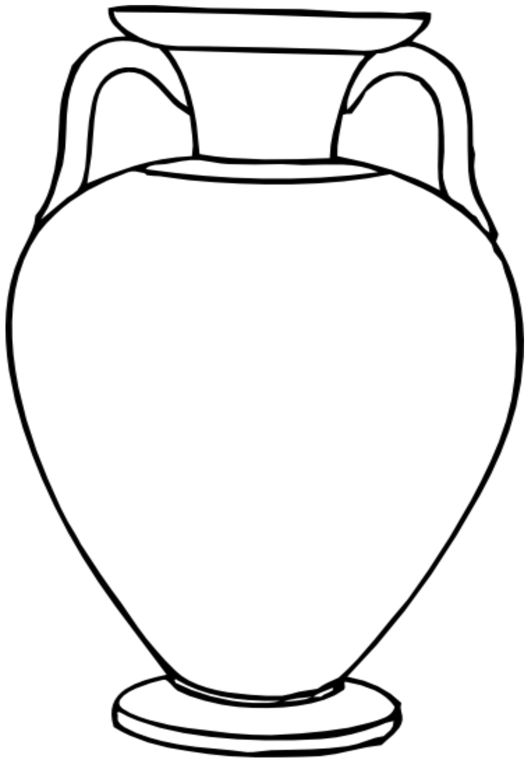
```
1: for each p-topic $s_k \in S$ do
2:     $j^* = \min_j$ KL-Divergence($a_j, s_k$) for $a_j \in A^t$;
3:     if KL-Divergence($a_{j^*}, s_k$) $\leq \pi$ then
4:         $M^t_{j^*} \leftarrow M^t_{j^*} \cup s_k$;
5:     end if
6: end for
7: $K^t \leftarrow \cup_{j^*}$ FIM($M^t_{j^*}$); // Frequent Itermset Mining.
```

Model Inference: Gibbs Sampling

- How to use the *must-links* knowledge?
  - e.g., {*price*, *cost*} & {*price*, *expensive*}
- Graphical model: same as LDA
- But the model inference is very different
  - Generalized Pólya Urn Model (GPU)
- Idea: When assigning a topic *t* to a word *w*, also assign *a fraction of t* to words in must-links sharing with *w*.



Simple Pólya Urn Model (SPU)



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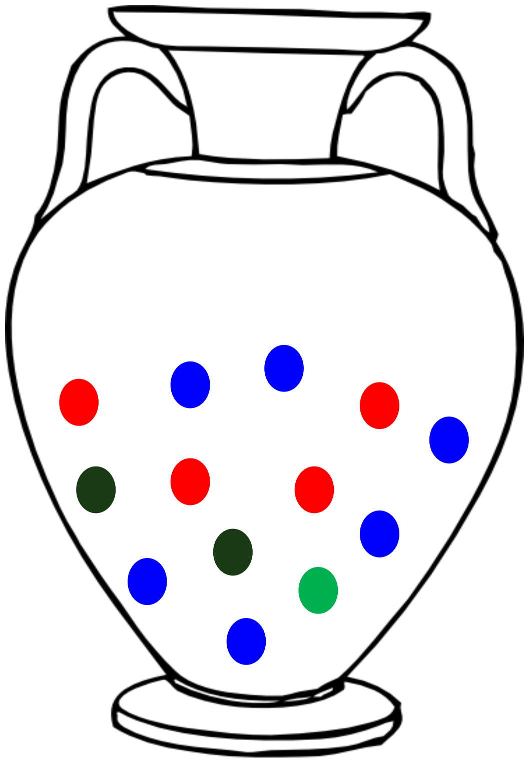

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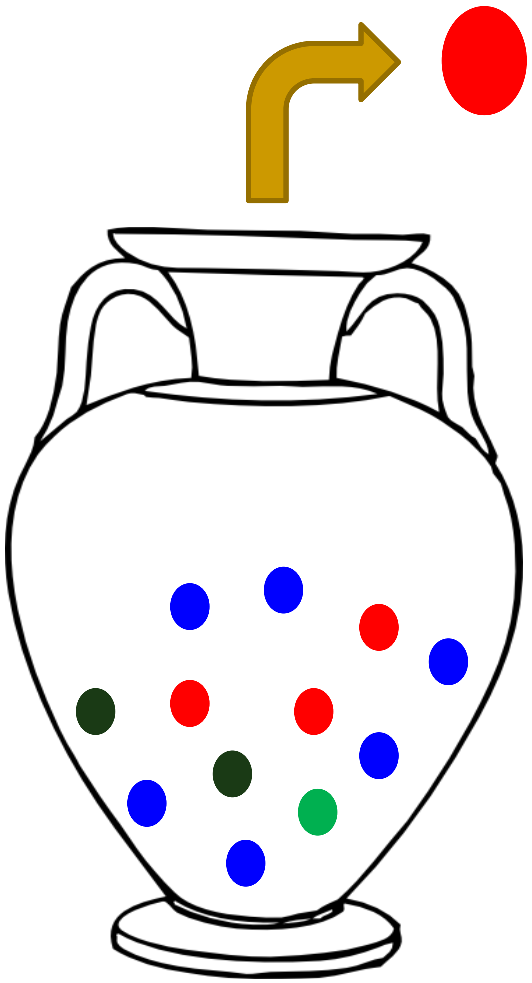

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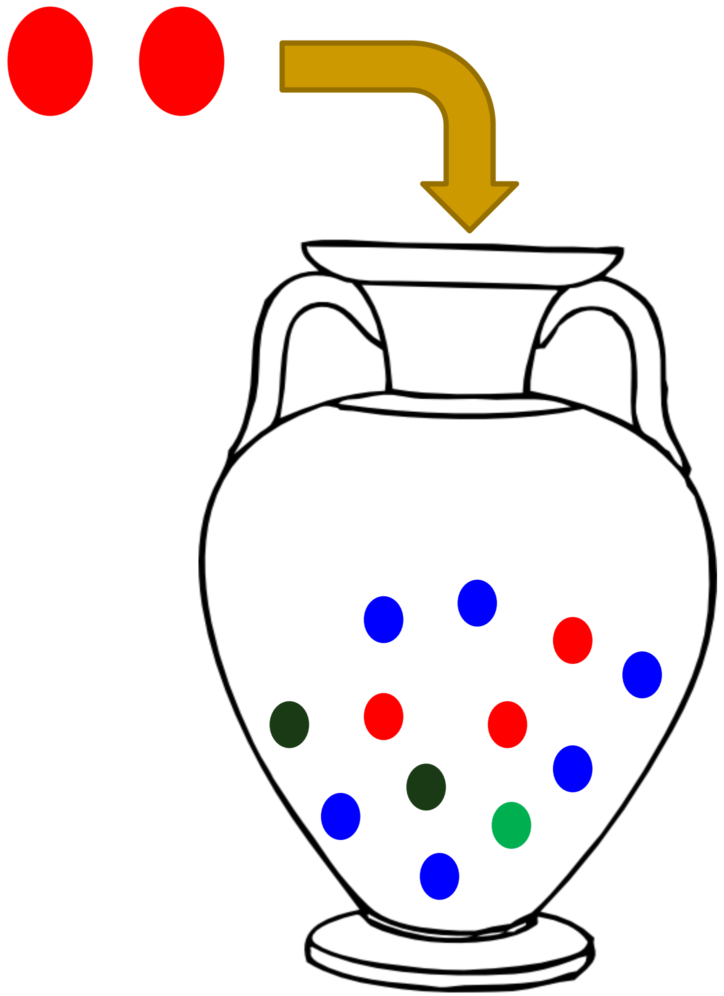

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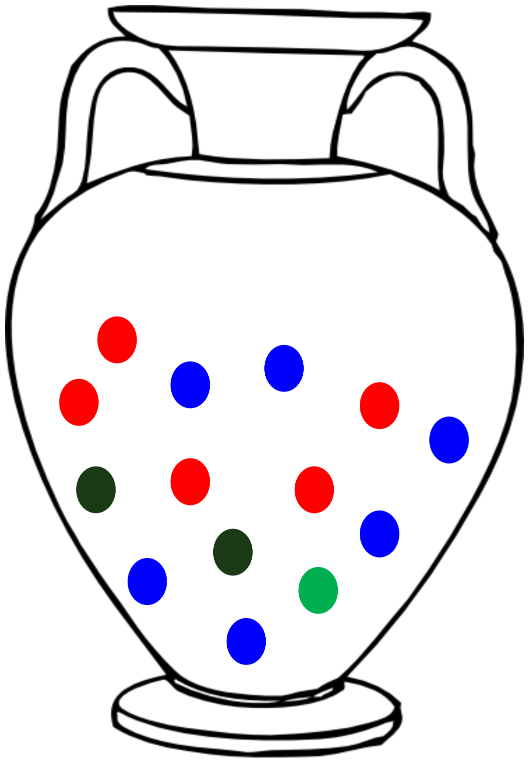
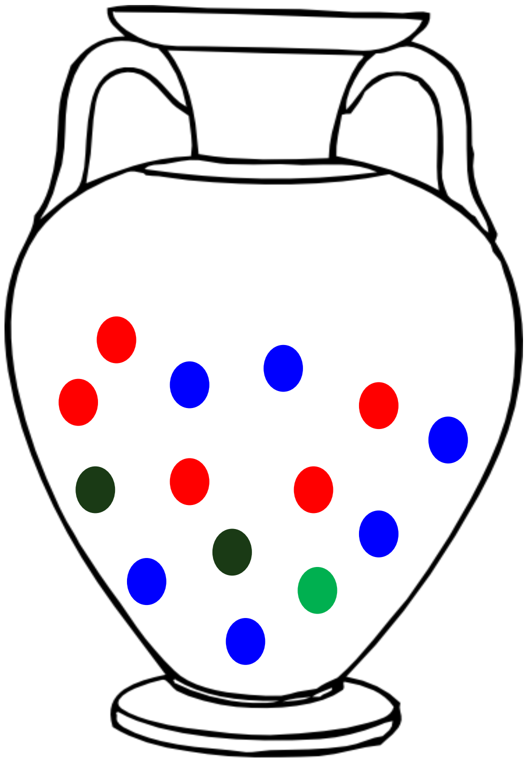


Simple Pólya Urn Model (SPU)

The rich get richer!



Interpreting LDA Under SPU

Drawing word w under a topic t:

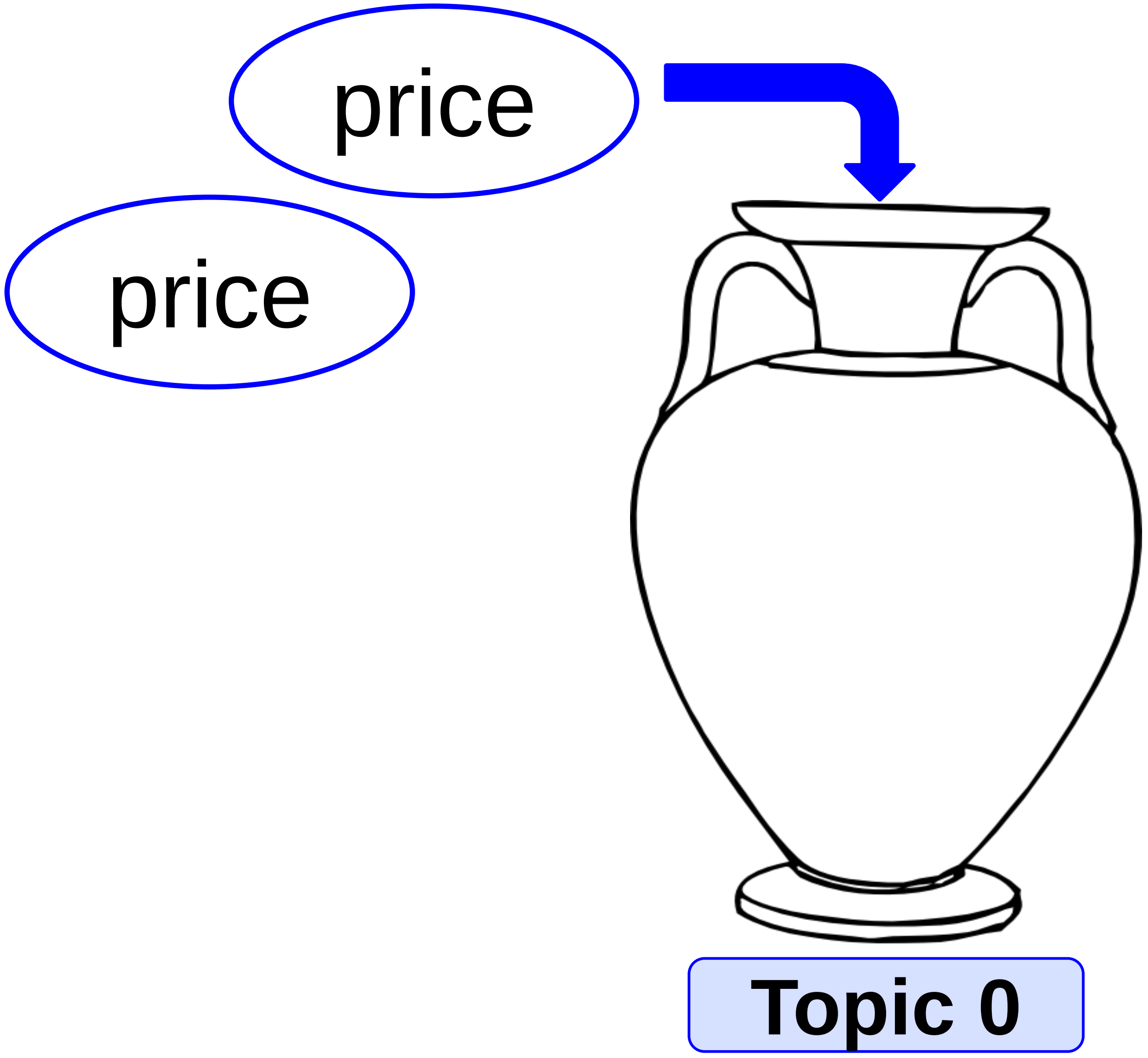
Increase the probability of seeing w under t

Decrease the probability of seeing $w' \neq w$ under t

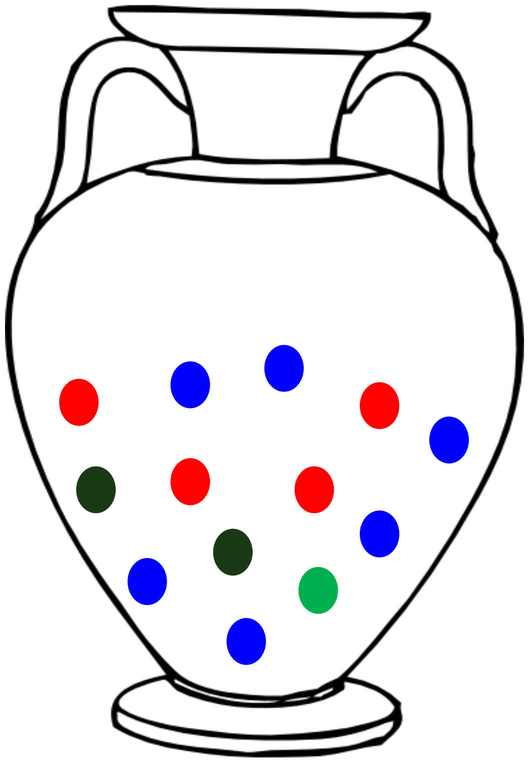
Interpreting LDA Under SPU

price
Topic 0

Interpreting LDA Under SPU



Generalized Pólya Urn Model (GPU)



