Part V: Other Text Mining Methods

KDD 2023 Tutorial

Pretrained Language Representations for Text Understanding: A Weakly-Supervised Perspective

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Tutorial Website:

Outline

- Aspect-based Sentiment Analysis
  - Weakly-Supervised Aspect-Based Sentiment Analysis via Joint Aspect-Sentiment Topic Embedding [EMNLP’20]
- Text Summarization
- Taxonomy Construction
- Summary & Future Directions

Aspect-based Sentiment Analysis

- Task definition
  - Given an opinionated document about a target entity (e.g., a laptop, a restaurant or a hotel), the goal is to identify the opinion tuple of <aspect, sentiment> of the document

S1: Mermaid Inn is an overall good restaurant with really good seafood. (good, food)
S2: Eye-pleasing with semi-private booths, place for a date. (good, ambience)
S3: It's to die for! (good, food)

- Most previous studies deal with the tasks of aspect extraction and sentiment polarity classification individually or sequentially
- Other methods jointly solve these two sub-tasks by first separating target words from opinion words and then learning joint topic distributions over words

Motivation

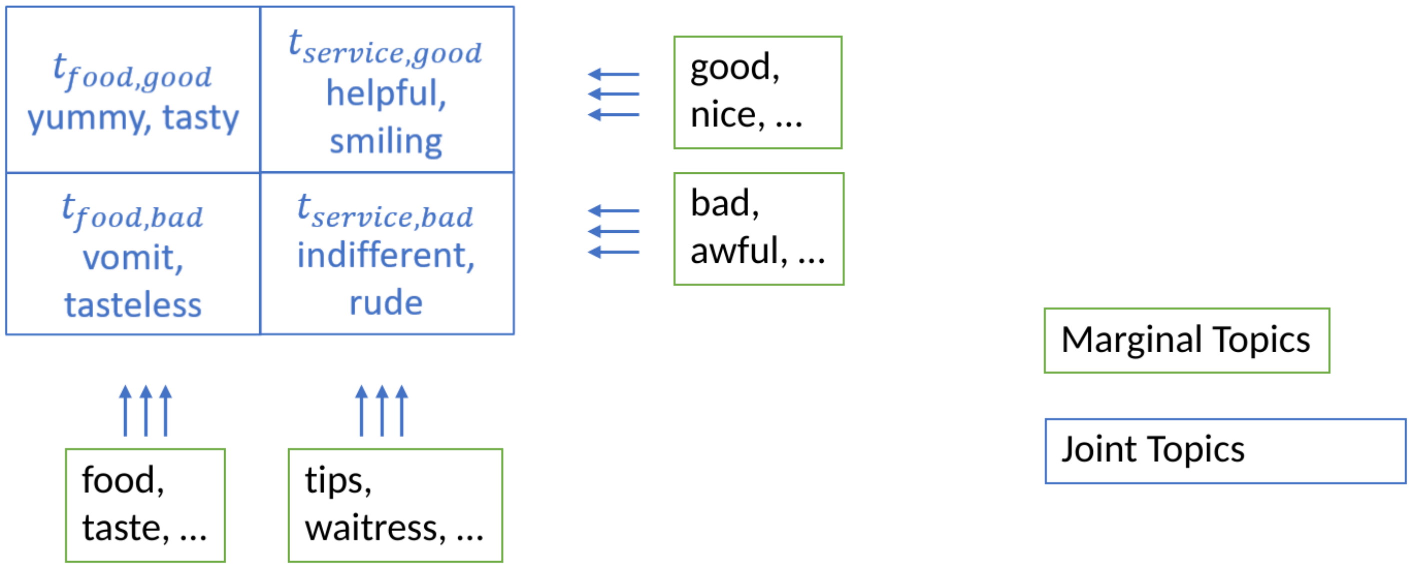
- Sample Reviews

  S1: Mermaid Inn is an overall good restaurant with really good seafood. (good, food)
  S2: Eye-pleasing with semi-private booths, place for a date. (good, ambience)
  S3: It's to die for! (good, food)

- Pure aspect words are in red, and general opinion words are in blue
- Words implying both aspects and opinions (which we define as **joint topics**) are underlined and in purple

- S1: general aspect, opinion words
- S2 and S3: Target is not explicitly addressed. Fine-grained words are used to imply both aspect and polarity

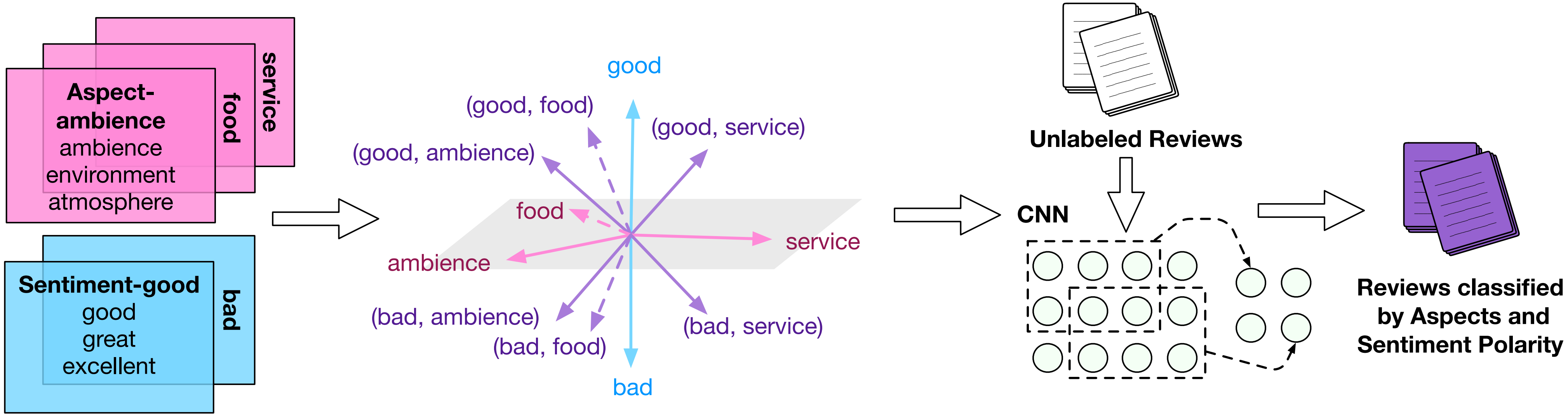
Joint "Sentiment-Aspect" topic



- If the semantics of each joint topic of <sentiment, aspect> can be automatically captured, machines will be able to identify representative terms of the joint topics such as "semi-private" for <good, ambience>
- Thus, it will benefit both aspect extraction and sentiment classification
- Our general idea is to learn and regularize the joint topics in the embedding space to enhance both tasks

Our Framework

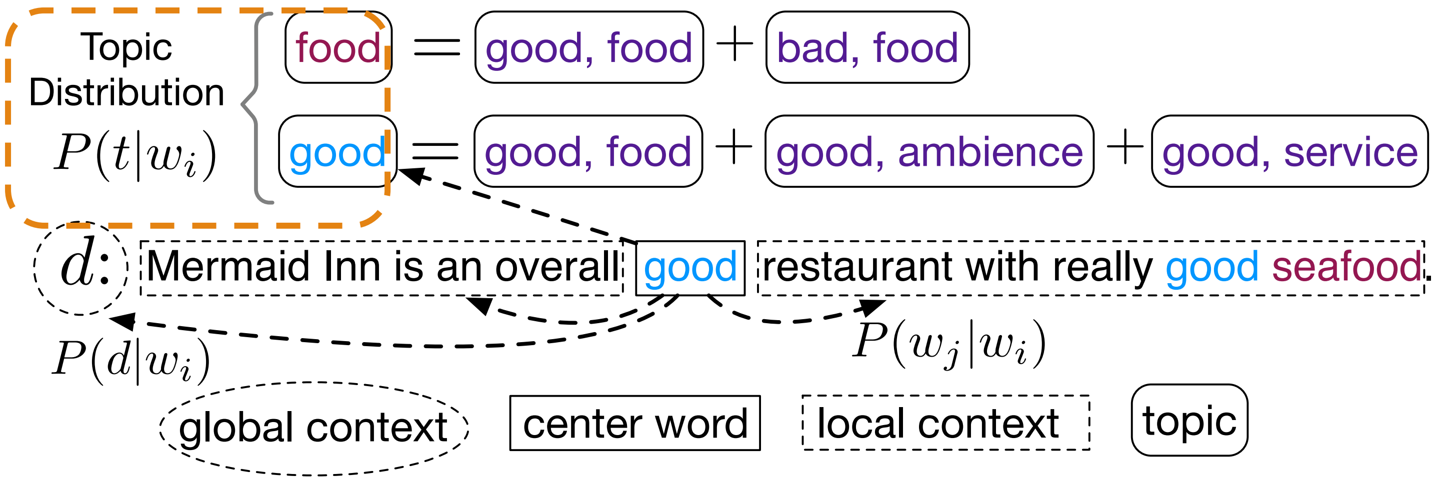
- Weakly-Supervised Aspect-Based Sentiment Analysis via Joint Aspect-Sentiment Topic Embedding [EMNLP'20]



- Step 1: Leverage the in-domain training corpus and user-given keywords to learn joint topic representation in the word embedding space

- Step 2: Embedding-based prediction on unlabeled data are then leveraged by neural models for pre-training and self-training