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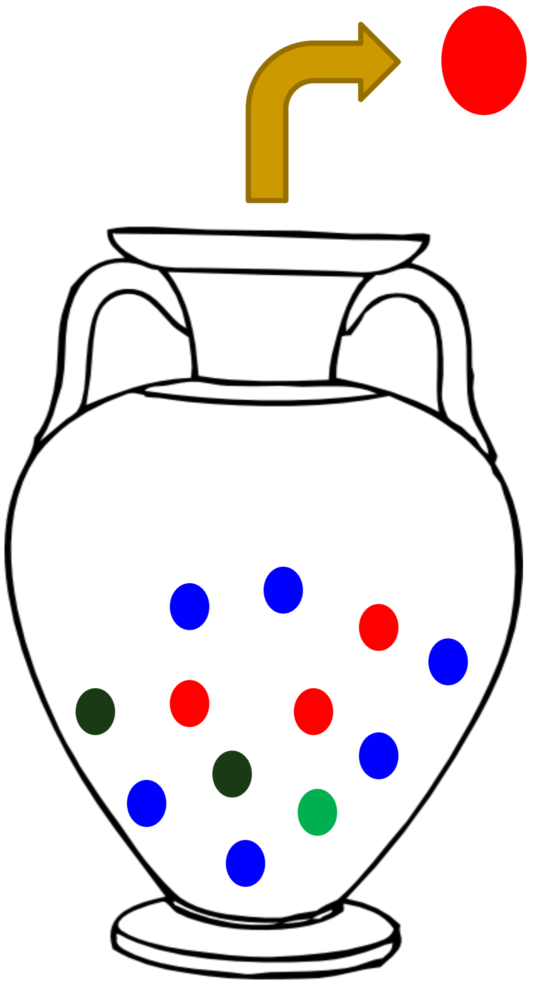

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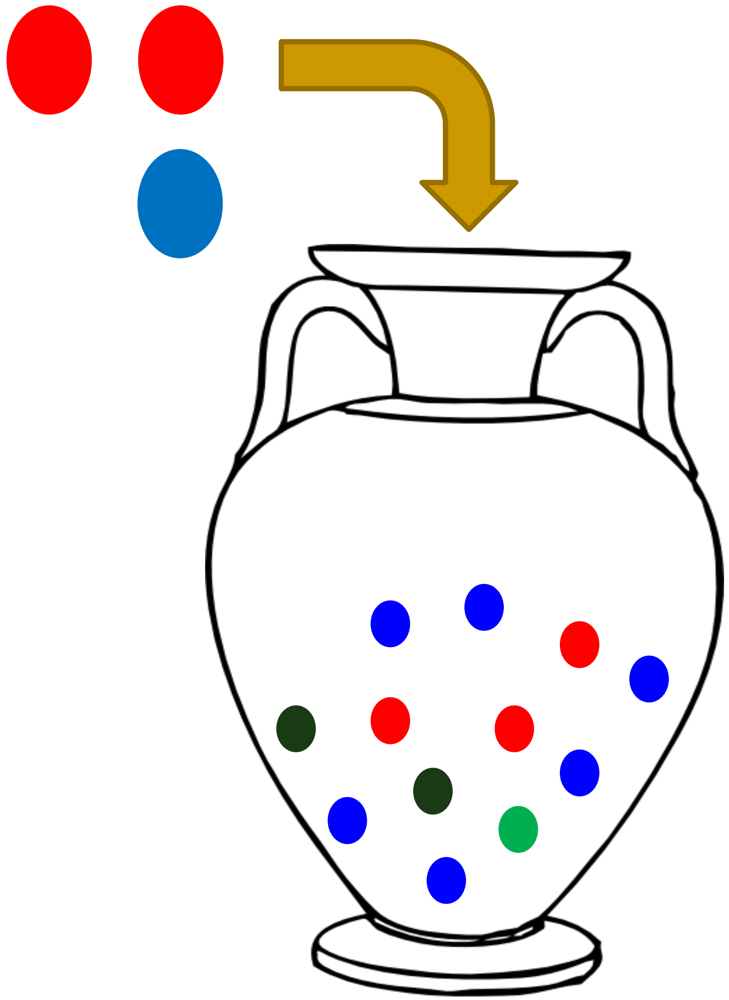

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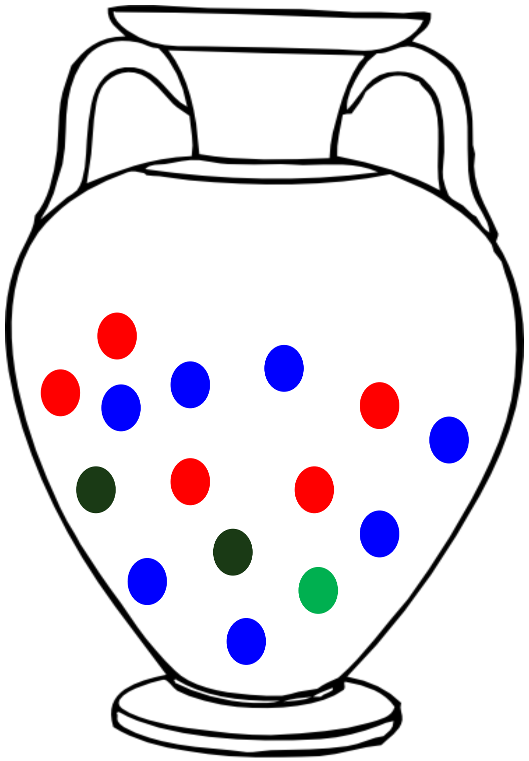
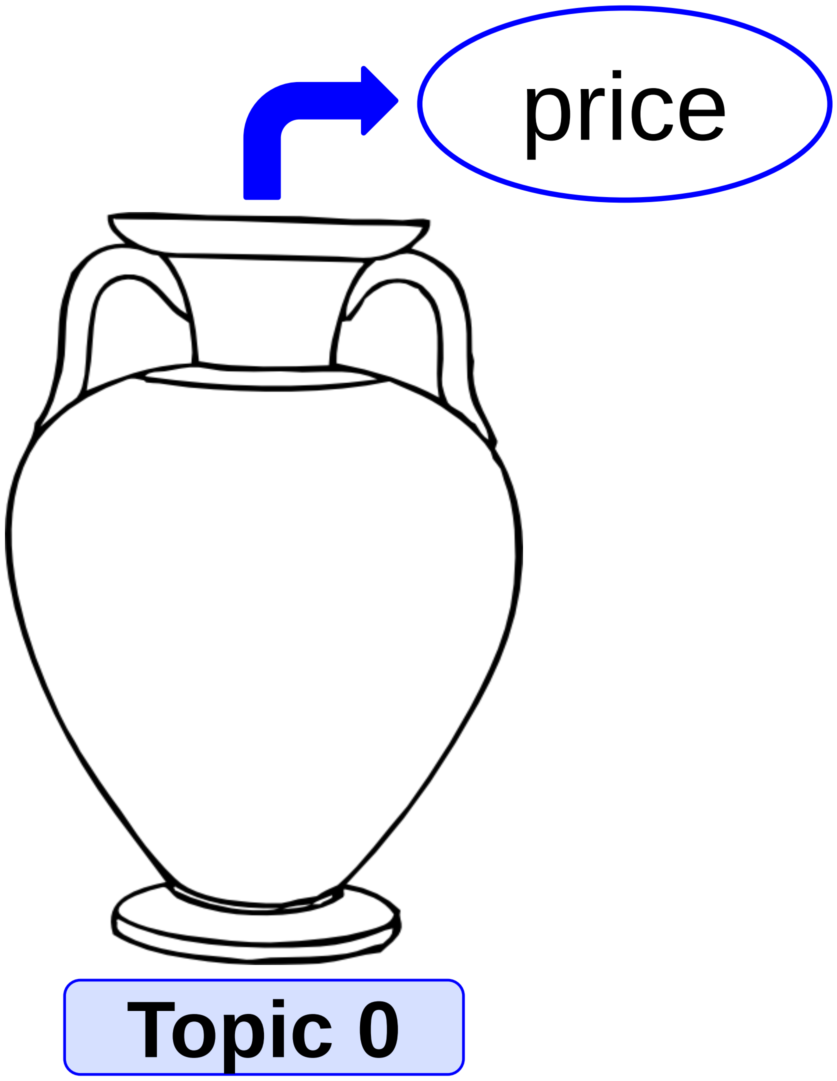


Applying GPU



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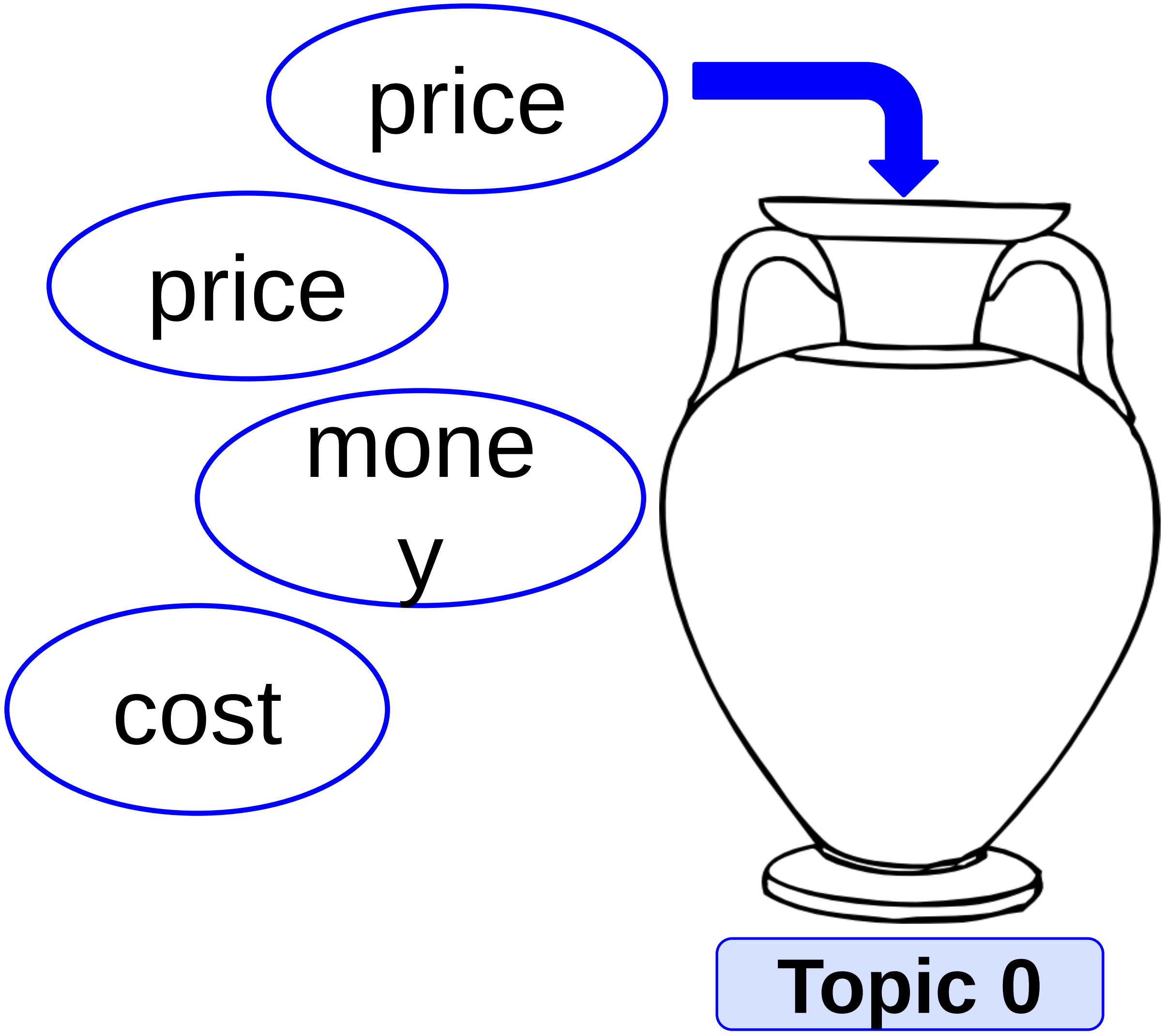


Gibbs Sampling

$$P(z_i = t | \boldsymbol{z}^{-i}, \boldsymbol{w}, \alpha, \beta, \mathbf{A}') \propto$$

$$\frac{n_{d,t}^{-i} + \alpha}{\sum_{t'=1}^{T} (n_{d,t'}^{-i} + \alpha)} \times \frac{\sum_{w'=1}^{V} \mathbf{A}'_{t,w',w_i} \times n_{t,w'}^{-i} + \beta}{\sum_{v=1}^{V} (\sum_{w'=1}^{V} \mathbf{A}'_{t,w',v} \times n_{t,w'}^{-i} + \beta)}$$