Joint-Topic Representation Learning

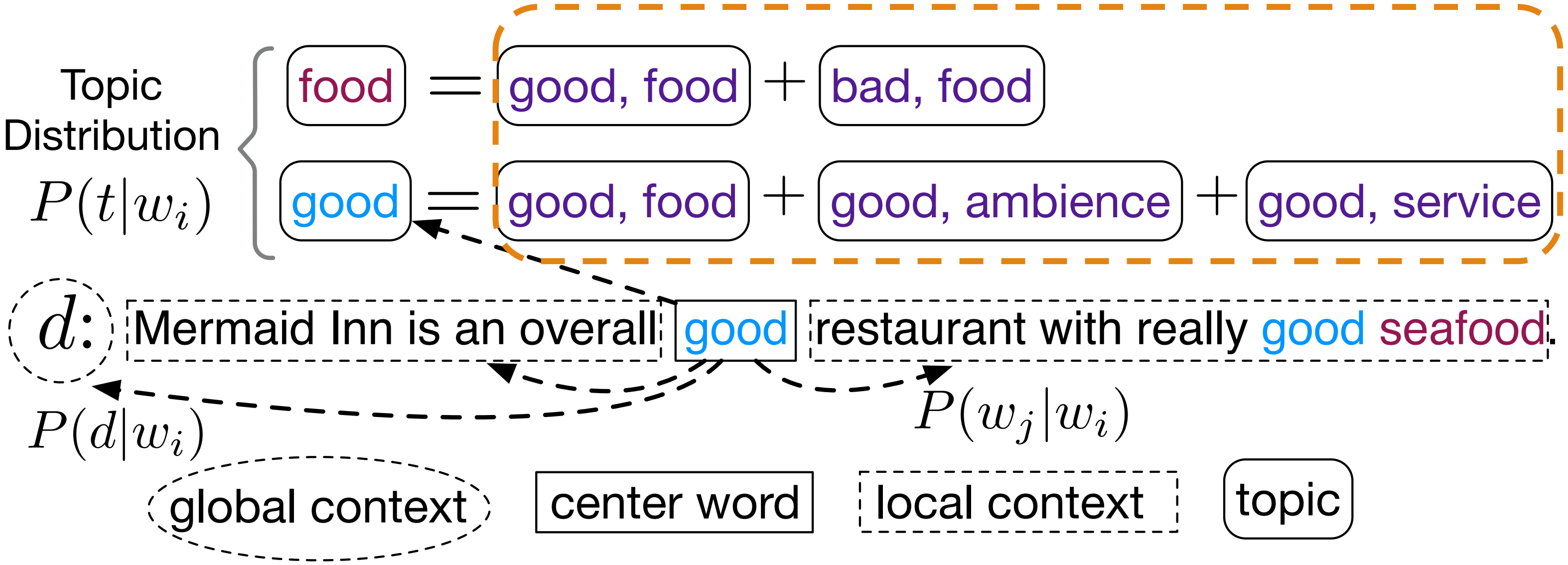


- Regularizing Pure Aspect/Sentiment Topics. We regularize the aspect topic embeddings t_a and sentiment topic embeddings t_s so that different topics are pushed apart
  - Marginal topic regularization:

$$\mathcal{L}_{reg}^{A} = -\sum_{a \in A} \sum_{w_i \in l_a} \log P(t_a|w_i) \qquad \mathcal{L}_{reg}^{S} = -\sum_{s \in S} \sum_{w_i \in l_s} \log P(t_s|w_i) \qquad P(t|w_i) \propto \exp(\boldsymbol{u}_i^\top \boldsymbol{t})$$

  - Words can be "classified" into topics based on embedding similarity
  - User-provided keywords are used for initialization, and more keywords are expanded based on cosine similarity in each embedding training epoch

Joint-Topic Representation Learning



- Regularizing Joint <Sentiment, Aspect> Topics
- We connect the learning of joint topic embeddings with pure aspect/sentiment topics by exploring the relationship between marginal distribution and joint distribution

$$P(t_a|w_i) = \sum_{s \in S} P\left(t_{\langle s,a \rangle} \middle| w_i\right) \qquad P(t_s|w_i) = \sum_{a \in A} P\left(t_{\langle s,a \rangle} \middle| w_i\right)$$

  - To form the joint topic regularization objective, we can replace the probability term in the pure aspect/sentiment regularization objective with the sum of joint probability

Representative Terms for Joint Topics

- To evaluate the quality of the joint topic representation, we retrieve their representative terms by ranking the embedding cosine similarity between words and each joint topic vector

	Ambience	Service	Food	Support	Keyboard	Battery
Good	cozy, intimate, comfortable, loungy, great music	professional, polite, knowledgable, informative, helpful	huge portion, flavourful, super fresh, husband loves, authentic italian	accidental damage protection, accidental damage warranty, generous, guarantee, commitment	tactile feedback, tactile feel, classic, nicely spaced, chiclet style	lasts long, charges quickly, high performance, lasting, great power
Bad	cramped, unbearable, uncomfortable, dreary, chaos	inattentive, ignoring, extremely rude, condescending, inexperienced	microwaved, flavorless, vomit, frozen food, undercooked	completely useless, denied, refused, blamed, apologize	large hands, shallow, cramped, wrong key, typos	completely dead, drained, discharge, unplugged, torture

- Representative terms are not restricted to be adjectives, such as “vomit” in (bad, food)and “commitment” in (good, support)
- “Cramped” appears in both (bad, ambience) in restaurant domain and (bad, keyboard) in laptop domain

Quantitative Evaluation

- Aspect Extraction

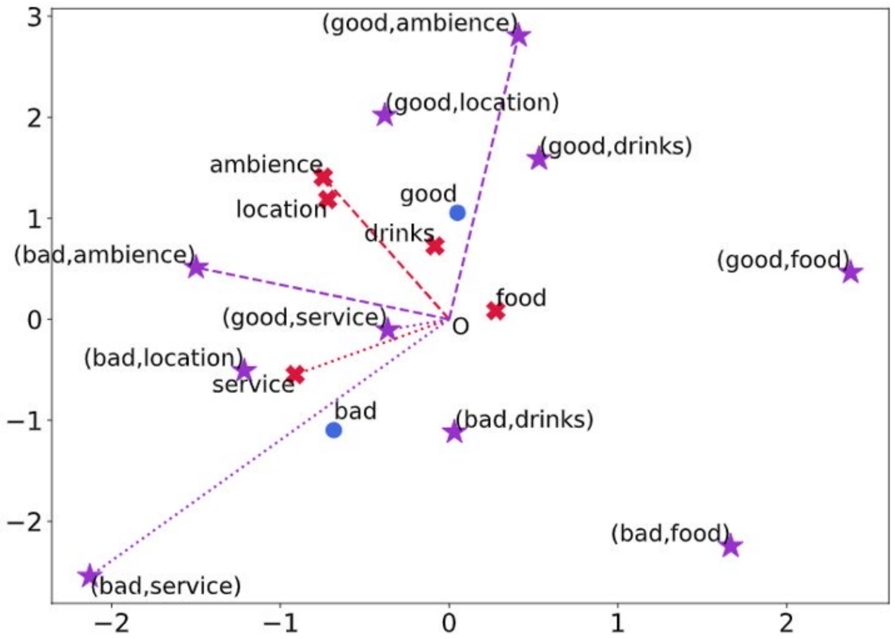
Methods	Restaurant				Laptop			
	Accuracy	Precision	Recall	macro-F1	Accuracy	Precision	Recall	macro-F1
CosSim	61.43	50.12	50.26	42.31	53.84	58.79	54.64	52.18
ABAE(He et al., 2017)	67.34	46.63	50.79	45.31	59.84	59.96	59.60	56.21
CAt(Tulkens and van Cranenburgh, 2020)	66.30	49.20	50.61	46.18	57.95	65.23	59.91	58.64
W2VLDA(García-Pablos et al., 2018)	70.75	58.82	57.44	51.40	64.94	67.78	65.79	63.44
BERT(Devlin et al., 2019)	72.98	58.20	**74.63**	55.72	67.52	68.26	67.29	65.45
JASen w/o joint	81.03	61.66	65.91	61.43	69.71	69.13	70.65	67.49
JASen w/o self train	82.90	63.15	72.51	64.94	70.36	68.77	70.91	68.79
JASen	**83.83**	**64.73**	72.95	**66.28**	**71.01**	**69.55**	**71.31**	**69.69**

- Sentiment Polarity Classification

Methods	Restaurant				Laptop			
	Accuracy	Precision	Recall	macro-F1	Accuracy	Precision	Recall	macro-F1
CosSim	70.14	74.72	61.26	59.89	68.73	69.91	68.95	68.41
W2VLDA	74.32	75.66	70.52	67.23	71.06	71.62	71.37	71.22
BERT	77.48	77.62	73.95	73.82	69.71	70.10	70.26	70.08
JASen w/o joint	78.07	80.60	72.40	73.71	72.31	72.34	72.25	72.26
JASen w/o self train	79.16	81.31	73.94	75.34	73.29	73.69	73.42	73.24
JASen	**81.96**	**82.85**	**78.11**	**79.44**	**74.59**	**74.69**	**74.65**	**74.59**

Joint Topic Representation Visualization

- Visualization of joint topics (purple stars), aspect topics (red crosses) and sentiment topics (blue dots) in the embedding space



- An interesting observation is that some aspect topics (e.g., ambience) lie approximately in the middle of their joint topics (“good, ambience” and “bad, ambience”), showing that our embedding learning objective understands the joint topics as decomposition of their “marginal” topics

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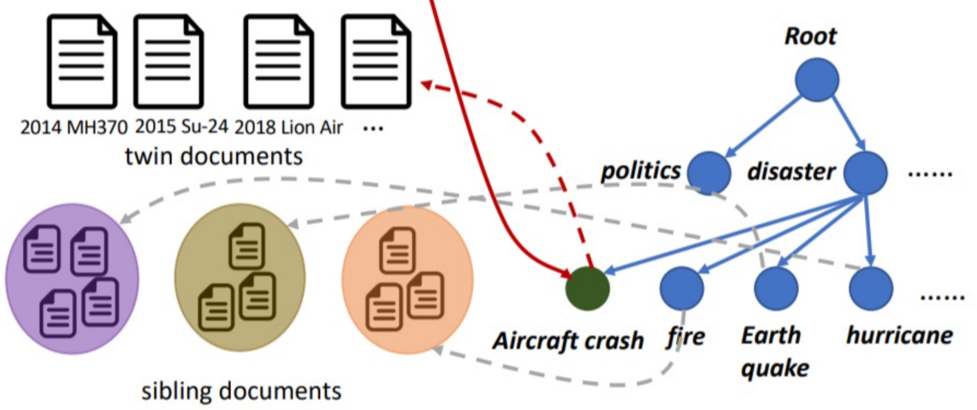
- Aspect-based Sentiment Analysis
- Text Summarization
  - SUMDocs: Extractive Summarization with Background Corpus [SDM'21]
  - Pre-trained Language Models for Summarization
    - Generating Representative Headlines for News Stories [WWW'20]
- Taxonomy Construction
- Summary & Future Directions

SUMDocS

- SUMDocS: Surrounding-aware Unsupervised Multi-Document Summarization (SDM'21)
- Leverage surrounding documents from the background corpus to obtain salient and discriminative extractive summarization

	Ethiopian Airlines Crash
d1	A doomed Ethiopian Airlines jet suffered from faulty readings by a key sensor, and pilots followed Boeing's recommended procedures when …
d2	Sunday's devasting plane crash in Ethiopia could renew safety questions about the newest version of Boeing's popular 737 airliner…
d3	Will the Boeing 737 MAX aircraft be cleared to fly again and, if so, will the traveling public be willing to fly on those airplanes? Obviously…



SUMDocS

- How to leverage the background corpus?
  - Twin documents: Documents belonging to the same category
  - Sibling documents: Documents belonging to orthogonal categories
- Consider three factors when generating extractive summarizations
  - Global novelty: Category-level frequent and discriminative phrases are likely to be salient phrases
  - Local consistency: Frequently co-occurred phrases should have similar salient score
  - Local saliency: Phrases that are salient in target documents but less salient in twin documents should be promoted

SUMDocS: Results

- Identified keywords and generated summaries on NLP corpus (left) and news corpus (right)

	SUMDocS
keywords	left-to-right, representation, mlm, context, bidirectional, state-of-the-art, left, feature-based
summary	Unlike left-to-right language model pre-training, the mlm objective enables the representation to fuse the left and the right context, which allows us to pretrain a deep bidirectional Transformer. both bert-base and bertlarge outperform all systems on all tasks by a substantial margin , obtaining 4.5% and 7.0% respective average accuracy improvement over the prior state-of-the-art. input/output representations to make bert handle a variety of down-stream tasks , our input representation is able to unambiguously represent both a single sentence and a pair of sentences in one token sequence.