Experiment Results

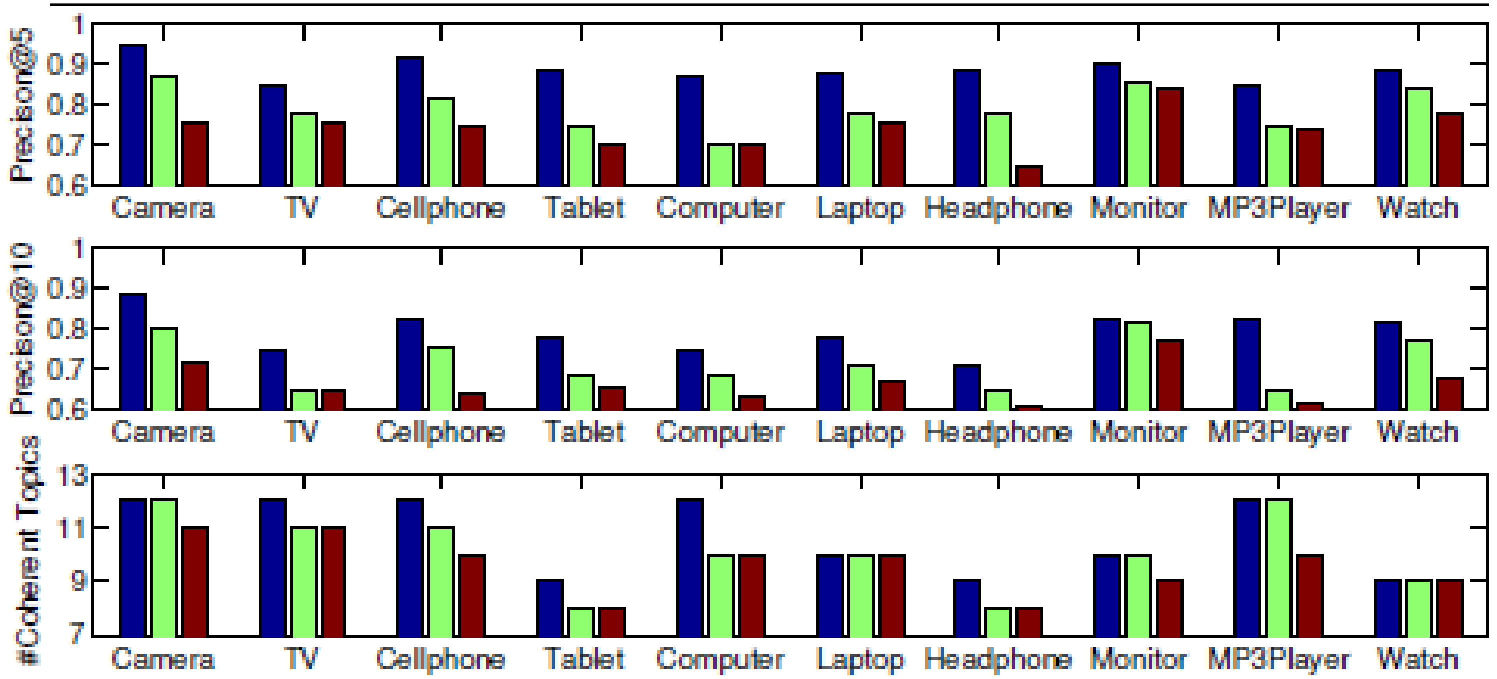


Figure 2. Top & Middle: Topical words *Precision@5* & *Presicion@10* of coherent topics of each model respectively; Bottom: number of coherent (#Coherent) topics discovered by each model. The bars from left to right in each group are for LTM, LDA, and DF-LDA. On average, for *Precision@5* and

LML Components of LTM

- **KB**
  - Stores topics/aspects generated in the past tasks
  - Knowledge: Must-Links
- **KBL**
  - LTM is based on Generalized Pólya Urn Model

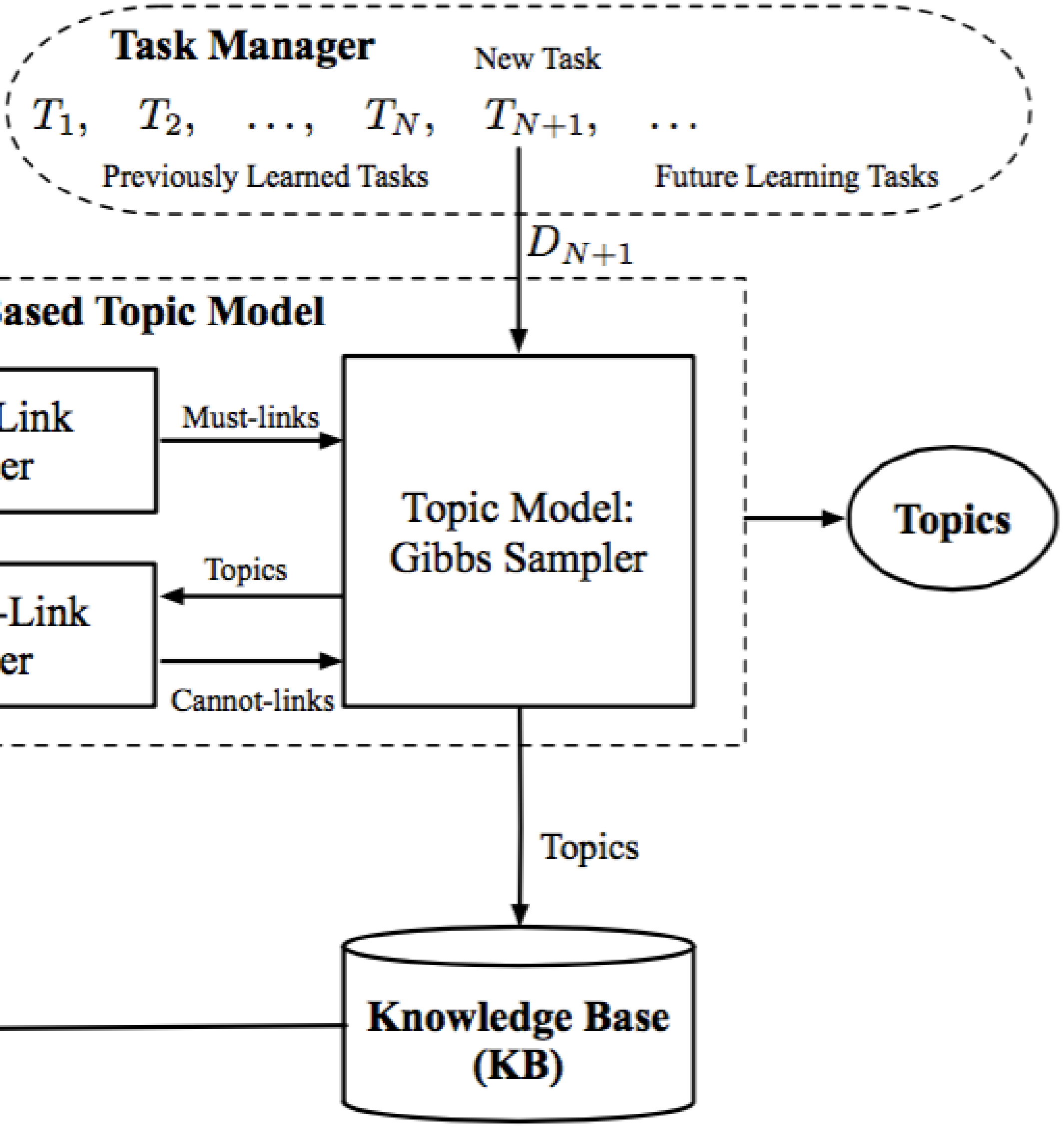
AMC: Modeling with Small Datasets
(Chen and Liu, KDD-2014)

- The LTM model is not sufficient when the data is small for each task because
    - It cannot produce good initial topics for matching to identify relevant past topics.
- AMC mines must-links differently
    - Mine must-links from the PIS without considering the target task/data

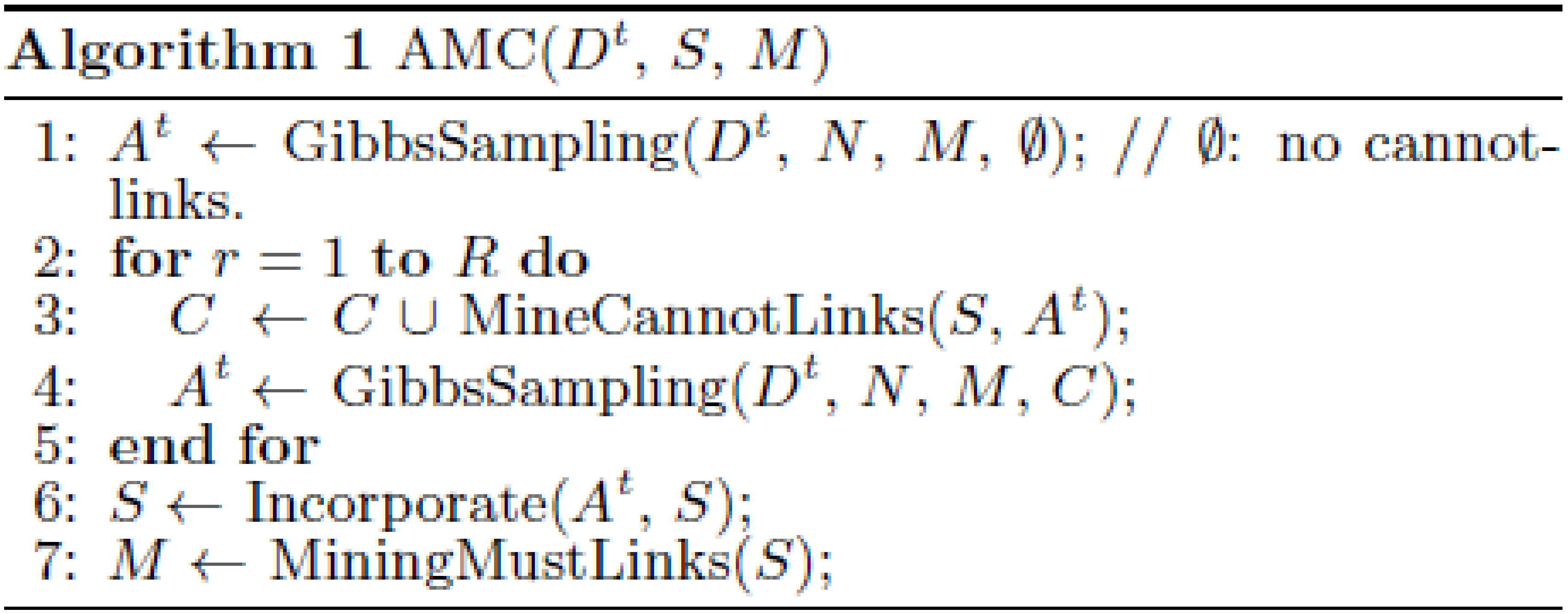
Cannot-Links

- In this case, we need to mine cannot-links, which is tricky because
  - There is a huge number of cannot-links $O(V^2)$
    - V is the vocabulary size
- We thus need to focus on only those terms that are relevant to target data D^t.
  - That is, we need to embed the process of finding cannot-links in the sampling

AMC System


Task Manager
New Task
T_1, T_2, …, T_N, T_{N+1}, …
Previously Learned Tasks
Future Learning Tasks
D_{N+1}
Knowledge-Based Topic Model
Must-Link Miner
Must-links
Topic Model: Gibbs Sampler
Topics
Cannot-Link Miner
Cannot-links
Topics
P-topics
Topics
Knowledge Base (KB)

Overall Algorithm

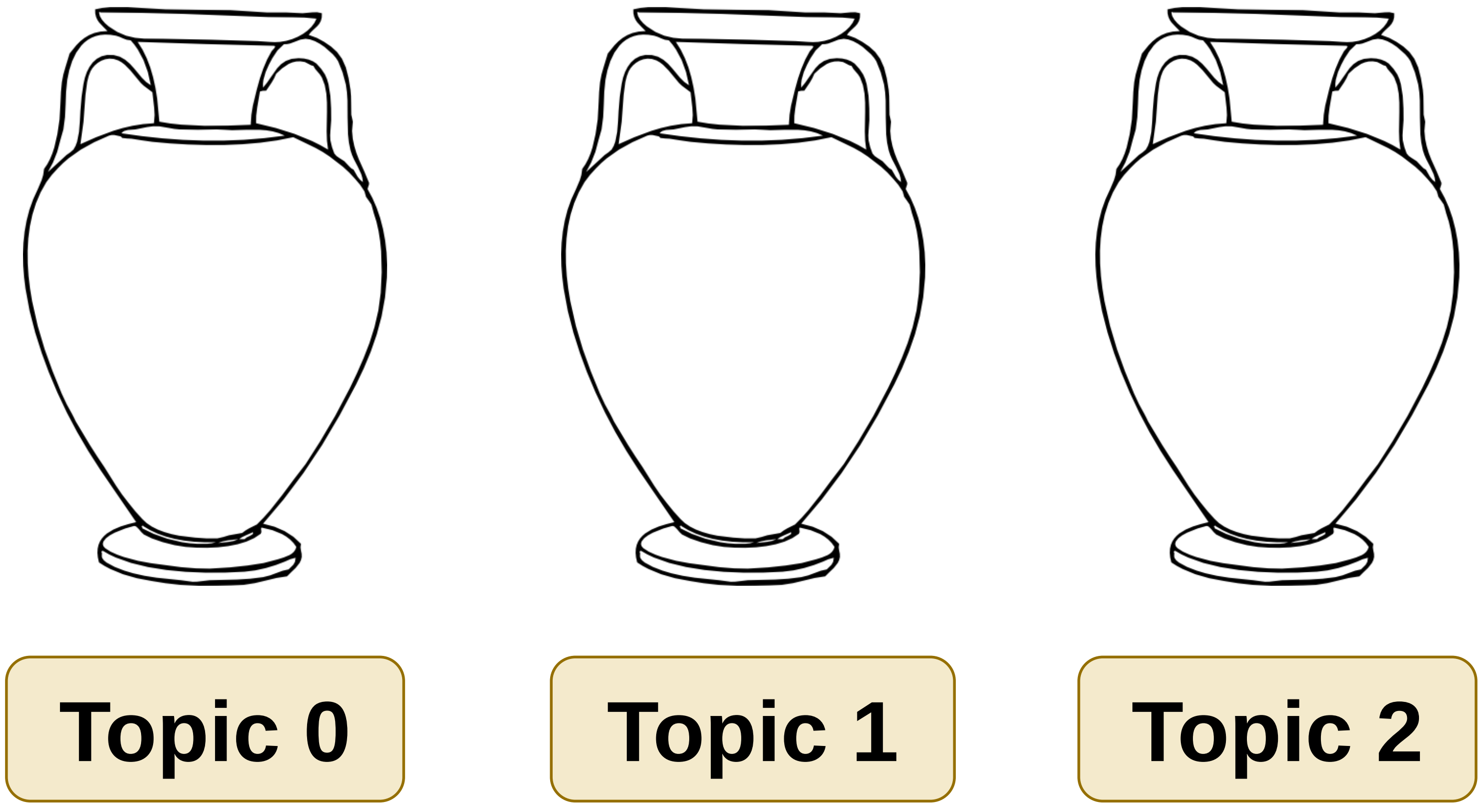


Algorithm 1 AMC(D^t, S, M)

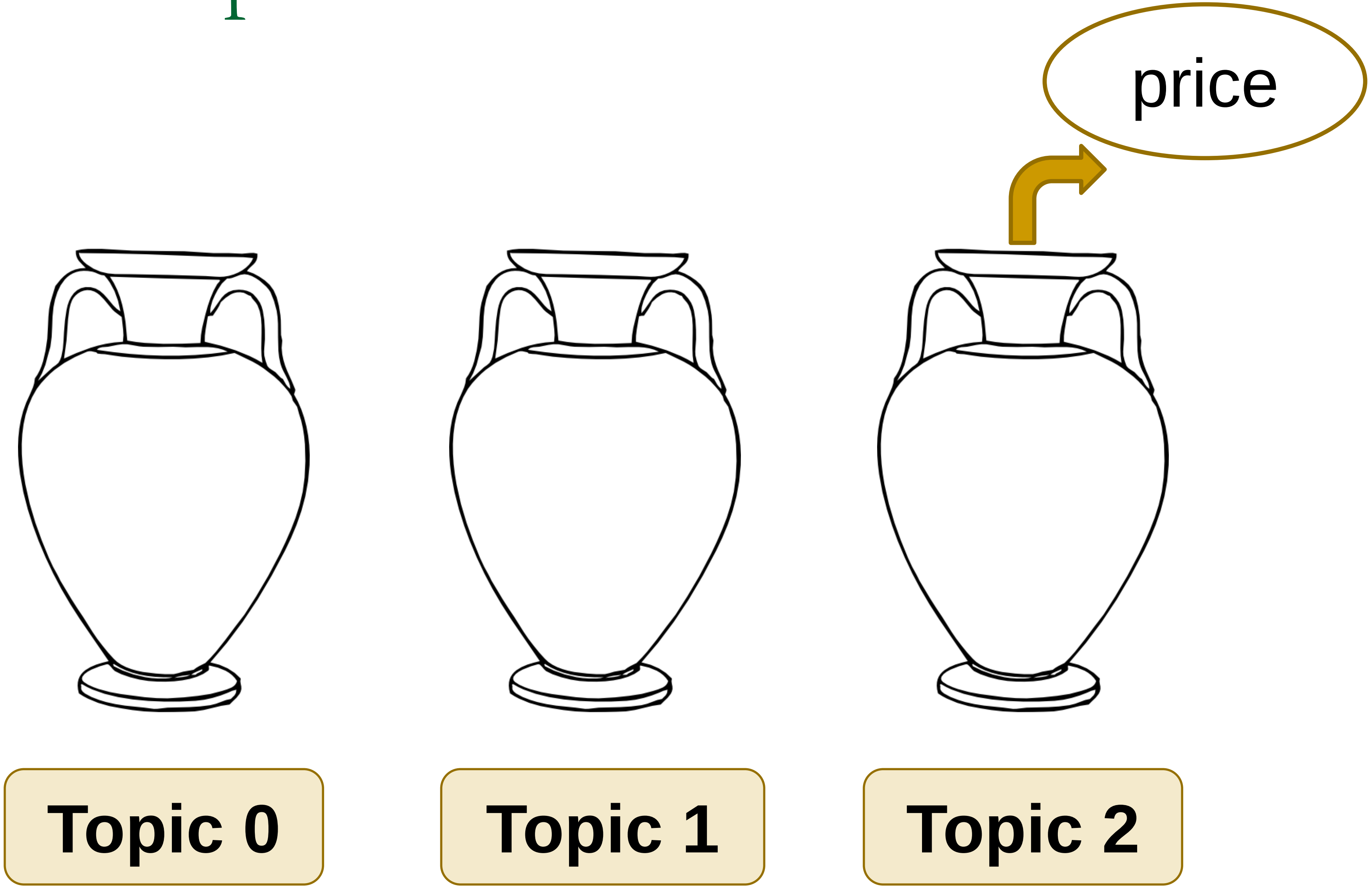
```
1: $A^t \leftarrow$ GibbsSampling($D^t$, $N$, $M$, $\emptyset$); // $\emptyset$: no cannot-links.
2: for $r = 1$ to $R$ do
3:     $C \leftarrow C \cup$ MineCannotLinks($S$, $A^t$);
4:     $A^t \leftarrow$ GibbsSampling($D^t$, $N$, $M$, $C$);
5: end for
6: $S \leftarrow$ Incorporate($A^t$, $S$);
7: $M \leftarrow$ MiningMustLinks($S$);
```

- Sampling becomes much more complex
  - It proposed M-GPU model (multi-generalized Polya urn model)