	SUMDocS
keywords	79, abbott, god, february, patriot, statement, 13, appeared, natural, 2016
summary	breaking : u.s. supreme court justice antonin scalia found dead at west texas ranch at 79 cbs news (@cbsnews) february 13, 2016 cbs news reported scalia appeared to die of natural causes, according to a u.s. marshals service spokesperson. bush said scalia will be missed. scalia was nominated to the u.s. supreme court in 1986 by president ronald reagan. abbott said scalia set an example for citizens. scalia's legacy is enormous. greg abbott released a statement saturday afternoon, calling scalia a man of god, a patriot and...

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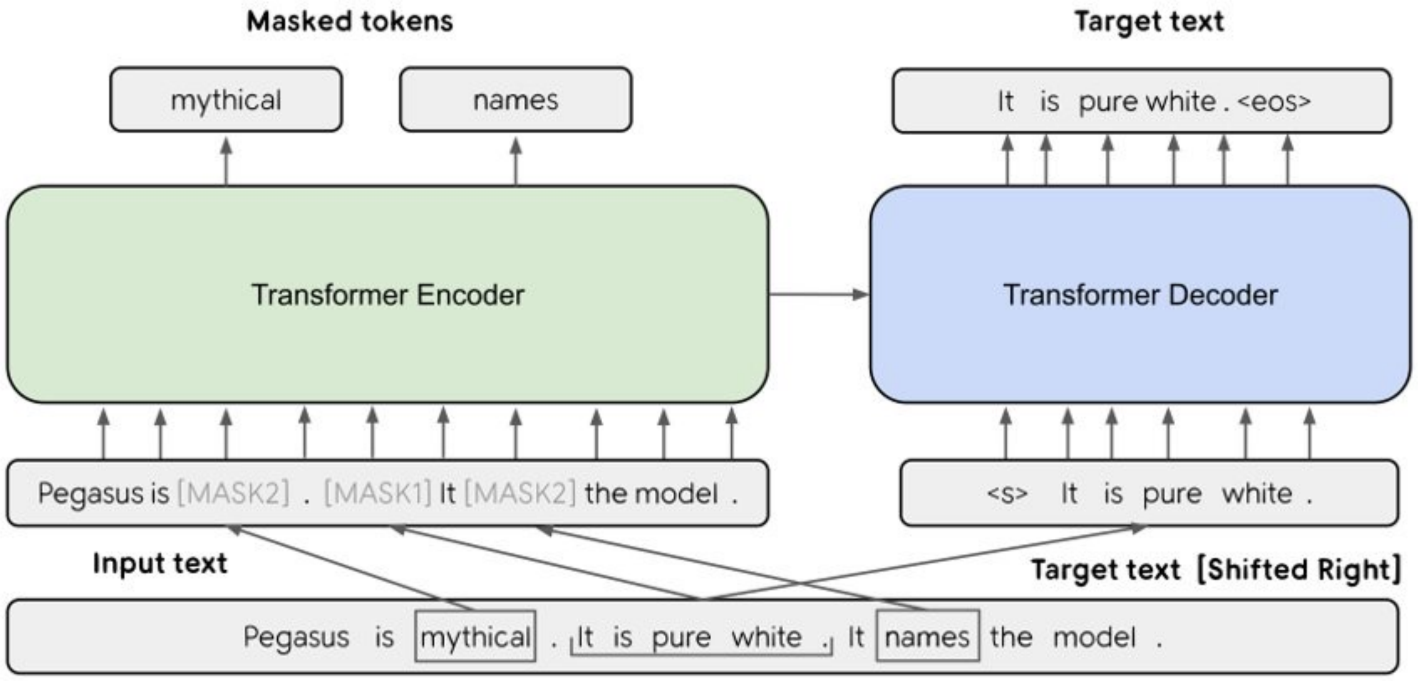
Self-supervised Pre-trained Summarization Model

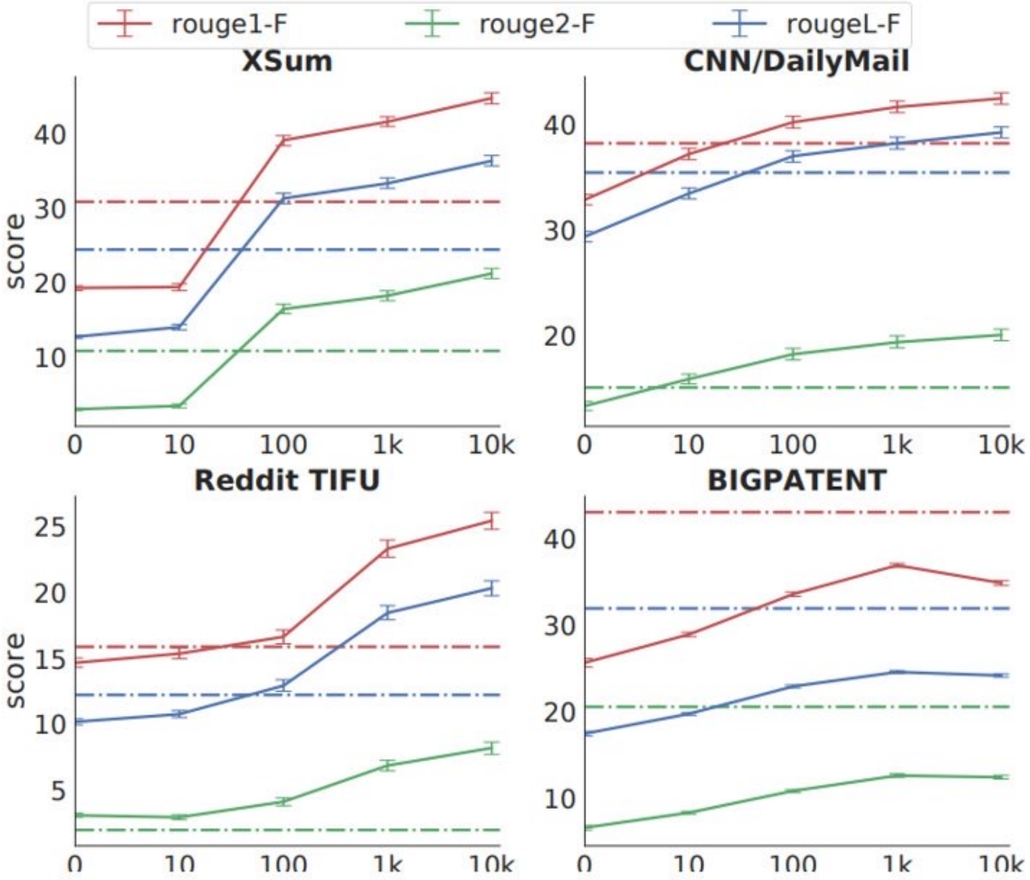
- PEGASUS: Pre-training with Extracted Gap-sentences for Abstractive Summarization (ICML'20)
- Transformer based encoder decoder framework
- Two Pre-training objectives:
- **Encoder**: masked language model
- **Decoder**: gap sentence generation
  - Choose important sentence by rouge score with remaining sentences in the document



Selected Sentence for Gap Sentence Generation

INVITATION ONLY We are very excited to be co-hosting a major drinks reception with our friends at Progress. This event will sell out, so make sure to register at the link above. Speakers include Rajesh Agrawal, the London Deputy Mayor for Business, Alison McGovern, the Chair of Progress, and Seema Malhotra MP. Huge thanks to the our friends at the ACCA, who have supported this event. The Labour Business Fringe at this year's Labour Annual Conference is being co-sponsored by Labour in the City and the Industry Forum. Speakers include John McDonnell, Shadow Chancellor, and Rebecca Long-Bailey, the Shadow Chief Secretary to the Treasury, and our own Chair, Kitty Ussher. Attendance is free, and refreshments will be provided.

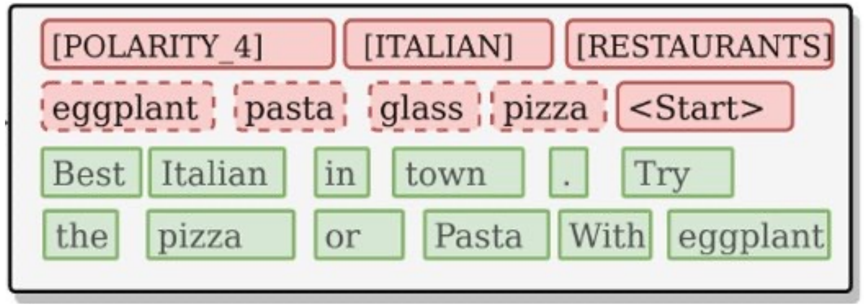
Figure 2: An example of sentences (from the C4 corpus) selected by Random, Lead and Ind-Orig respectively. Best viewed in color.



Fine-tuning with limited supervised samples
Solid: few-shot with pre-trained weights
Dashed: supervised with initial weights

Keyword-Guided Summarization

- Self-Supervised and Controlled Opinion Summarization [EACL'21]
  - Control tokens are used to let the generated summary align with the input documents.
- Inputs to the model:



- Summary guided by tokens:

Correct Control Tokens: ***eat***, ***lentil***, ***eggplant***, ***new***, **remember**, ***flavourful***, ***friendly***

Seriously best we've had in Toronto. We were looking for a *new* place to *eat* and stumbled upon this place. The atmosphere is very authentic, the food is authentic, and the service is very *friendly* and attentive. We started with the *lentil* soup, which was very *flavourful* and full of flavor. For dinner, I had the lamb shank and my husband had the *eggplant* dish. Both were very good. We also had the baklava for dessert and it was amazing. We can't wait to come back and try more of the menu

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Generating Representative Headlines for News Stories

Raptors vs. Bucks Prediction

Article 1

The Toronto Raptors will play in the NBA Eastern Conference final for just the second time in team history when they visit the Milwaukee Bucks on Wednesday to kick off a best-of-seven series.

- **Raptors counting on momentum from Game 7 win to propel them in Milwaukee**

Here's a look at how the teams match up:

Article 2

Leading into tonight's game:

- Injury report: For the Raptors, OG Anunoby (appendectomy) and Jordan Loyd (coach's decision) are listed as out. Chris Boucher (back spasms) is listed as probable. For the Bucks, Donte DiVincenzo (Bilateral heel bursitis), Pau Gasol (left foot surgery) and D.J. Wilson (left ankle sprain) are all listed as out.

- Introducing Round 3: The Raptors will begin the Eastern Conference Finals in Milwaukee for Games 1 and 2 of their best-of-seven series against the Bucks. This is just the second time in franchise history that the Raptors have made it to the Eastern Conference Finals, returning for the first time since facing the Cleveland Cavaliers in 2016. The Bucks have homecourt advantage in this series as the only team in the NBA to finish with a better regular-season record (60-22) than the Raptors (58-24).

Article 3

Milwaukee versus Toronto has been the matchup we have been waiting for since the playoffs started. It's the number one team against the number two team and two of the top players in the league going head to head with Giannis Antetokounmpo and Kawhi Leonard ready to lead their teams into battle. Both players have been special and have looked unstoppable in these playoffs.

The Bucks are coming into the series with a full week of rest after dispatching the Boston Celtics in five games, while the Raptors needed a Game 7 miracle at the hands of Leonard to get past the Philadelphia 76ers.

The Bucks won the regular season series 3-1, including the most recent game on January 31, a 105-92 victory, with Giannis leading the way with 19 points and nine rebounds, while Pascal Siakam had 28 points.

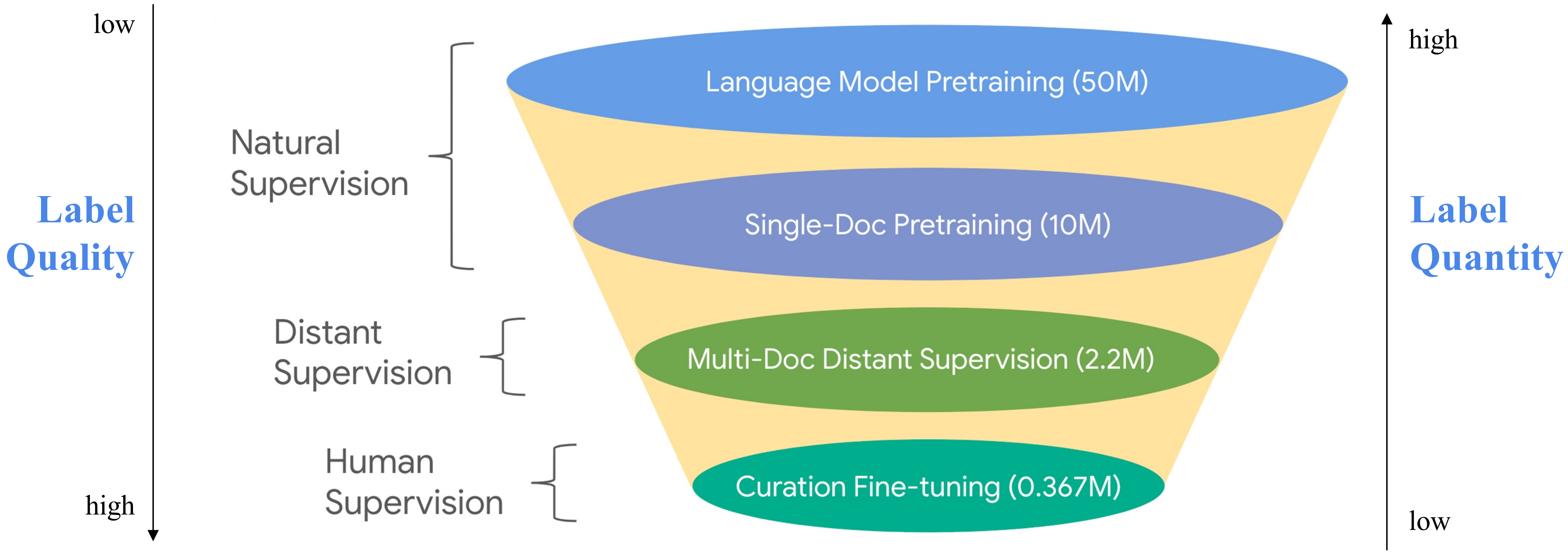
The NewSHead Dataset

- For standard research and evaluation
  - Release the first dataset for **news** **s**tory **head**line generation
  - 3-5 news articles per story; Label: human edition + validation
  - 357K stories, >1M articles, 20x larger than the biggest MDS dataset
- Still **a drop** in the **ocean** compared with massive unlabeled news (**50M** articles)!

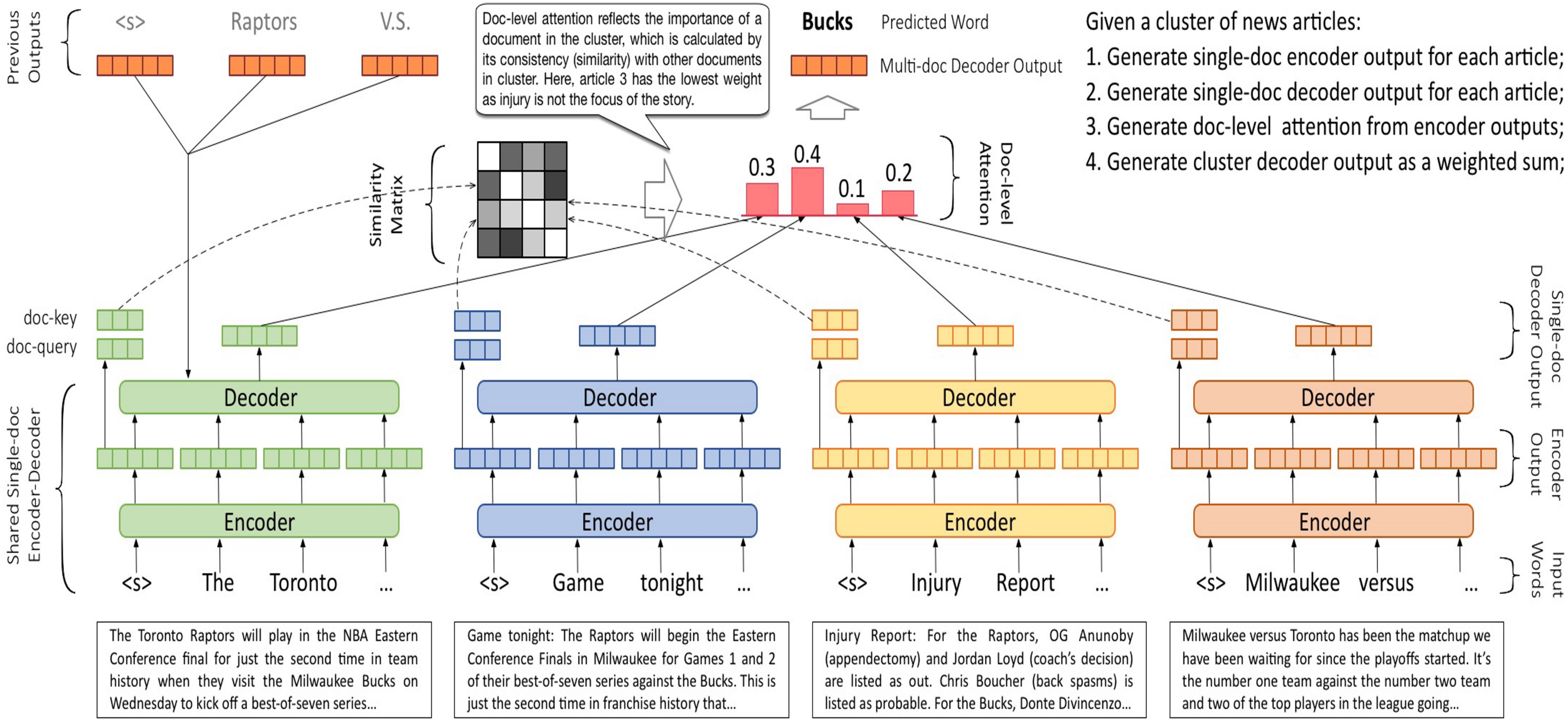
The NewSHead$_{\text{heuristic}}$ Dataset

- Heuristically generated from unlabeled news articles
  - Cluster news articles into news stories by embedding (same as NewSHead)
    - Label: select an existing article title from the cluster as story headline
    - train a title scorer: given the content of an article and a title, predict whether they match
    - the scorer can be directly trained from existing article/title pairs: no human annotation
    - given all article titles in the cluster, rank them by average matching score with other articles
    - the top article title is representative: can match all articles well
    - prune those under threshold, too long or too short labels
  - Leading to 2.2M (6x larger) news stories with free-to-get labels
  - Question: how far can we go without expensive manual story headline annotations?
- Propose: a three-level pretraining framework

Multi-level Pretraining



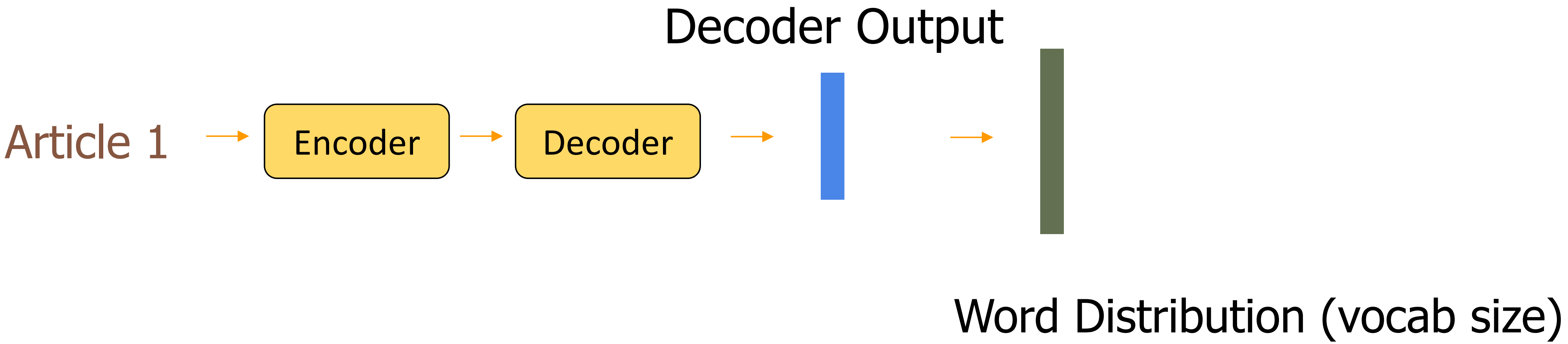
Framework



Given a cluster of news articles:

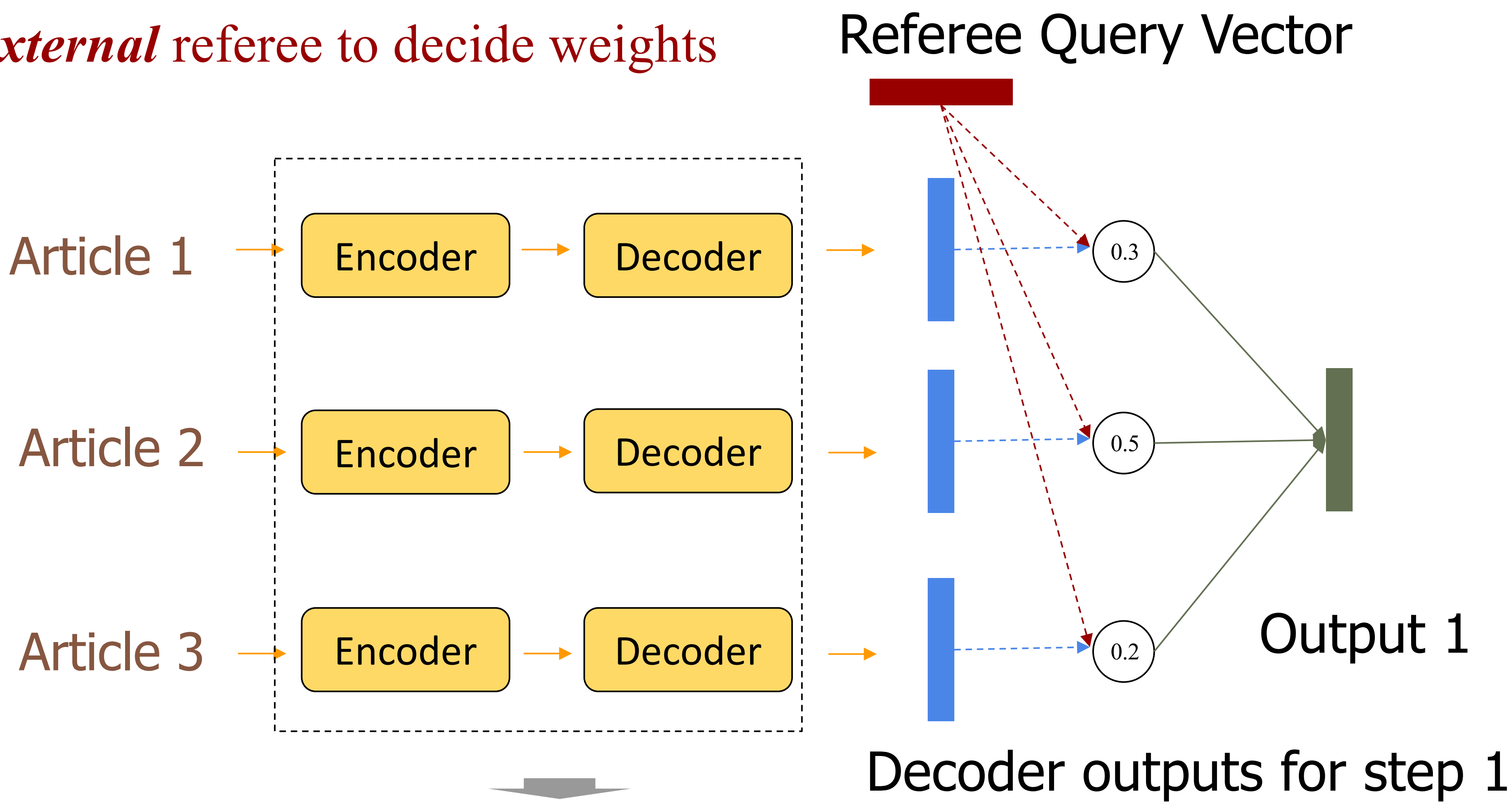
1. Generate single-doc encoder output for each article;
2. Generate single-doc decoder output for each article;
3. Generate doc-level attention from encoder outputs;
4. Generate cluster decoder output as a weighted sum;

Architecture: Single-doc Headline Generation



Doc-level Attention 1: Referee Attention

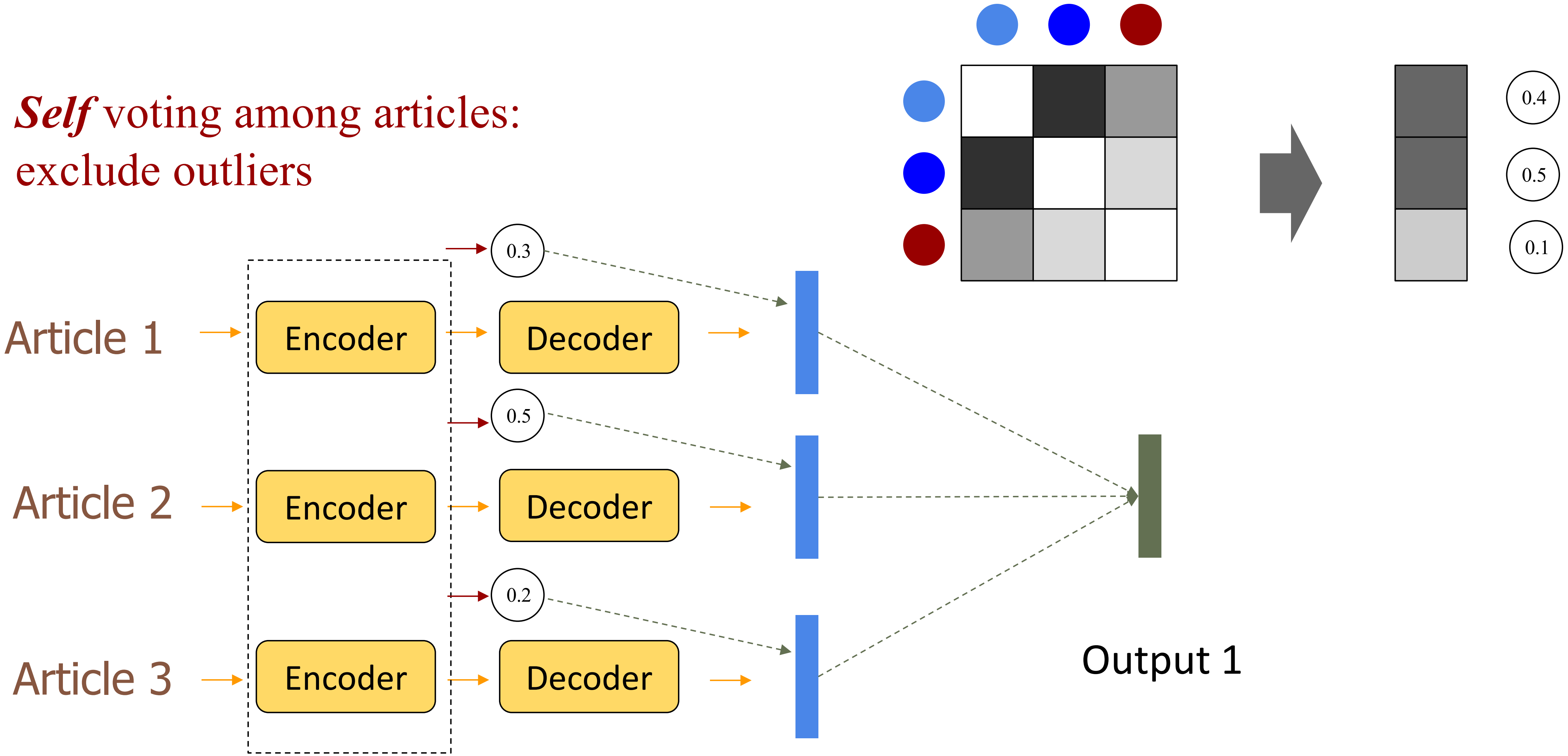
External referee to decide weights



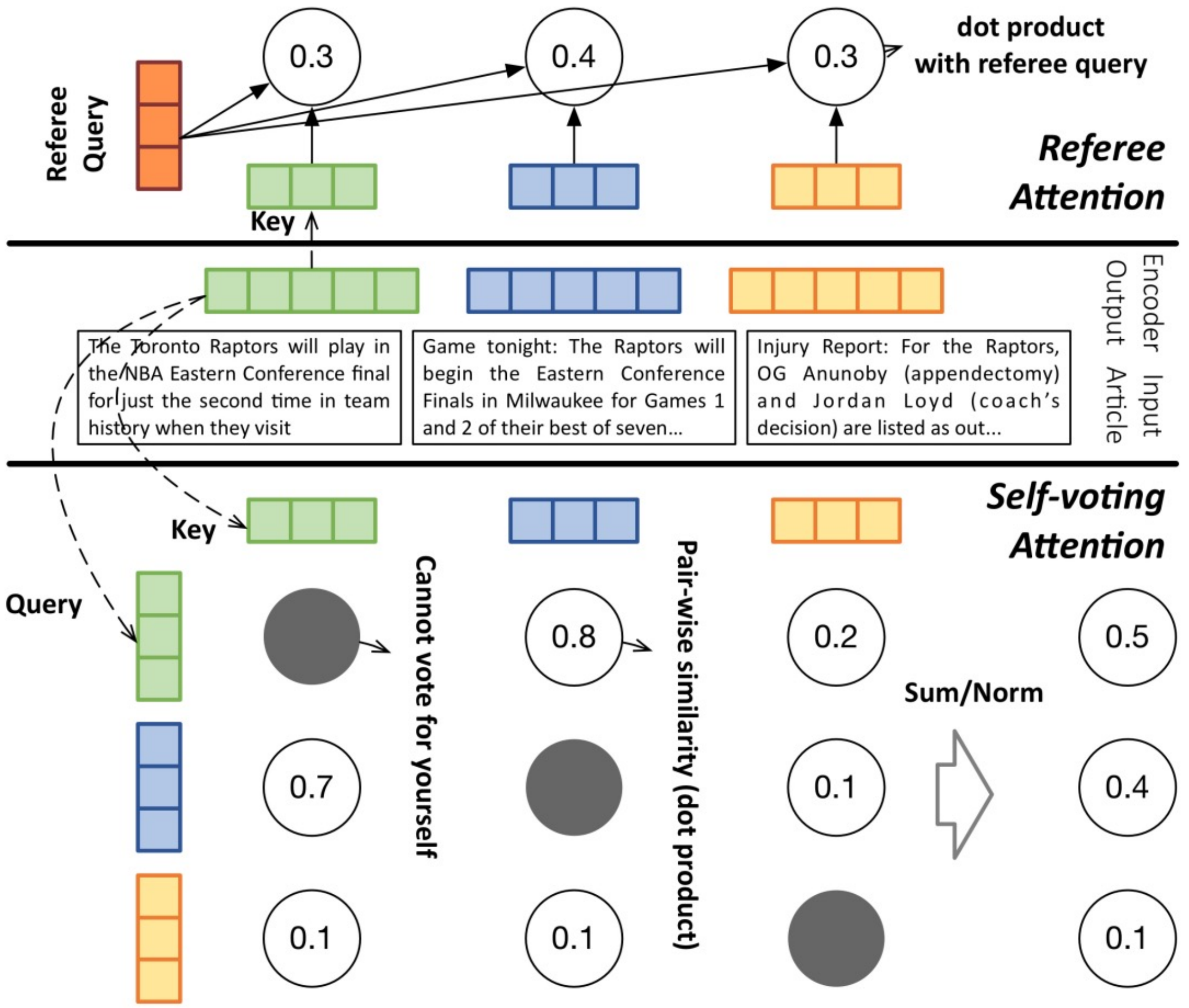
Keep the architecture of single-doc encoder decoder to fully leverage pretraining

Doc-level Attention 2: Self-voted Attention

Self voting among articles:
exclude outliers



Doc-Attention: Comparison



Performance Comparison

Table 2: Performance comparison of different methods.