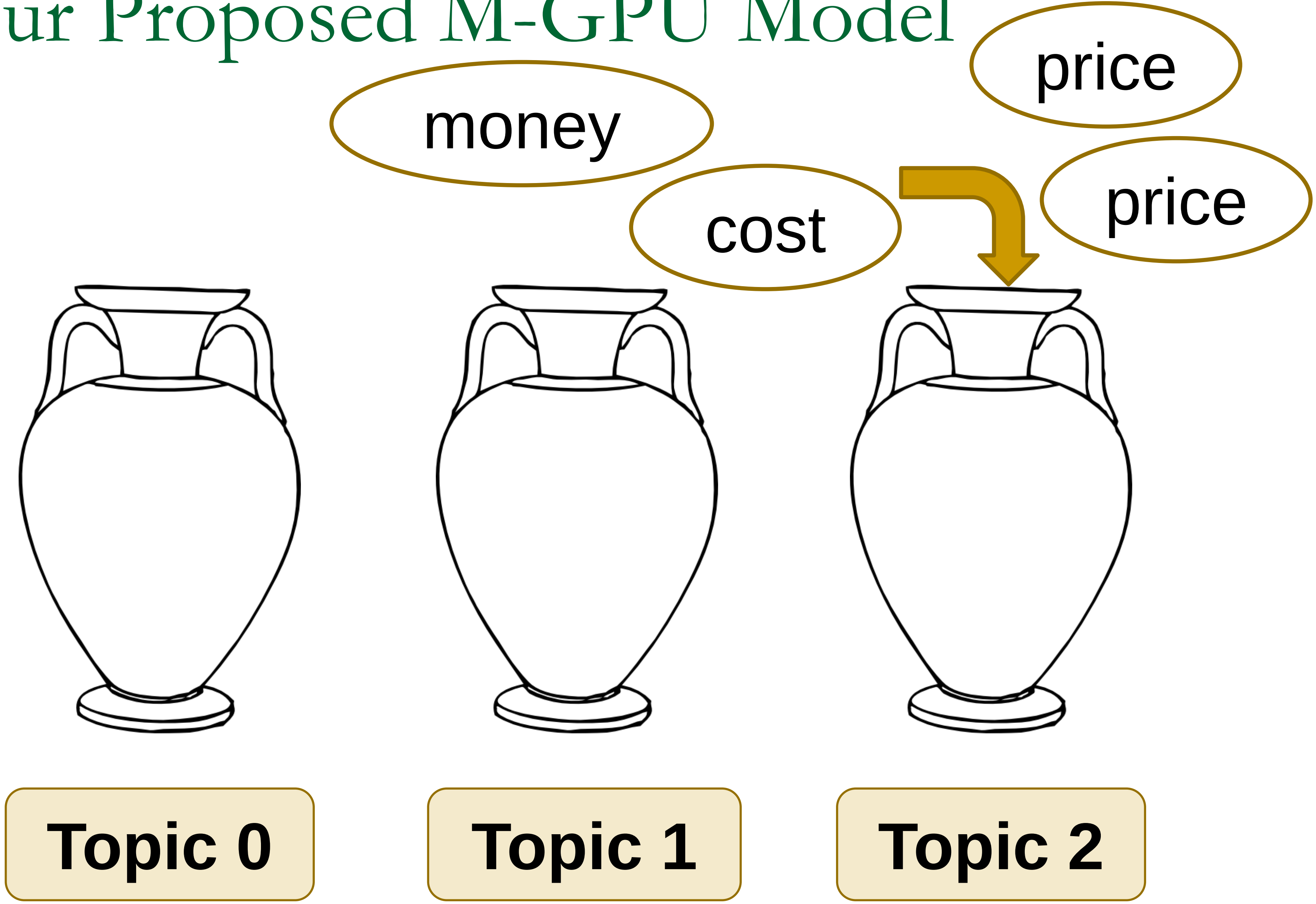
Our Proposed M-GPU Model



Our Proposed M-GPU Model

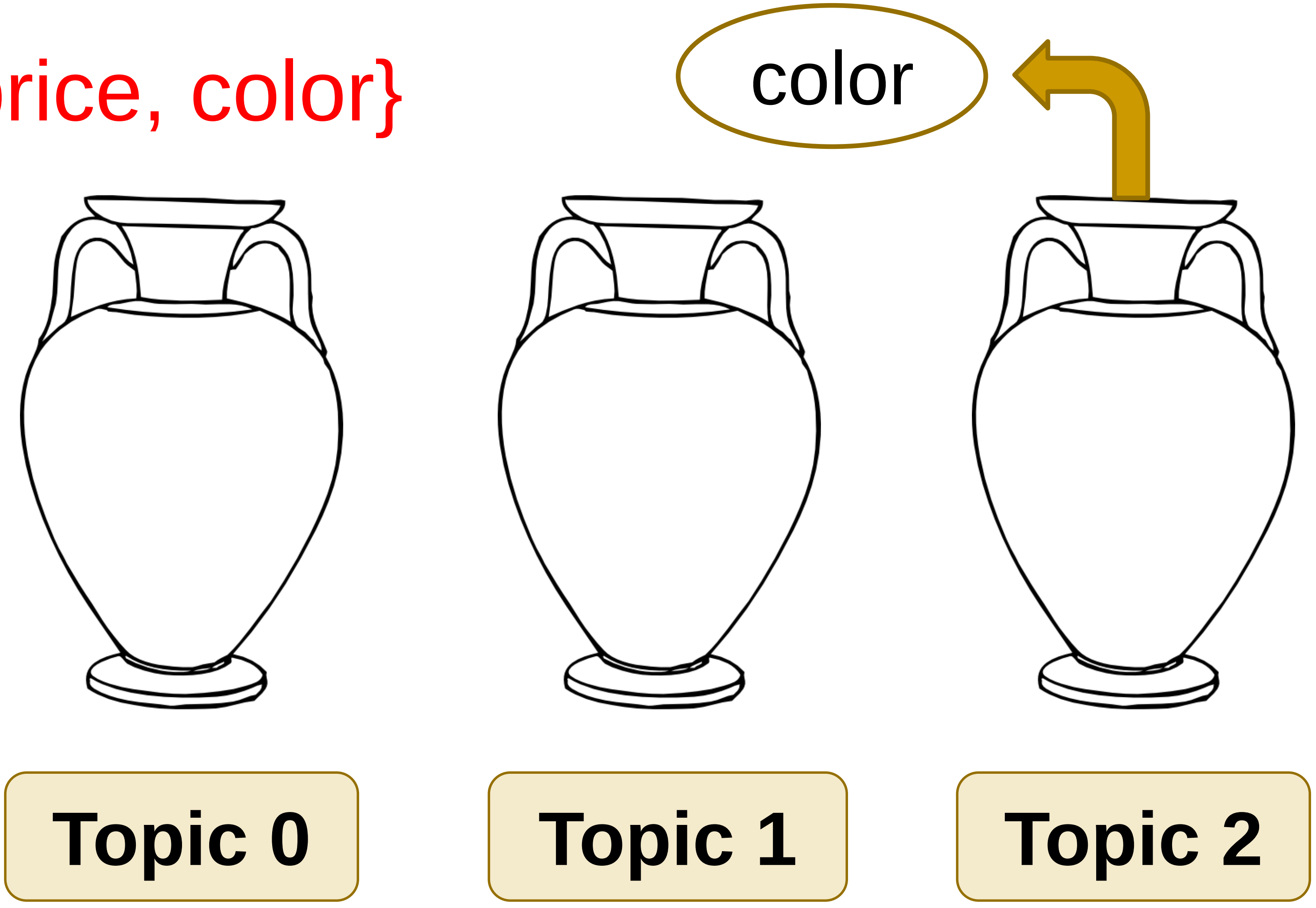


Our Proposed M-GPU Model



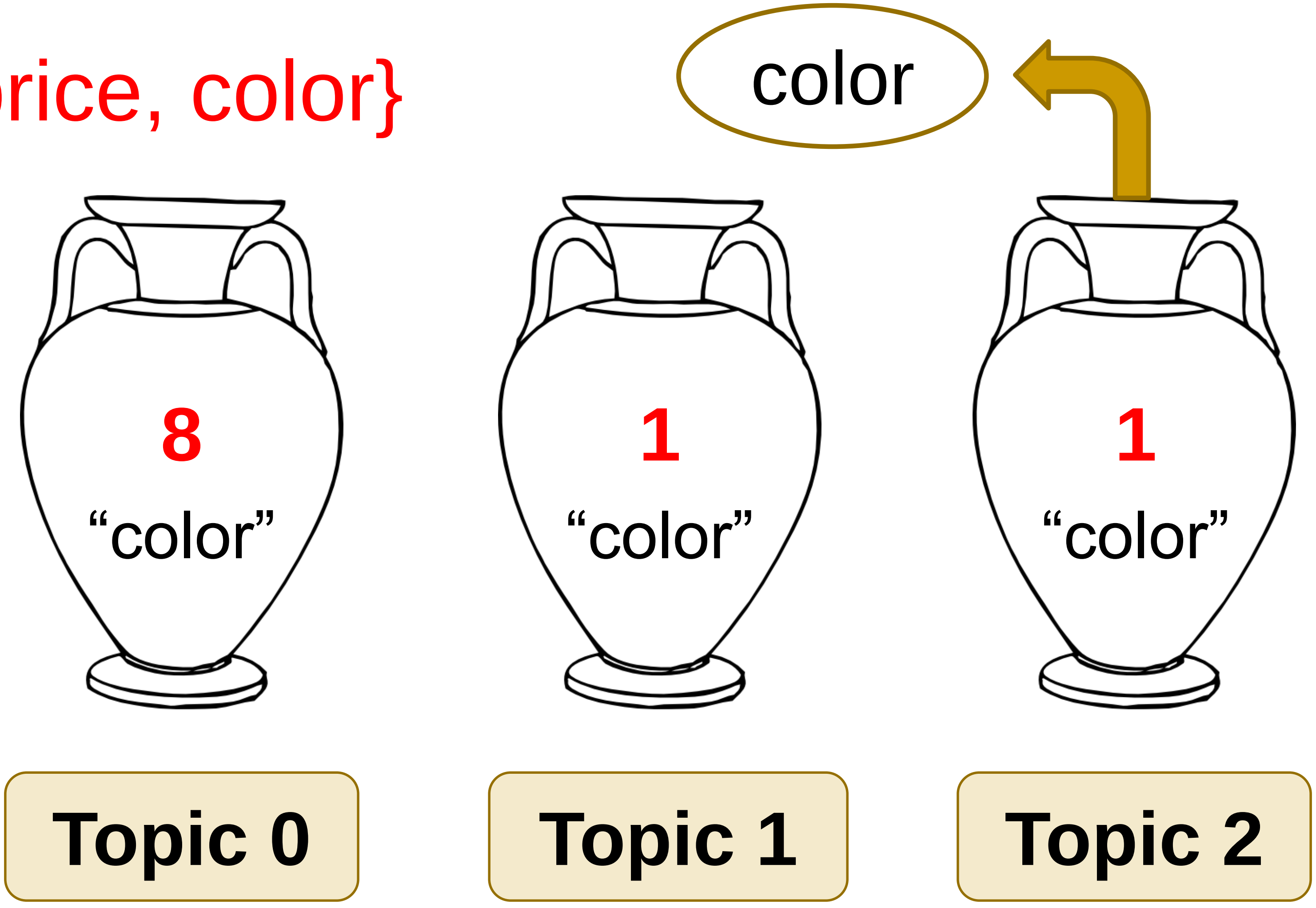
Our Proposed M-GPU Model

- {price, color}

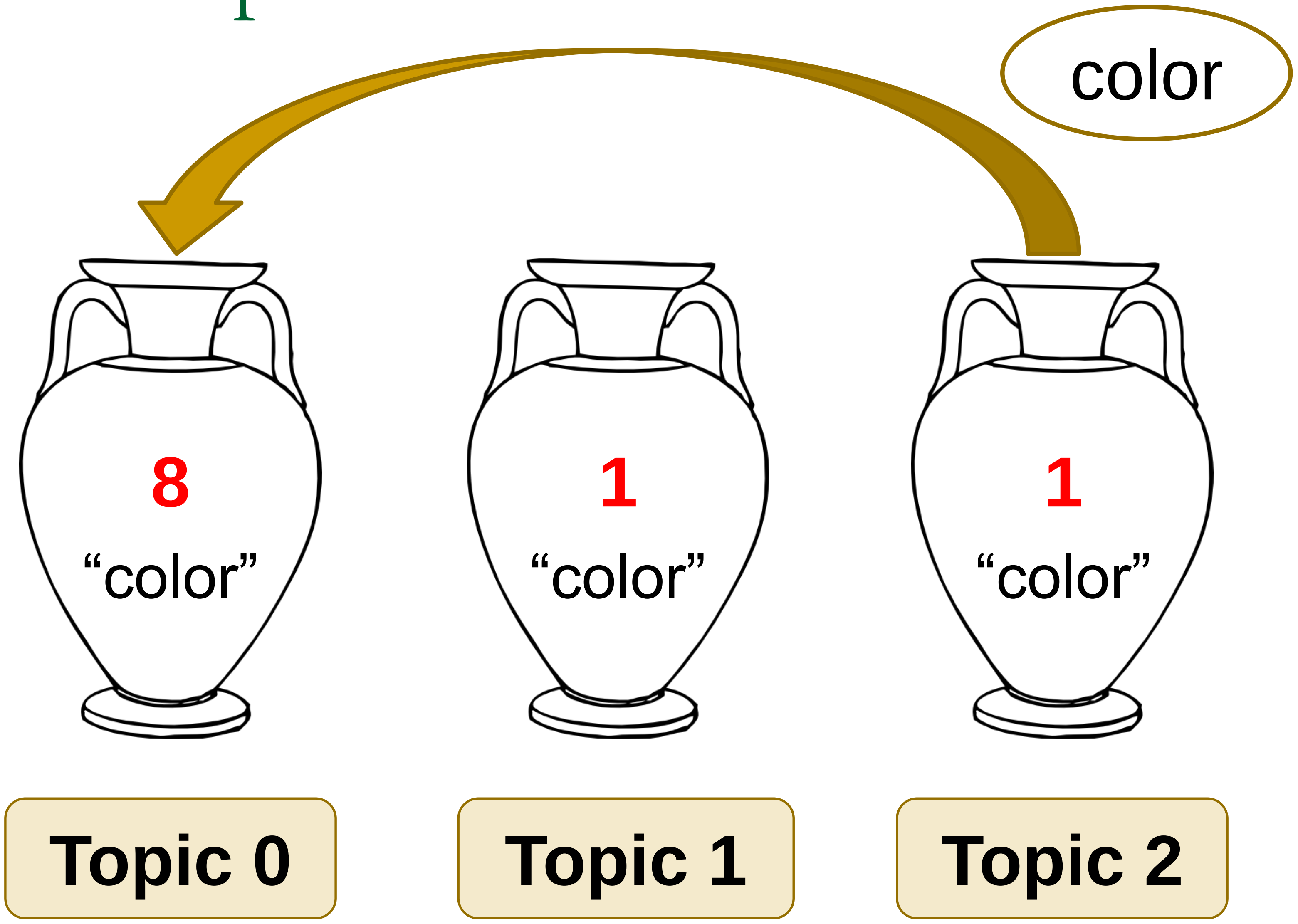


Our Proposed M-GPU Model

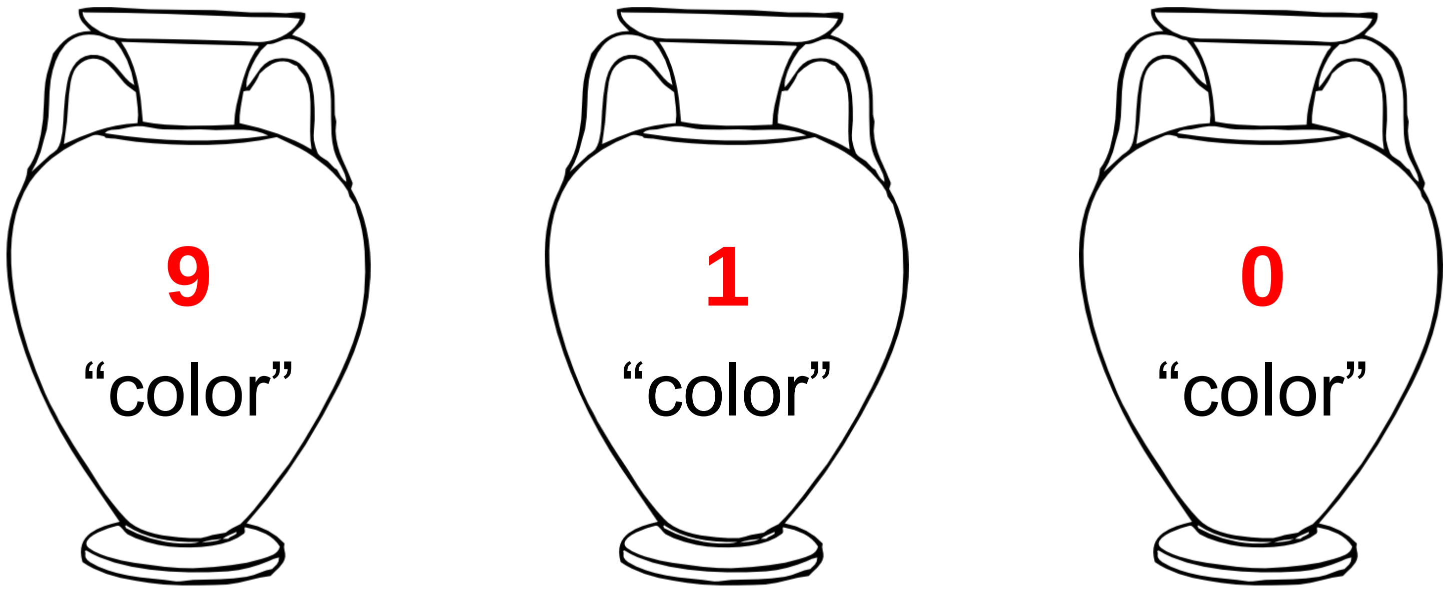
- {price, color}



Our Proposed M-GPU Model



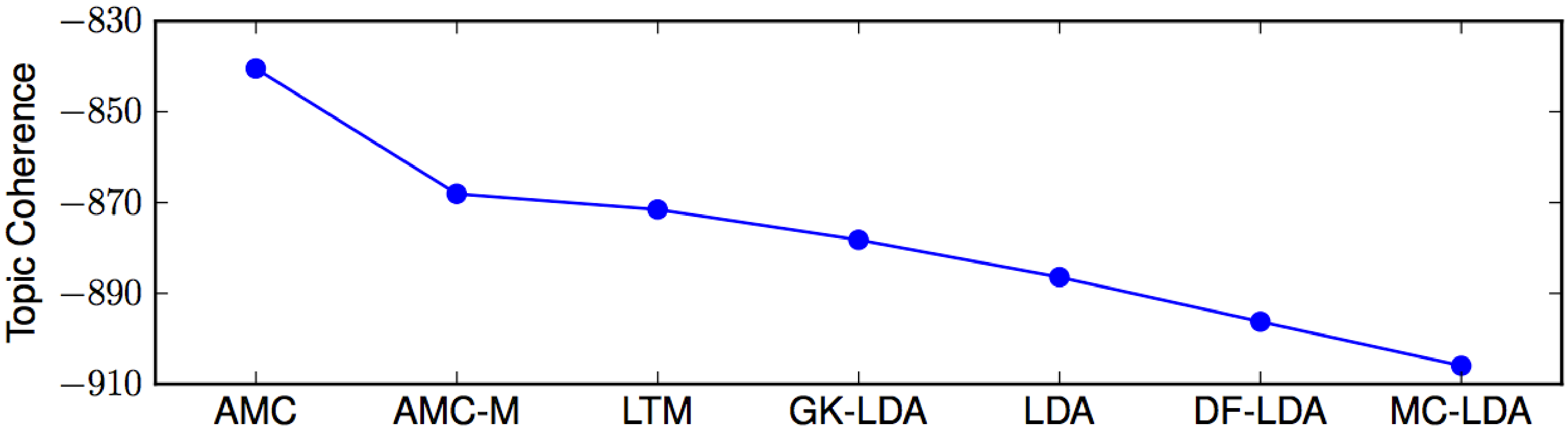
Our Proposed M-GPU Model



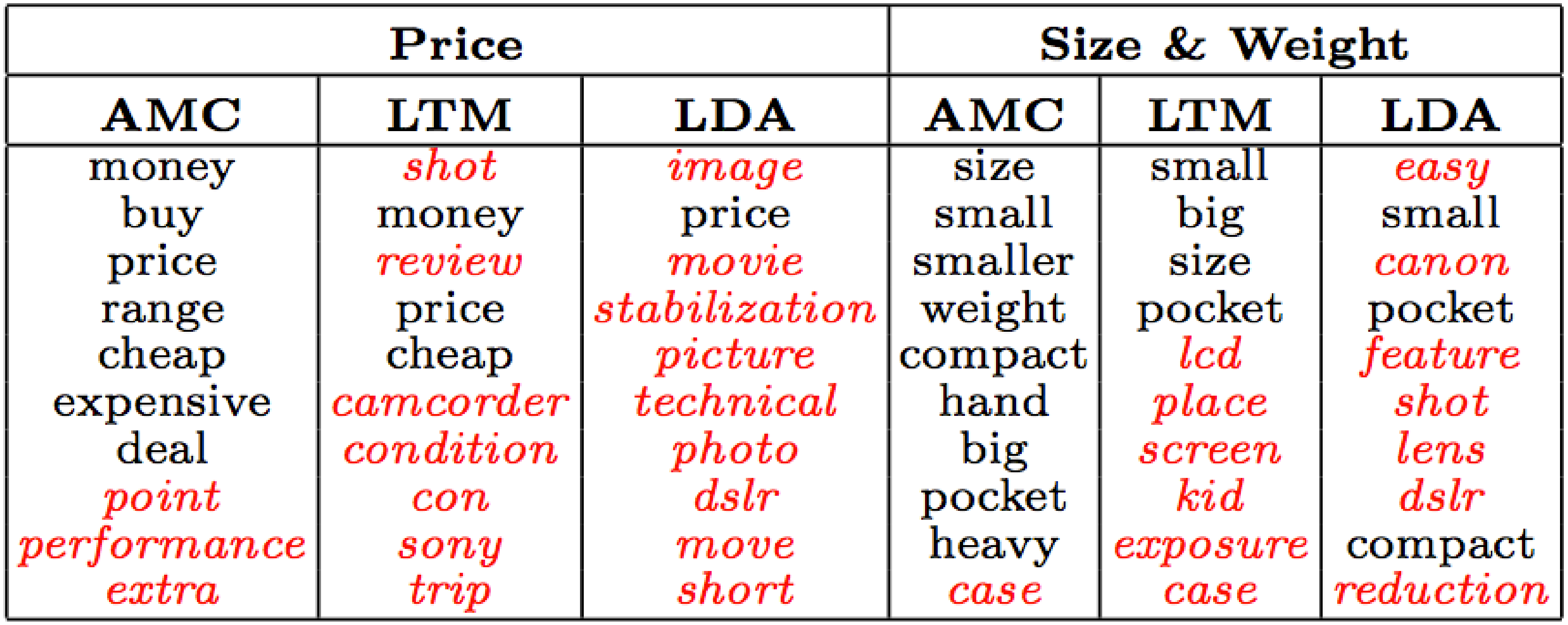
Topic 0 Topic 1 Topic 2

AMC results

Metrics: Topic Coherence (Mimno et al., 2011)



AMC results



Price			Size & Weight		
AMC	**LTM**	**LDA**	**AMC**	**LTM**	**LDA**
money	*shot*	*image*	size	small	*easy*
buy	money	price	small	big	small
price	*review*	*movie*	smaller	size	*canon*
range	price	*stabilization*	weight	pocket	pocket
cheap	cheap	*picture*	compact	*lcd*	*feature*
expensive	*camcorder*	*technical*	hand	*place*	*shot*
deal	*condition*	*photo*	big	*screen*	*lens*
point	*con*	*dslr*	pocket	*kid*	*dslr*
performance	*sony*	*move*	heavy	*exposure*	compact
extra	*trip*	*short*	*case*	*case*	*reduction*

Table 2: Example topics of AMC, LTM and LDA from the Camera domain. Errors are italicized and marked in red.

LML Components of AMC

- **KB**
  - Stores topics/aspects generated in the past tasks
  - Knowledge: Must-Links and Cannot-Links
- **KBL**
  - AMC is based on multi-generalized Pólya Urn Model

LAST Model

- Lifelong aspect-based sentiment topic model (Wang et al., 2016)
- Knowledge
  - Aspect-opinion pair, e.g., {shipping, quick}
  - Aspect-aspect pair, e.g., {shipping, delivery}
  - Opinion-opinion pair, e.g, {quick, fast}

Lifelong Information Extraction
(Liu et al., 2016)

- Specifically: aspect extraction
- "*The size is great, but pictures are poor*."
  - Aspects (product features): size, picture
- An effective approach
  - Double Propagation (DP) (Qiu et al 2011): a syntactic rule-based extraction method
    - Still has a lot of room for improvement.

Problem and Solution

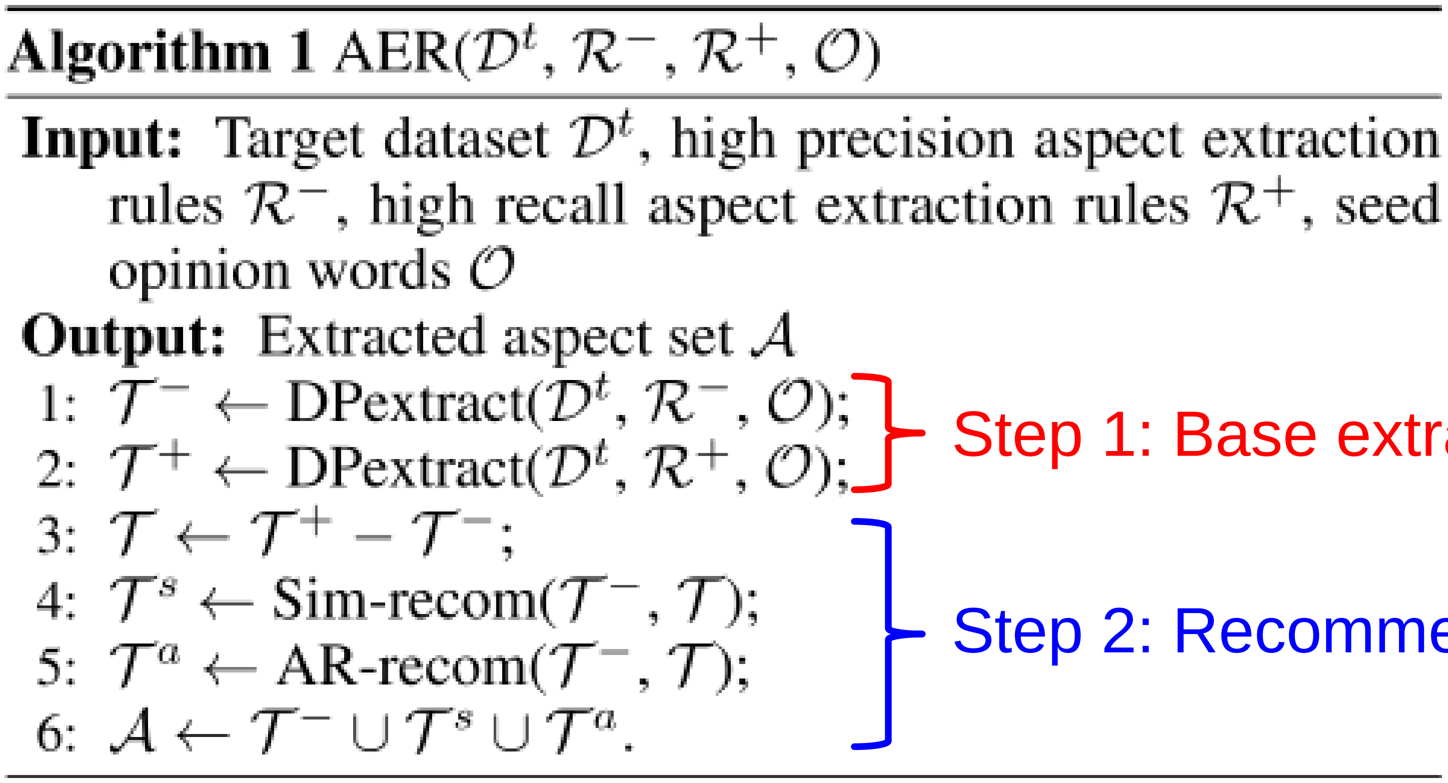
- Problem of syntactic rule-based methods
  - hard to design a set of rules to perform extraction with high precision and recall.
- Possible solution
  - Use prior knowledge mined by exploiting the abundance of reviews for all kinds of products since many products share aspects.
    - e.g., many electronic products have aspect battery.

How to Use Prior Knowledge?

- Use extracted aspects from reviews of a large number of other products to help extract aspects from reviews of the current product.
  - Using recommendation.

- This work uses DP as the base and improve its results dramatically through
  - aspect recommendation.

Overall Algorithm



Algorithm 1 AER($\mathcal{D}^t, \mathcal{R}^-, \mathcal{R}^+, \mathcal{O}$)

Input: Target dataset $\mathcal{D}^t$, high precision aspect extraction rules $\mathcal{R}^-$, high recall aspect extraction rules $\mathcal{R}^+$, seed opinion words $\mathcal{O}$

Output: Extracted aspect set $\mathcal{A}$

```
1: $\mathcal{T}^- \leftarrow$ DPextract($\mathcal{D}^t, \mathcal{R}^-, \mathcal{O}$);
2: $\mathcal{T}^+ \leftarrow$ DPextract($\mathcal{D}^t, \mathcal{R}^+, \mathcal{O}$);
3: $\mathcal{T} \leftarrow \mathcal{T}^+ - \mathcal{T}^-$;
4: $\mathcal{T}^s \leftarrow$ Sim-recom($\mathcal{T}^-, \mathcal{T}$);
5: $\mathcal{T}^a \leftarrow$ AR-recom($\mathcal{T}^-, \mathcal{T}$);
6: $\mathcal{A} \leftarrow \mathcal{T}^- \cup \mathcal{T}^s \cup \mathcal{T}^a$.
```

Step 1: Base extraction

Step 2: Recommendation

- Algorithm AER, short for Aspect Extraction based on Recommendation.

Step 1: Base Extraction

- Use the DP method (DPextract) to extract an initial (or base) set T^- of aspects employing a set R^- of high precision rules.
  - Set $T^-$of extracted aspects has very high precision but low recall.
- Extract a set T^+ of aspects from a larger set R^+ of high recall rules also using DPextract.
  - Set $T^+$of extracted aspects has very high recall but low precision.

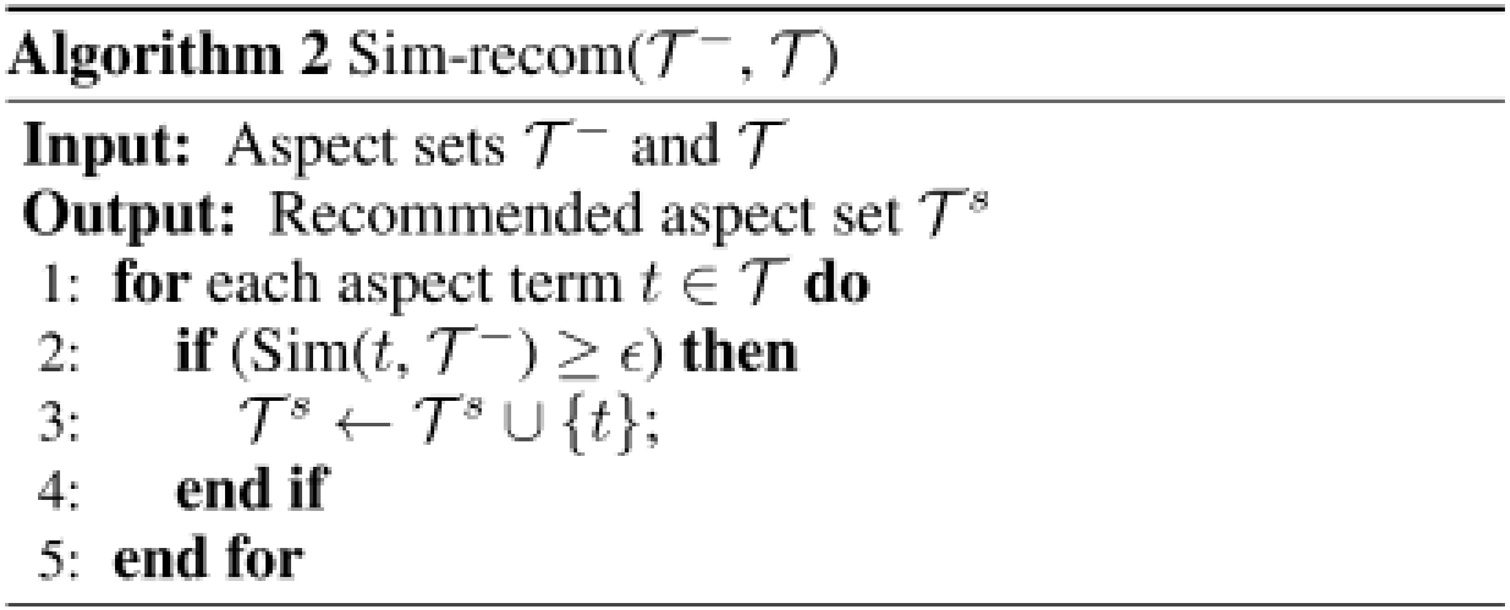
Step 2: Recommendation

- Recommend more aspects using T^{-} as the base to improve the recall. To ensure recommendation quality, AER requires
  - Aspects must be from $T = T^{+} - T^{-}$.
- Two forms of recommendation
  - similarity-based (Sim-recom) and
  - association-based (AR-recom).

Similarity-based Recommendation

- Solve the problem of missing synonymous aspects.
  - e.g., we can recommend “photo” and “image” through “picture” as they are similar in meaning.
- Employ word vectors trained from a large corpus of 5.8 million reviews for similarity comparison.
  - But can also be trained using past data

Algorithm Sim-recom



Algorithm 2 Sim-recom($\mathcal{T}^-$, $\mathcal{T}$)

```
Input: Aspect sets $\mathcal{T}^-$ and $\mathcal{T}$
Output: Recommended aspect set $\mathcal{T}^s$
1: for each aspect term $t \in \mathcal{T}$ do
2:     if (Sim($t$, $\mathcal{T}^-$) $\geq \epsilon$) then
3:         $\mathcal{T}^s \leftarrow \mathcal{T}^s \cup \{t\}$;
4:     end if
5: end for
```

- For each term $t \in T$, if the similarity between t and any term in T^- is at least ϵ, then recommend t as an aspect

Association-based Recommendation

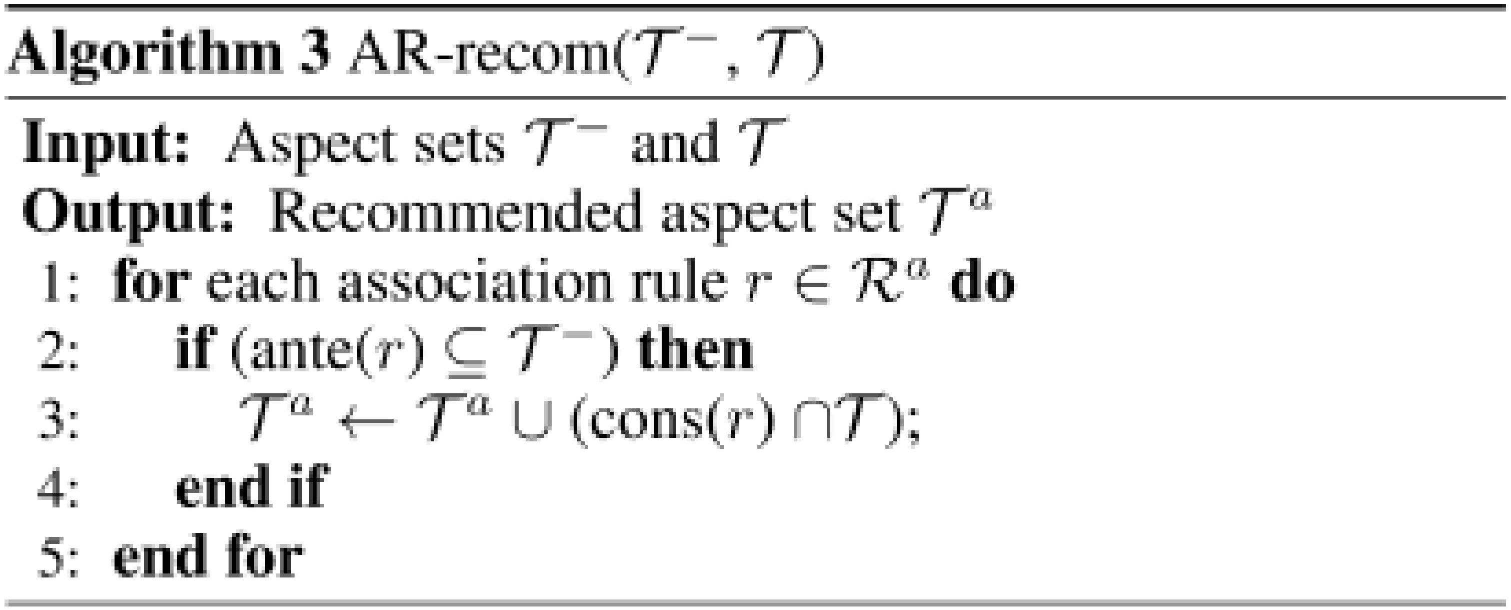
- It aims to solve the problem of missing correlated or co-occurring aspects.
  - e.g., we can recommend "battery" through "picture" as they are highly related -- pictures are taken by digital devices which need batteries.
- To mine aspect associations,
  - apply association rule mining to aspects extracted from reviews of previous products/domains.

Association Rule Generation

- The set of aspects extracted from each domain in the past forms a transaction in *DB*.
- Apply an association rule mining algorithm to *DB* to generate a set of rules.
  - An association rule in could be:

- antecedent $\boxed{\text{picture, display}} \rightarrow \boxed{\text{video, purchase}}$ consequent

Algorithm AR-recom



Algorithm 3 AR-recom($\mathcal{T}^-$, $\mathcal{T}$)

```
Input:  Aspect sets $\mathcal{T}^-$ and $\mathcal{T}$
Output: Recommended aspect set $\mathcal{T}^a$
1: for each association rule $r \in \mathcal{R}^a$ do
2:     if (ante($r$) $\subseteq \mathcal{T}^-$) then
3:         $\mathcal{T}^a \leftarrow \mathcal{T}^a \cup$ (cons($r$) $\cap \mathcal{T}$);
4:     end if
5: end for
```

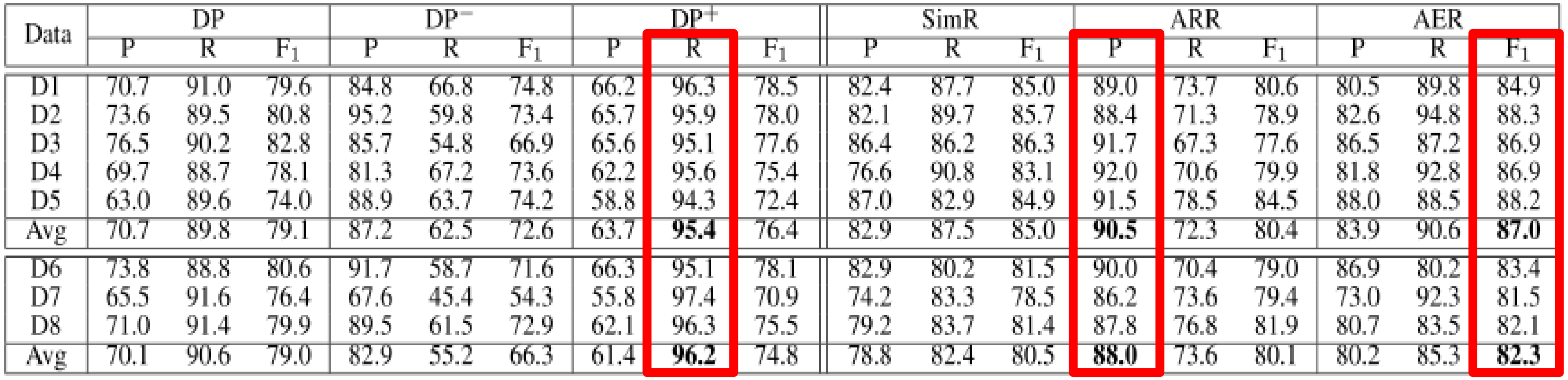
- For each association rule *r* ∈ R^a,
  - if ante(*r*) is a subset of T^-, then recommend the terms in cons(r) ∩ T as aspects.

Evaluation

- Compared Approaches
  - SimR uses only aspect similarities for recommendation.
  - ARR uses only aspect associations for recommendation.
  - AER uses both aspect similarities and associations for recommendation.