Method	R1-P	R1-R	**R1-F**	R2-P	R2-R	**R2-F**	RL-P	RL-R	**RL-F**	**Len-C**	**Len-W**
Cheating	0.768	0.995	0.853	0.565	0.719	0.621	0.768	0.995	0.853	0.789	0.772
					Extractive						
SelectTitle	0.664	0.364	0.458	0.340	0.172	0.220	0.598	0.328	0.413	1.984	1.933
LCS	0.437	0.646	0.486	0.241	0.385	0.272	0.413	0.620	0.462	0.796	0.788
					Abstractive (+BERT+Single)						
Concat+Titles	0.752	0.756	0.746	0.510	0.510	0.503	0.689	0.694	0.685	1.017	1.013
SinABS [55]	0.744	0.748	0.738	0.499	0.501	0.493	0.680	0.682	0.674	1.021	1.018
SinABS+Titles	0.758	0.769	0.755	0.522	0.530	0.518	0.695	0.704	0.692	1.004	1.006
					Ours						
NoFinetune	0.726	0.590	0.639	0.440	0.354	0.382	0.667	0.542	0.588	1.327	1.286
NoPretrain	0.596	0.621	0.600	0.327	0.338	0.327	0.539	0.560	0.542	0.983	0.980
+BERT	0.716	0.728	0.714	0.466	0.471	0.462	0.657	0.668	0.656	1.003	**1.000**
+Single	0.751	0.776	0.755	0.514	0.530	0.514	0.688	0.710	0.691	0.992	0.988
+Titles	**0.762**	**0.779**	**0.762**	**0.531**	**0.542**	**0.529**	**0.703**	**0.718**	**0.703**	**1.003**	0.997

A Case Study on Noisy Dataset

Gold Label: austin riley mlb debut
Referee Attention: austin riley homers in game 7 **Self-Voting Attention: austin riley mlb debut**
Article$_1$: Braves prospect Riley homers in 2nd MLB AB ATLANTA – As **Austin Riley** soaked in the excitement of highlighting his Major League **debut** with a monstrous home run that helped the Braves claim a 4-0 win over the Cardinals on Wednesday night... **Article$_2$** (noise): **SMB completes PH Cup five-peat after gripping Game 7 win over Magnolia** FIVE rings to adorn this San Miguel dynasty. The Beermen extended their reign in the PBA Philippine Cup in dramatic fashion, overcoming a 17-point deficit to beat Magnolia, 72-71, in a **Game Seven** to remember... **Article$_3$: Called Up: Austin Riley** Yesterday, the Braves called up **Austin Riley**, who we ranked second in their system and 33rd in our Top 100. He continued his blazing hot 2019, going 1-for-3 in his big league **debut** last night, including a home run...

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- Aspect-based Sentiment Analysis
- Text Summarization
- Taxonomy Construction
  - Taxonomy Basics and Construction
  - Taxonomy Construction with Minimal User Guidance
  - Taxonomy Expansion
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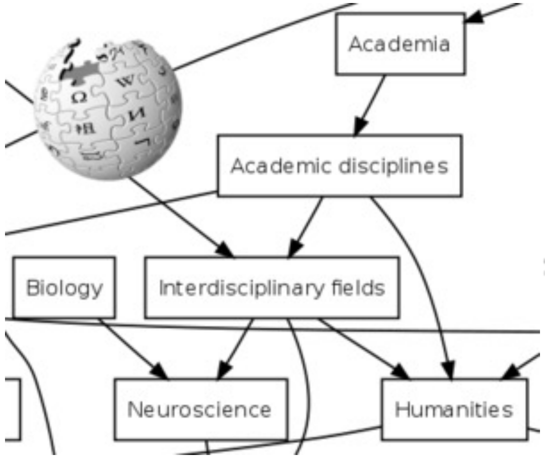
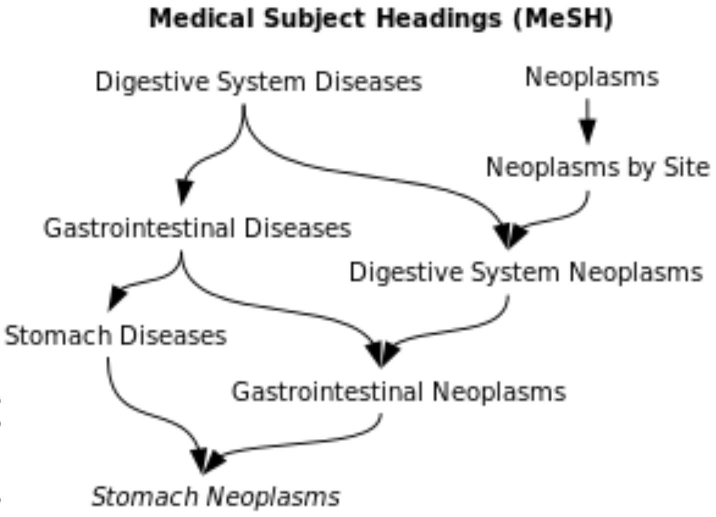
What is a Taxonomy?

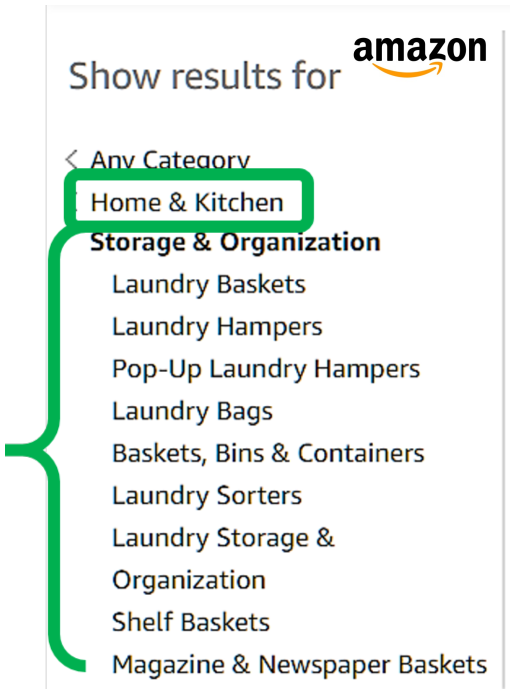
- Taxonomy is a hierarchical organization of concepts
- Taxonomy can benefit many knowledge-rich applications
  - Knowledge Organization, Document Categorization, Recommender System …