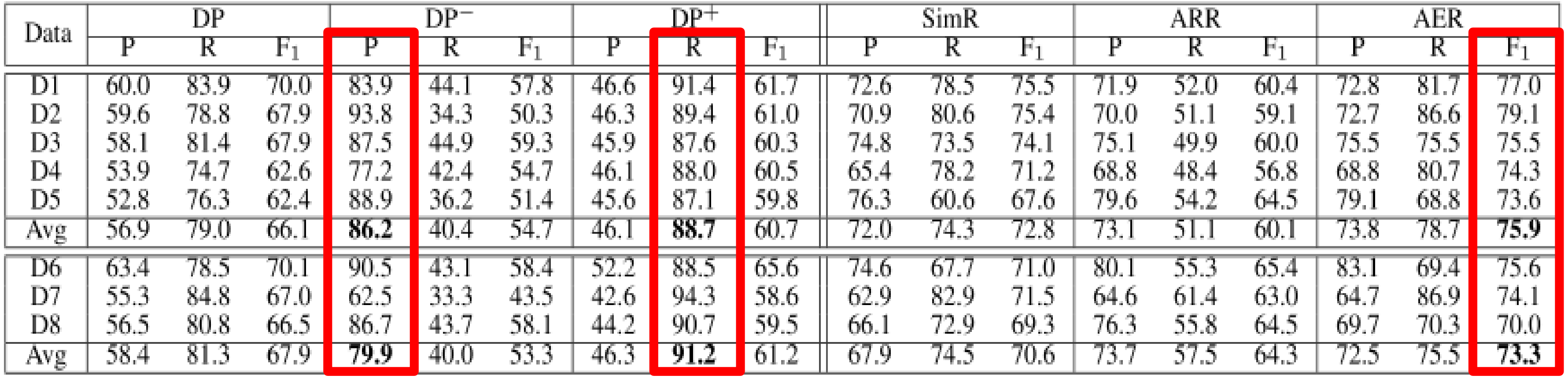
Experimental Results (Overall results)

Table 2: Precision, Recall and F$_1$-score of DP, DP$^-$, DP$^+$, SimR, ARR and AER evaluated based on multiple aspect term occurrences.



Data	DP			DP$^-$			DP$^+$			SimR			ARR			AER		
	P	R	F$_1$	P	R	F$_1$	P	R	F$_1$	P	R	F$_1$	P	R	F$_1$	P	R	F$_1$
D1	70.7	91.0	79.6	84.8	66.8	74.8	66.2	96.3	78.5	82.4	87.7	85.0	89.0	73.7	80.6	80.5	89.8	84.9
D2	73.6	89.5	80.8	95.2	59.8	73.4	65.7	95.9	78.0	82.1	89.7	85.7	88.4	71.3	78.9	82.6	94.8	88.3
D3	76.5	90.2	82.8	85.7	54.8	66.9	65.6	95.1	77.6	86.4	86.2	86.3	91.7	67.3	77.6	86.5	87.2	86.9
D4	69.7	88.7	78.1	81.3	67.2	73.6	62.2	95.6	75.4	76.6	90.8	83.1	92.0	70.6	79.9	81.8	92.8	86.9
D5	63.0	89.6	74.0	88.9	63.7	74.2	58.8	94.3	72.4	87.0	82.9	84.9	91.5	78.5	84.5	88.0	88.5	88.2
Avg	70.7	89.8	79.1	87.2	62.5	72.6	63.7	**95.4**	76.4	82.9	87.5	85.0	**90.5**	72.3	80.4	83.9	90.6	**87.0**
D6	73.8	88.8	80.6	91.7	58.7	71.6	66.3	95.1	78.1	82.9	80.2	81.5	90.0	70.4	79.0	86.9	80.2	83.4
D7	65.5	91.6	76.4	67.6	45.4	54.3	55.8	97.4	70.9	74.2	83.3	78.5	86.2	73.6	79.4	73.0	92.3	81.5
D8	71.0	91.4	79.9	89.5	61.5	72.9	62.1	96.3	75.5	79.2	83.7	81.4	87.8	76.8	81.9	80.7	83.5	82.1
Avg	70.1	90.6	79.0	82.9	55.2	66.3	61.4	**96.2**	74.8	78.8	82.4	80.5	**88.0**	73.6	80.1	80.2	85.3	**82.3**

Table 3: Precision, Recall and F$_1$-score of DP, DP$^-$, DP$^+$, SimR, ARR, and AER evaluated based on distinct aspect terms.



Data	DP			DP$^-$			DP$^+$			SimR			ARR			AER		
	P	R	F$_1$	P	R	F$_1$	P	R	F$_1$	P	R	F$_1$	P	R	F$_1$	P	R	F$_1$
D1	60.0	83.9	70.0	83.9	44.1	57.8	46.6	91.4	61.7	72.6	78.5	75.5	71.9	52.0	60.4	72.8	81.7	77.0
D2	59.6	78.8	67.9	93.8	34.3	50.3	46.3	89.4	61.0	70.9	80.6	75.4	70.0	51.1	59.1	72.7	86.6	79.1
D3	58.1	81.4	67.9	87.5	44.9	59.3	45.9	87.6	60.3	74.8	73.5	74.1	75.1	49.9	60.0	75.5	75.5	75.5
D4	53.9	74.7	62.6	77.2	42.4	54.7	46.1	88.0	60.5	65.4	78.2	71.2	68.8	48.4	56.8	68.8	80.7	74.3
D5	52.8	76.3	62.4	88.9	36.2	51.4	45.6	87.1	59.8	76.3	60.6	67.6	79.6	54.2	64.5	79.1	68.8	73.6
Avg	56.9	79.0	66.1	**86.2**	40.4	54.7	46.1	**88.7**	60.7	72.0	74.3	72.8	73.1	51.1	60.1	73.8	78.7	**75.9**
D6	63.4	78.5	70.1	90.5	43.1	58.4	52.2	88.5	65.6	74.6	67.7	71.0	80.1	55.3	65.4	83.1	69.4	75.6
D7	55.3	84.8	67.0	62.5	33.3	43.5	42.6	94.3	58.6	62.9	82.9	71.5	64.6	61.4	63.0	64.7	86.9	74.1
D8	56.5	80.8	66.5	86.7	43.7	58.1	44.2	90.7	59.5	66.1	72.9	69.3	76.3	55.8	64.5	69.7	70.3	70.0
Avg	58.4	81.3	67.9	**79.9**	40.0	53.3	46.3	**91.2**	61.2	67.9	74.5	70.6	73.7	57.5	64.3	72.5	75.5	**73.3**

LML Components of AER

- **KB**
  - Word vectors
  - Aspects extracted from previous tasks
  - Learned association rules
- **KBL**
  - DP + Two forms of recommendations

Lifelong Relaxation Labeling
(Shu et al., 2016)

- Relaxation Labeling (RL) is an unsupervised graph-based label propagation algorithm.
  - Unsupervised classification

- It is augmented with lifelong learning (*Lifelong-RL*) to exploit past knowledge learned from previous tasks.

Relaxation Labeling (RL)

- Graph consists of nodes and edges.
  - Node: object to be labeled
  - Edge: a binary relationship between two nodes.
- Each node n_i in the graph is associated with a multinomial distribution $P(L(n_i))$
  - $L(n_i)$ is the label of n_i on a label set Y .
- Each edge has two conditional distributions:
  - $P(L(n_i) \mid L(n_j))$ and $P(L(n_j) \mid L(n_i))$

Relaxation Labeling (contd)

- Neighbors *Ne*(n_i) of a node n_i are associated with a weight distribution w(n_j | n_i)

$$\sum_{n_j \in Ne(n_i)} w(n_j | n_i) = 1.$$

- RL iteratively updates the label distribution of each node until convergence.
- Initially, we have $P^0(L(n_i))$. Let $\Delta P^{r+1}(L(n_i))$ be the change of $P(L(n_i))$ at iteration r + 1.

$$\Delta P^{r+1}(L(n_i)) = \sum_{n_j \in Ne(n_i)} \left(w(n_j|n_i) \times \sum_{y \in Y} P(L(n_i)|L(n_j) = y) \times P^r(L(n_j) = y) \right)$$

Relaxation Labeling (contd)

- Updated label distribution for iteration *r* + 1 is computed as follows:

$$P^{r+1}(L(n_i)) = \frac{P^r(L(n_i)) \times (1 + \Delta P^{r+1}(L(n_i)))}{\sum_{y \in Y} P^r(L(n_i) = y) \times (1 + \Delta P^{r+1}(L(n_i) = y))}$$

- The final label of node n_i is its highest probable label.

$$L(n_i) = \underset{y \in Y}{\operatorname{argmax}}(P(L(n_i) = y))$$

What past knowledge can be used?

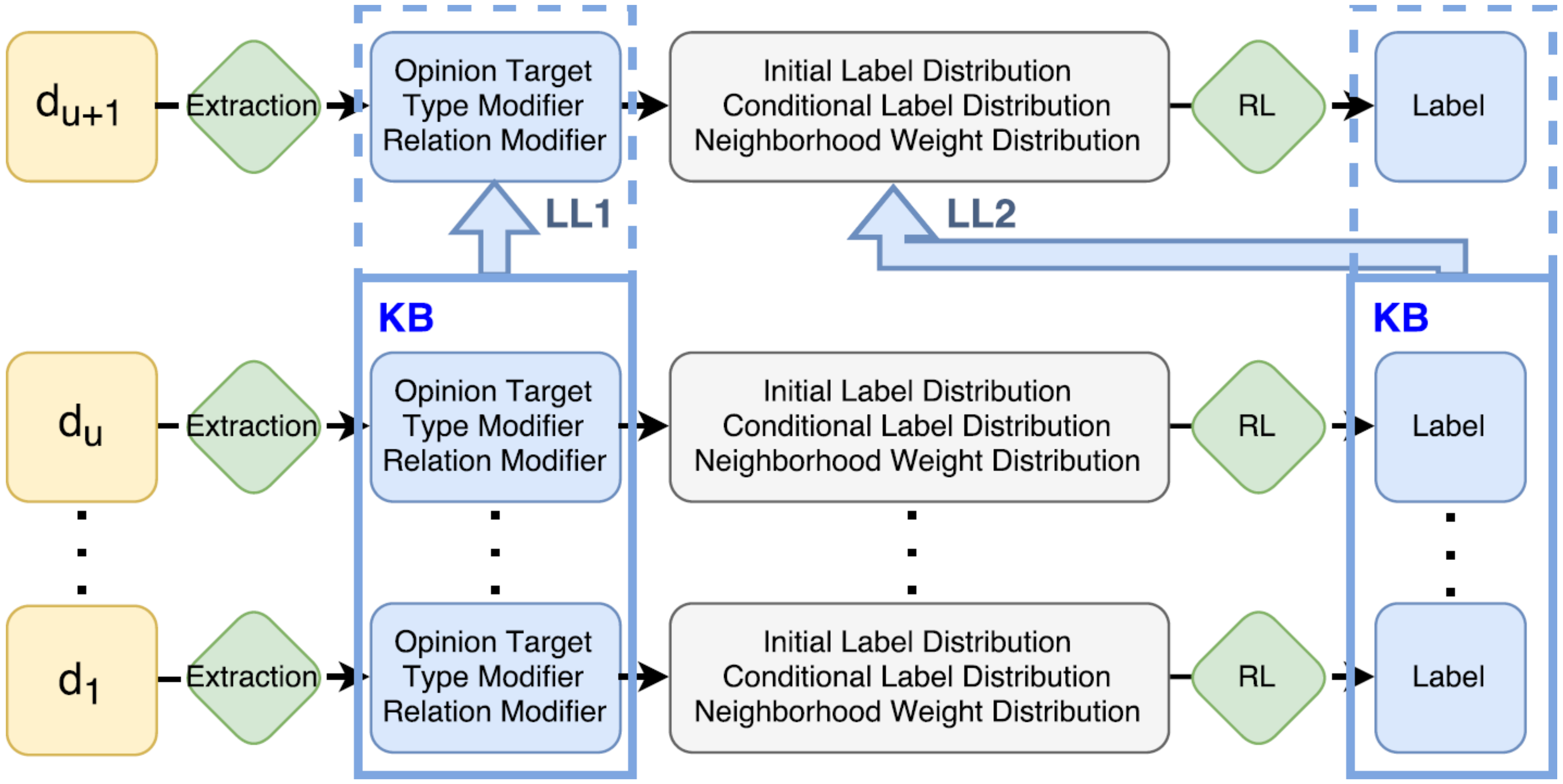
Lifelong-RL uses two forms of knowledge

- Prior edges: graphs are usually not given or fixed but are built based on text data.
  - If the data is small, many edges may be missing
  - But such edges may existing in the graphs of some previous tasks
- Prior labels: initial $P^0(L(n_i))$ is quite hard to set, but results from previous tasks can be used to set it more accurately.

Lifelong-RL for a SA task
(Shu et al., 2016)

- Problem: opinion target labeling
  - Separating entities and aspects
  - Example: "Although the engine is slightly weak, this car is great."
    - Entity: car; Aspect: engine
  - Target extract often cannot distinguish the two
- Suitable for lifelong learning
  - Shared edges, and shared entities and aspects and their labels across domains

Lifelong-RL architecture



d_{u+1}
Extraction
Opinion Target Type Modifier Relation Modifier
Initial Label Distribution Conditional Label Distribution Neighborhood Weight Distribution
RL
Label
LL1
LL2
KB
d_u
Extraction
Opinion Target Type Modifier Relation Modifier
Initial Label Distribution Conditional Label Distribution Neighborhood Weight Distribution
RL
Label
KB
d_1
Extraction
Opinion Target Type Modifier Relation Modifier
Initial Label Distribution Conditional Label Distribution Neighborhood Weight Distribution
RL
Label

- Relation modifiers indicate edges.
- Type modifiers and prior labels help set $P^0(L(n_i))$

LML Components of Lifelong-RL

- **KB**
  - Edges from previous tasks
  - Node labels from previous tasks
- **KBL**
  - Relaxation labeling

Outline

Never Ending Language Learner
(Carlson et al., 2010; Mitchell et al., 2015)

- NELL: Never Ending Language Learner
- Perhaps the only live LML system
  - it has been reading the Web to extract certain types of information (or knowledge)
  - 24/7 since January 2010.
- NELL has accumulated millions of facts with attached confidence weights
  - called beliefs,

Input to NELL

- An ontology defining a set of target categories and relations to be learned,
  - a handful of seed training examples for each, and
  - a set of coupling constraints about categories and relations (Person & Sport are mutually exclusive).
- Webpages crawled from the Web
- Interactions with human trainers to correct some mistakes made by NELL