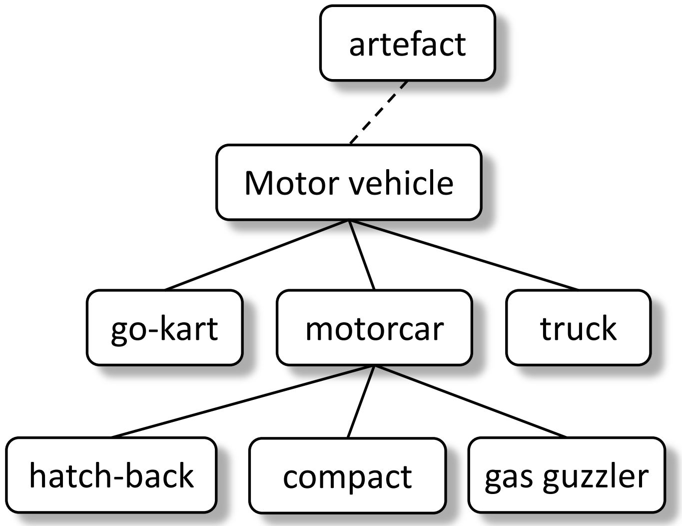
Wikipedia Category



MeSH



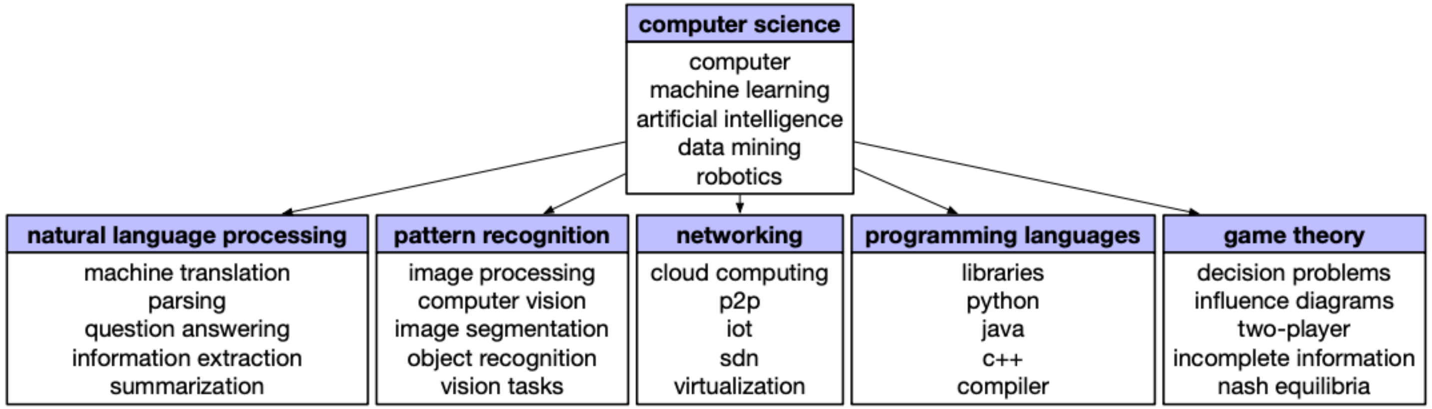
Amazon Product Category



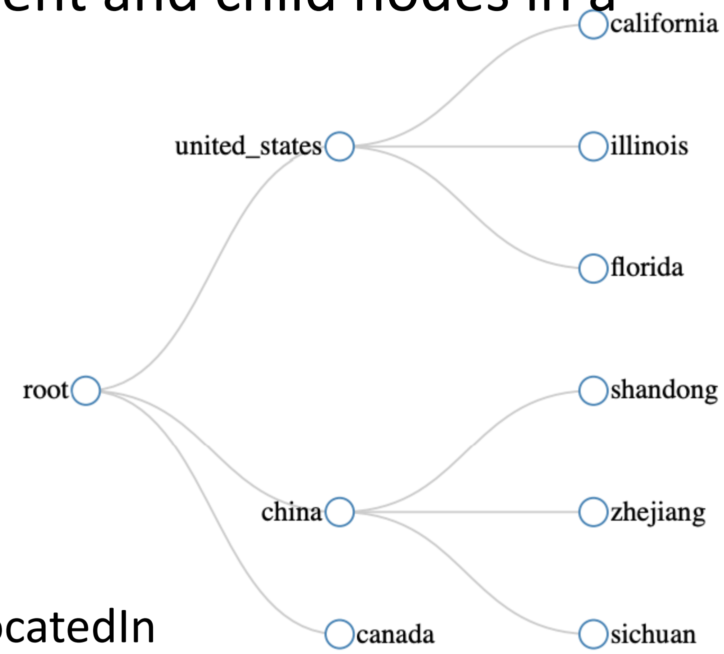
WordNet

Multi-faceted Taxonomy Construction

- Limitations of existing taxonomy:
  - A generic taxonomy with fixed "is-a" relation between nodes
  - Fail to adapt to users' specific interest in special areas by dominating the hierarchical structure of irrelevant terms
- Multi-faceted Taxonomy
  - One facet only reflects a certain kind of relation between parent and child nodes in a user-interested field.



Relation: IsSubfieldOf



Relation: IsLocatedIn

Two stages in constructing a complete taxonomy

- Taxonomy Construction
  - Use a set of entities (possibly a seed taxonomy in a small scale) and unstructured text data to build a taxonomy organized by certain relations
- Taxonomy Expansion
  - Update an already constructed taxonomy by attaching new items to a suitable node on the existing taxonomy. This step is useful since reconstructing a new taxonomy from scratch can be resource-consuming.

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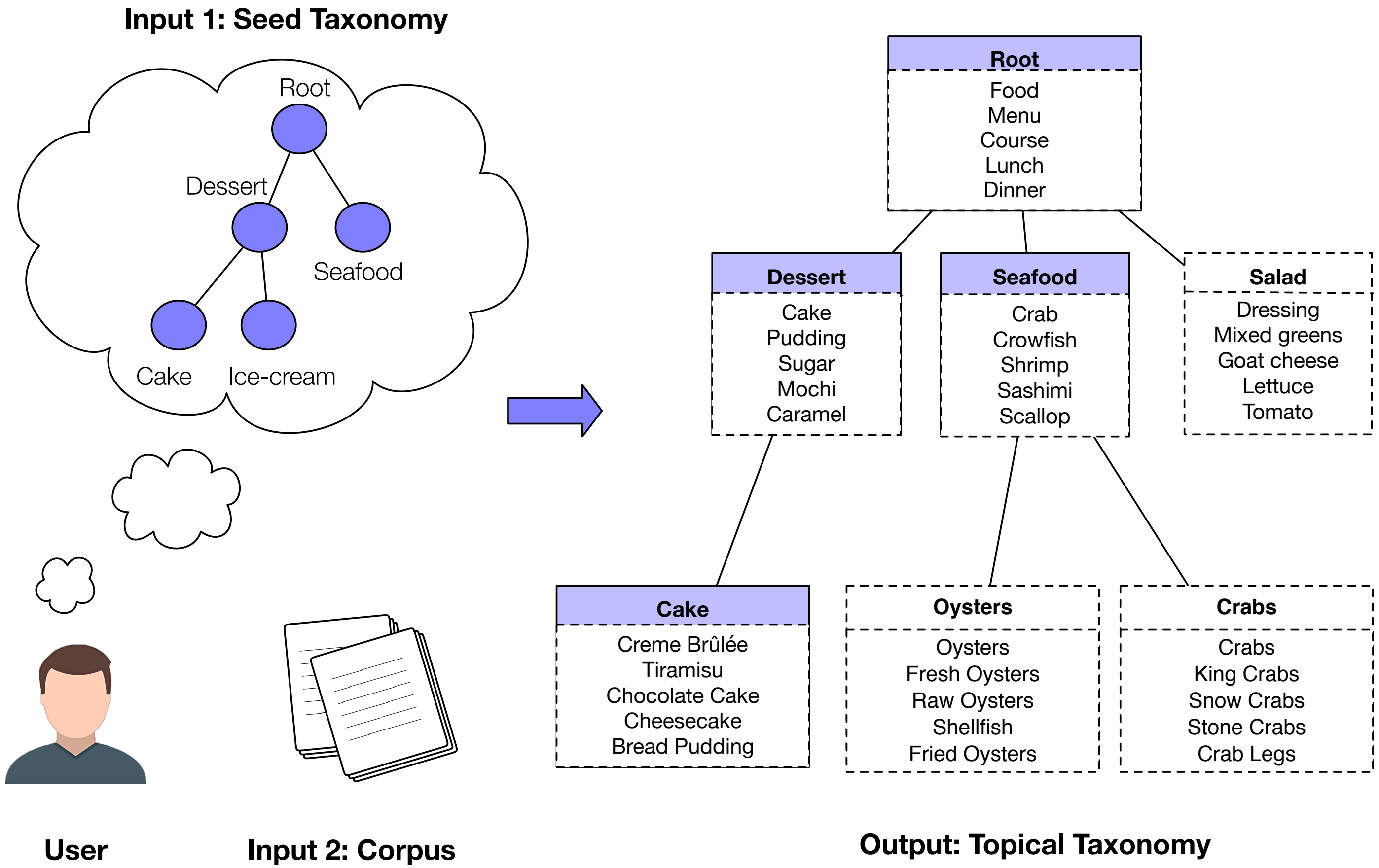
  - Taxonomy Construction with Minimal User Guidance
  - Taxonomy Expansion
- Summary & Future Directions

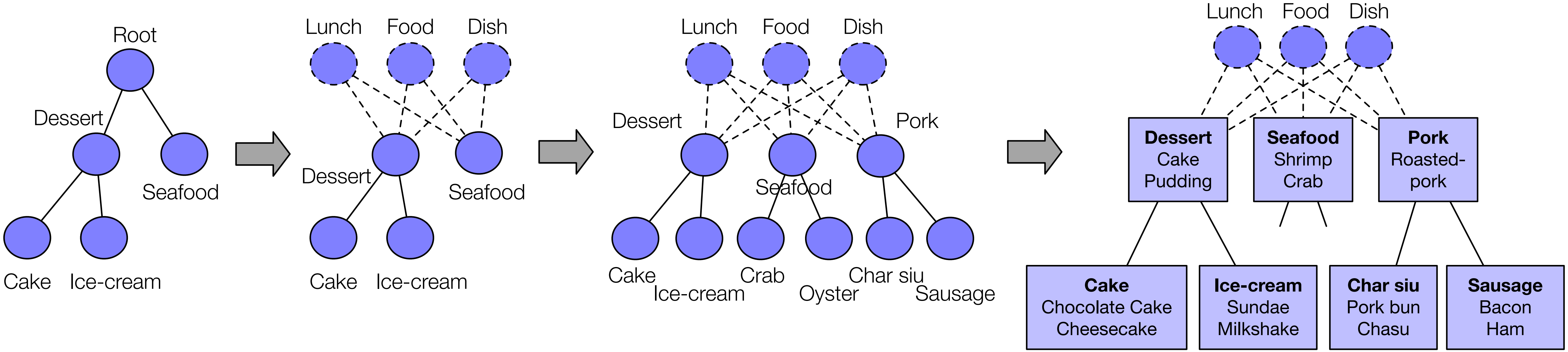
Seed-Guided Topical Taxonomy Construction

- User gives a seed taxonomy as guidance
- A more complete topical taxonomy is generated from text corpus, with each node represented by a cluster of terms (topics)



- A user might want to learn about concepts in a certain aspect (e.g., *food* or *research areas*) from a corpus
- He wants to know more about other kinds of food

CoRel: Seed-Guided Topical Taxonomy Construction by Concept Learning and Relation Transferring



Step 1: Relation transferring upwards

Step 2: Relation transferring downwards

Step 3: Concept learning for generating topical clusters

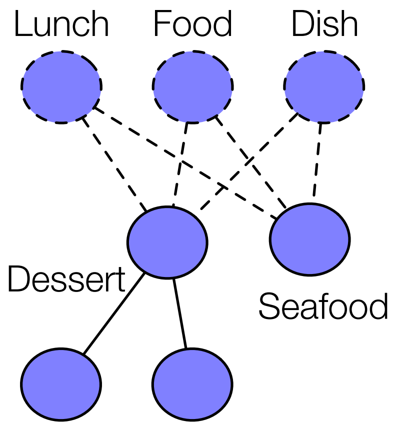
Three Steps:

1. Learn a relation classifier and transfer the relation upwards to **discover common root concepts** of existing topics
2. Transfer the relation downwards to **find new topics/subtopics** as child nodes of root/topics
3. Learn a discriminative embedding space to **find distinctive terms for each concept** node in the taxonomy

Jiaxin Huang, Yiqing Xie, Yu Meng, Yunyi Zhang and Jiawei Han, "CoRel: Seed-Guided Topical Taxonomy Construction by Concept Learning and Relation Transferring", KDD (2020)

Relation Learning and Transferring

- Learn a relation classifier using pretrained language model (e.g., BERT)
  - Using a weakly-supervised text embedding framework
- Transfer the relation upwards to discover possible root nodes (e.g., “Lunch” and “Food”)
  - The root node would have more general contexts for us to find connections with potential new topics



- Extract a list of parent nodes for each seed topic using the relation classifier
  - The common parent nodes shared by all user-given topics are treated as root nodes
- To discover new topics (e.g., Pork), we transfer the relation downwards from the root nodes