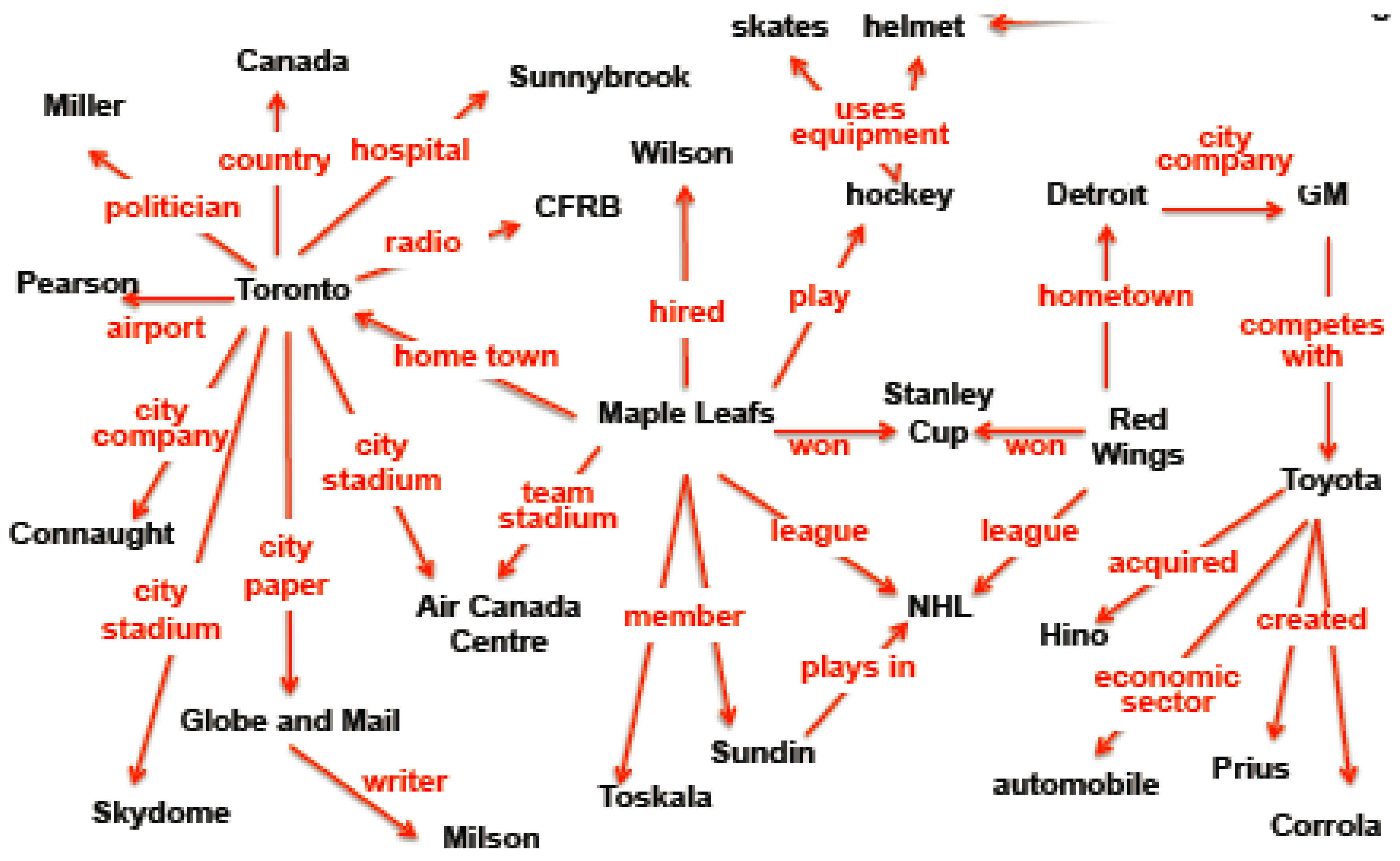
Goal of NELL

- Reading - extract facts from webpages to populate the initial ontology
  - *category* of a noun or noun phrase, e.g., Los Angeles is a *city*
  - *relations* of a pair of noun phrases
    - hasMajor(Stanford, Computer Science)
- Learn to perform the above extraction tasks better each day.

Knowledge Base

- Instance of category: which noun phrases refer to which specified semantic categories
  - For example, *Los Angeles* is in the category *city*.
- Relationship of a pair of noun phrases, e.g., given a name of an organization and the location, check if
  - *hasOfficesIn(<organization>, <location>)*.
- …

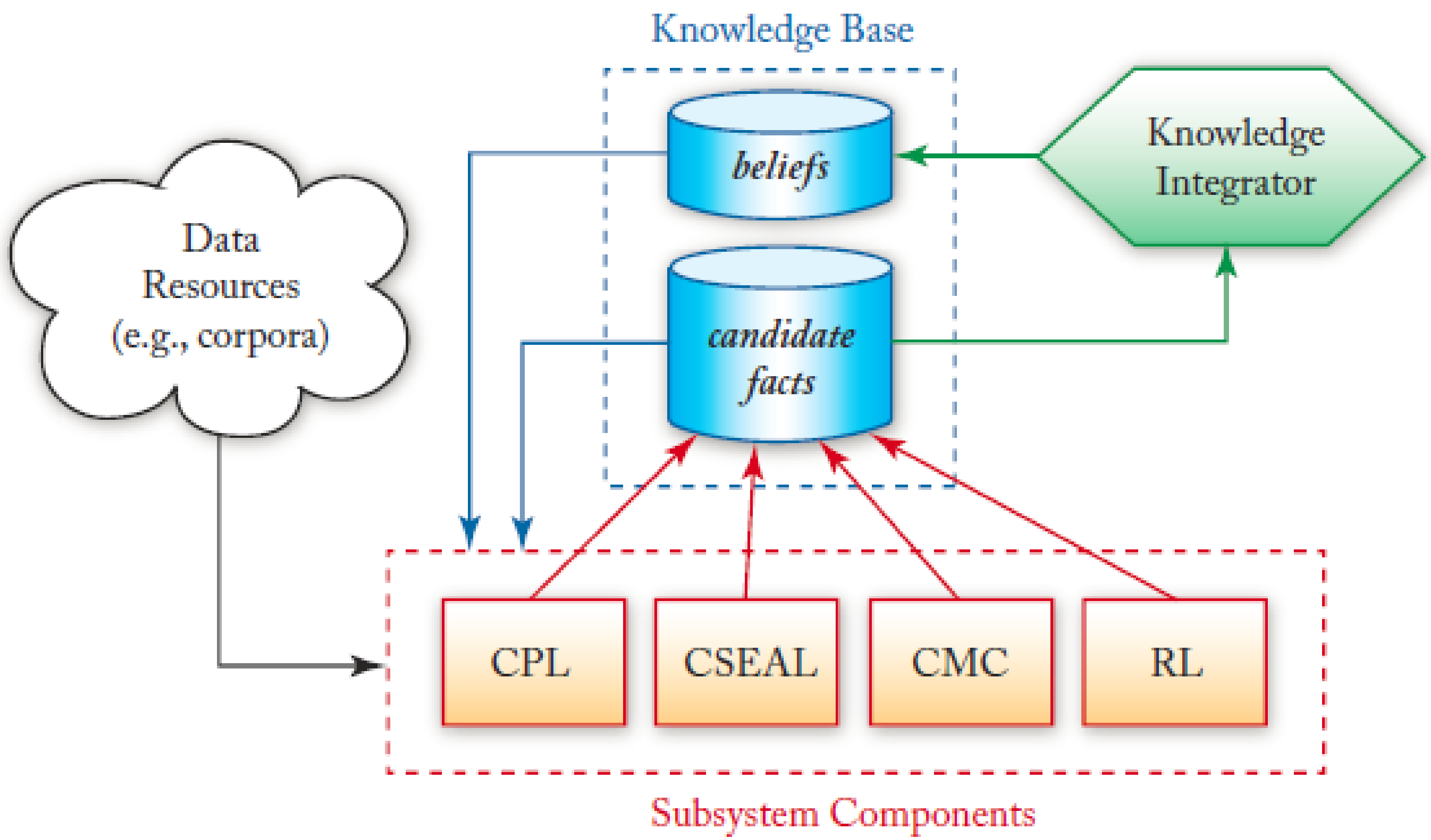
NELL Knowledge Fragment



Semi-supervised Learning

- Training examples
  - human-labeled instances in NELL's ontology
  - labeled examples contributed over time through NELL's crowdsourcing website,
  - a set of NELL self-labeled training examples corresponding to NELL's current knowledge base,
  - a large amount of unlabeled Web text.
- 2nd and 3rd sets of the training examples propel NELL's lifelong learning

NELL Architecture



Coupled Pattern Learner (CPL)

- CPL: extractors extracting both category and relation instances using contextual patterns.
  - Examples
    - Category pattern: “mayor of X” and
    - Relation pattern: “X plays for Y”

- Such patterns can also be learned.
- Mutual exclusion & type-checking constraints
  - filter candidate facts to ensure quality

Coupled SEAL (CSEAL)

- CSEAL: an extraction and learning system that extracts facts from semi-structured webpages using wrapper induction
- Based on set expansion or PU learning
  - Wrapper: html strings specifying the left and right context of an entity.
- Mutual exclusion & type-checking constraints:
  - filtered out likely errors

Coupled Morphological Classifier (CMC)

- CMC: a set of binary classifiers, one for each category,
  - To classify whether the extracted candidate facts/beliefs by other subsystems are indeed of their respective categories.
- Positive training examples:
  - beliefs in the current knowledge base.
- Negative training examples
  - beliefs satisfying mutual exclusion constraints

Rule Learner (RL)

- Its goal is to learn probabilistic Horn clauses
  - to use them to infer new relations from the existing relations in the knowledge base.
- Reasoning capability
  - represents an important advance of NELL
  - It does not exist in most current LML systems.

Coupling Constraints in NELL

- *Multi-view co-training coupling constraint*
  - Agreement: the same category or relation learned from different data sources, or *views*.
- *Subset/superset coupling constraint*
  - When a new category is added to NELL's ontology, its parents (supersets) are also specified.
- *Horn clause coupling constraint*
  - E.g., "X living in Chicago" and "Chicago being a city in U.S." $\rightarrow$ "X lives in U.S."

LML Components of NELL

- **KB**
  - Extracted facts and relations
  - Reasoning capability
- **KBL**
  - All the learners and extractors

ALICE: Lifelong Info. Extraction
(Banko and Etzioni 2007)

- Similar to NELL, Alice performs similar continuous/lifelong information extraction of
  - concepts and their instances,
  - attributes of concepts, and
  - various relationships among them.
  - The knowledge is iteratively updated

- Extraction based on syntactic patterns like
  - (<x> *such as* <y>) and (*fruit such as* <y>),

Lifelong Strategy

- The output knowledge upon completion of a learning task is used in two ways:
    - to update the current domain theory (i.e., domain concept hierarchy and abstraction) and
    - to generate subsequent learning tasks.
- This behavior makes Alice a lifelong agent
    - i.e., Alice uses the knowledge acquired during the *nth* task to specify its future learning agenda.

Outline

- A motivating example
- What is lifelong machine learning?
- Related learning paradigms
- Lifelong supervised learning
- Lifelong unsupervised learning
- Semi-supervised never-ending learning
- Lifelong reinforcement learning
- Summary

Reinforcement Learning

- An agent learns actions through trial and error interactions with a dynamic environment
- The agent gets reward/penalty after each action
- Each action changes the state of the environment
- The agent usually needs a large amount of quality experience (cost is high)

Lifelong Reinforcement Learning (LRL)

- Utilize the experience accumulated from other tasks
- Learn faster in a new task with fewer interactions

Example LRL Works

- Lifelong robot learning with knowledge memorization (Thrun and Mitchell 1995)
- Treating each environment as a task (Tanaka and Yamamura 1997)
- Hierarchical Bayesian approach (Wilson et al., 2007)
- Policy Gradient Efficient Lifelong Learning Algorithm (PG-ELLA) (Bou Ammar et al., 2014)

Outline

- A motivating example
- What is lifelong machine learning?
- Related learning paradigms
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Summary

- This tutorial gave an introduction to LML with a focus on NLP applications
- Existing LML research is still in its infancy
  - Understanding of LML is very limited
  - Current research mainly focuses on
    - Only one type of tasks in a system
- LML needs big data – to learn a large amount of reliable knowledge of different types.
  - The more we know the better we can learn

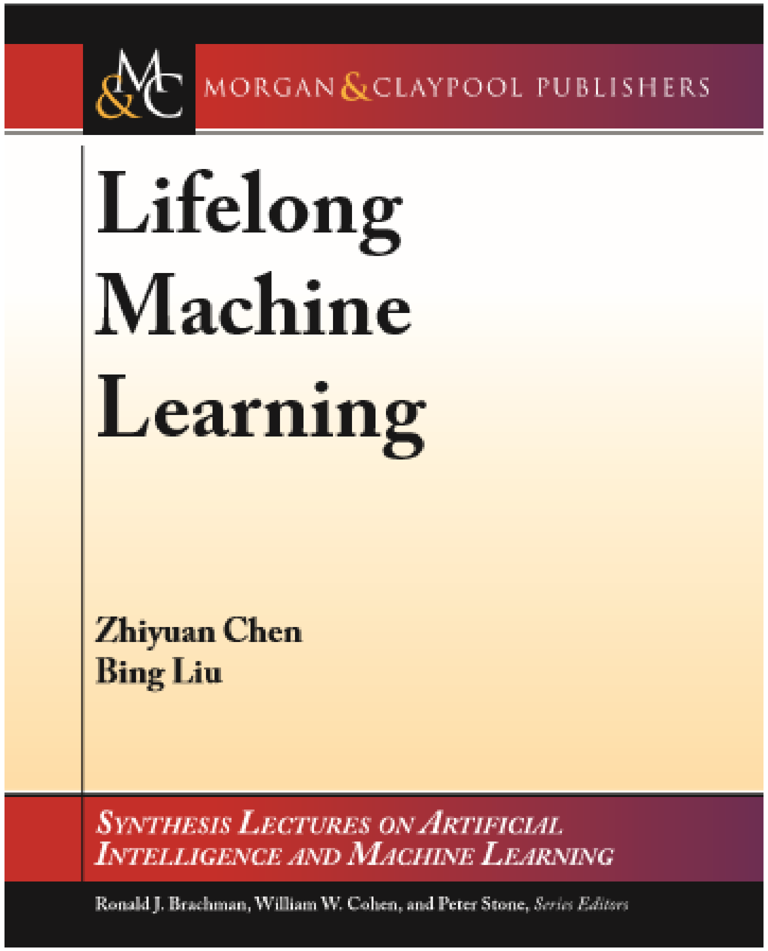
Summary
(Chen and Liu 2016-book)

There are many challenges for LML, e.g.,

- Correctness of knowledge
- Applicability of knowledge
- Knowledge representation and reasoning
- Learn with tasks of multiple types
- Self-motivated learning
- Compositional learning
- Learning in interaction with humans & systems

Coming Soon (Nov 2016)
(Chen and Liu 2016-book)

- Introduction
- Related Learning Paradigms
- Lifelong Supervised Learning
- Lifelong Unsupervised Learning
- Lifelong Semi-supervised Learning for Information Extraction
- Lifelong Reinforcement Learning
- Conclusion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Lifelong Machine Learning

Zhiyuan Chen
Bing Liu

SYNTHESIS LECTURES ON ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Ronald J. Brachman, William W. Cohen, and Peter Stone, *Series Editors*

Thank You!

Q & A

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