Qualitative and Quantitative Results

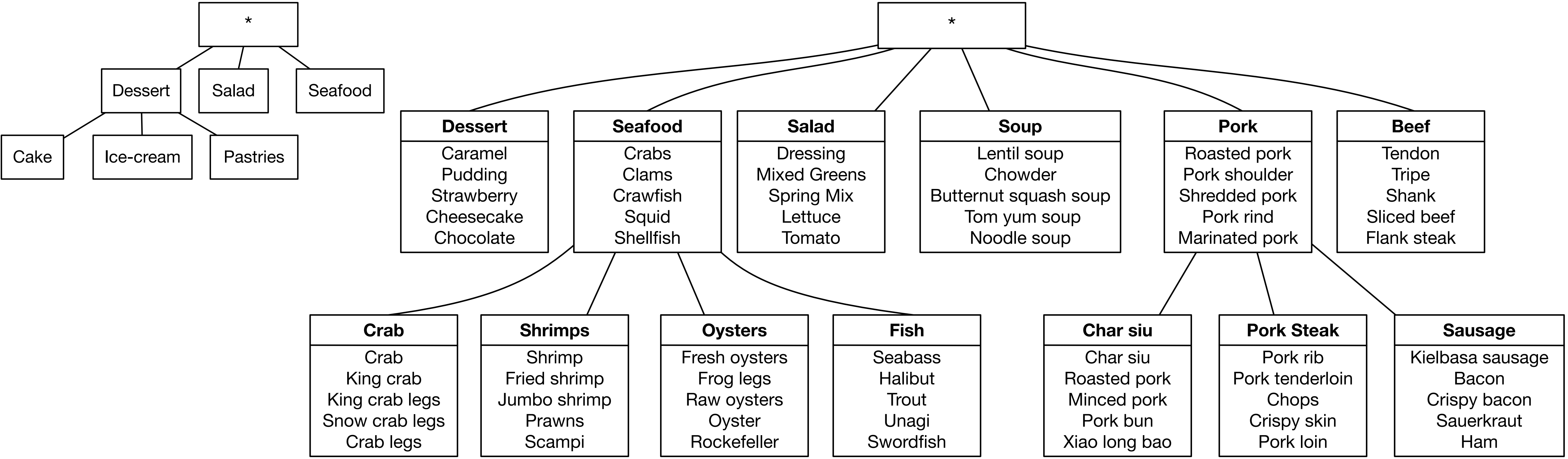


Table 5: Quantitative evaluation on topical taxonomies.

Methods	DBLP					Yelp				
	TC	SD	Precision$_r$	Recall$_r$	F1-score$_r$	TC	SD	Precision$_r$	Recall$_r$	F1-score$_r$
HLDA	0.582	0.981	0.188	0.577	0.283	0.517	0.991	0.135	0.387	0.200
HPAM	0.557	0.905	0.362	0.538	0.433	0.687	0.898	0.173	0.615	0.271
TaxoGen	0.720	0.979	0.450	0.429	0.439	0.563	0.965	0.267	0.381	0.314
Hi-Expan + CoL.	0.819	0.996	0.676	0.532	0.595	0.815	**1.000**	0.429	0.677	0.525
CoRel	**0.855**	**1.000**	**0.730**	**0.607**	**0.663**	**0.825**	**1.000**	**0.564**	**0.710**	**0.629**

Outline

- Aspect-based Sentiment Analysis
- Text Summarization
- Taxonomy Construction
  - Taxonomy Basics and Construction
  - Taxonomy Construction with Minimal User Guidance
  - Taxonomy Expansion

Taxonomy Expansion: Motivation

- Why taxonomy expansion instead of construction from scratch?
  - Already have a decent taxonomy built by experts and used in production
  - Most common terms are covered
  - New items (thus new terms) incoming everyday, cannot afford to rebuild the whole taxonomy frequently
  - Downstream applications require stable taxonomies to organize knowledge

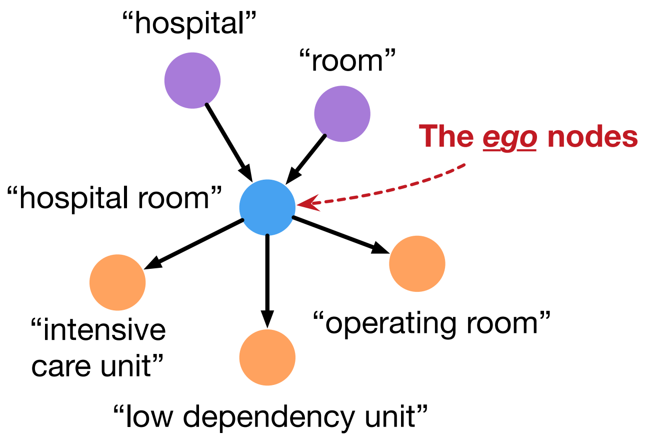
TaxoExpan: Self-supervised Taxonomy Expansion with Position-Enhanced Graph Neural Network [WWW' 20]

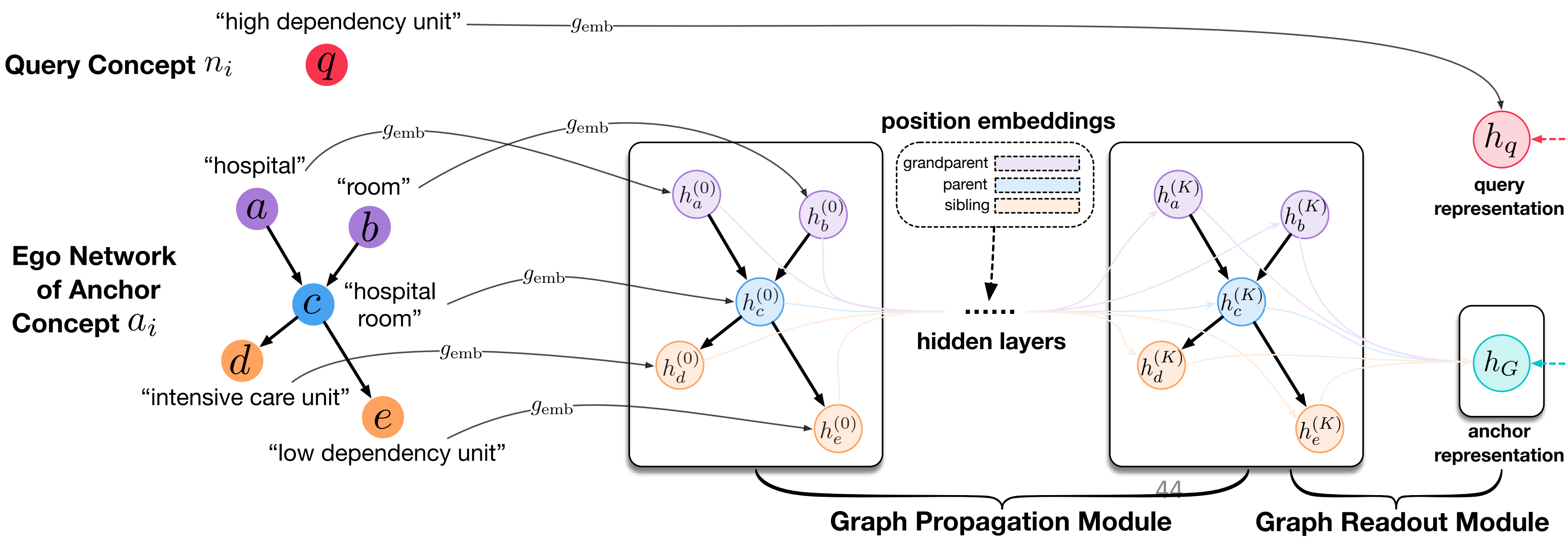
- **Two steps** in solving the problem:
  - Self-supervised term extraction
    - Automatically **extracts emerging terms** from a target domain
  - Self-supervised term attachment
    - A multi-class classification to match a new node to its potential parent
    - Heterogenous sources of information (structural, semantic, and lexical) can be used

Self-supervised Term Attachment

- **TaxoExpan** uses a matching score for each <*query*, *anchor*> pair to indicate how likely the *anchor concept* is the parent of *query concept*
- Key ideas:
  - Representing the *anchor concept* using its ego network (egonet)
  - Adding position information (relative to the *query concept*) into this egonet

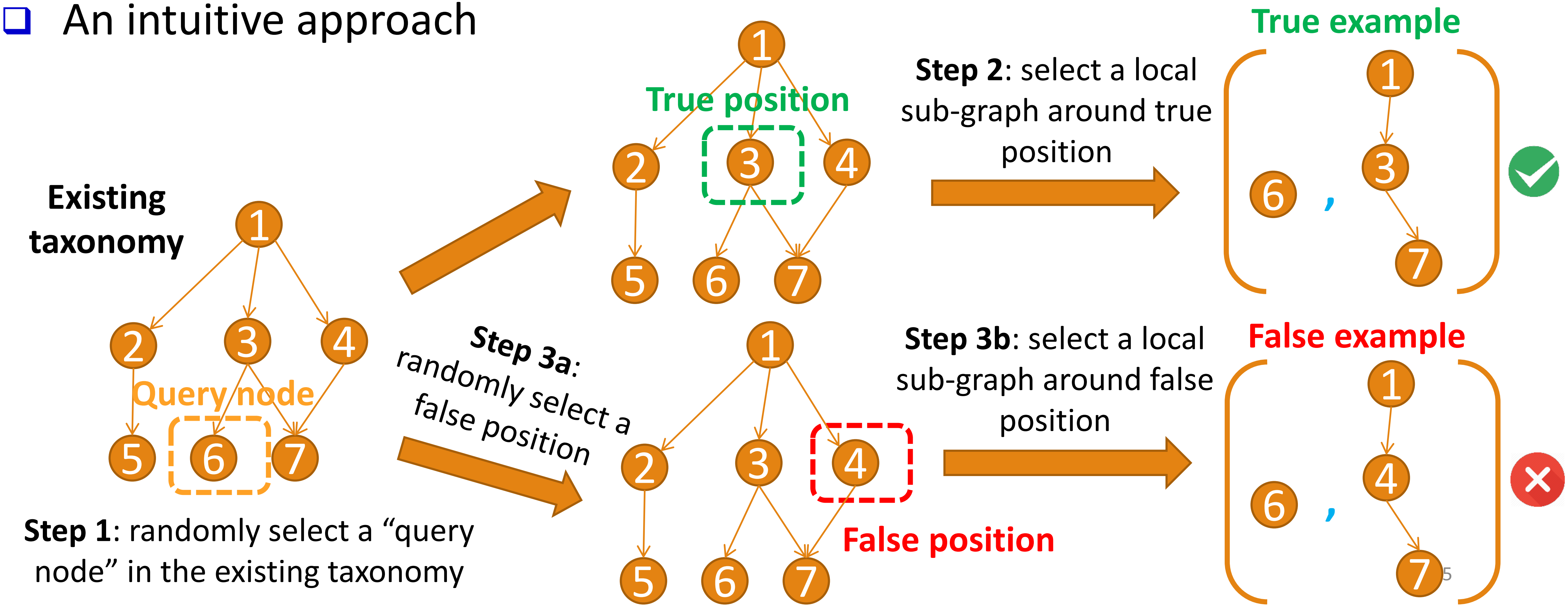
Query: "high dependency unit"





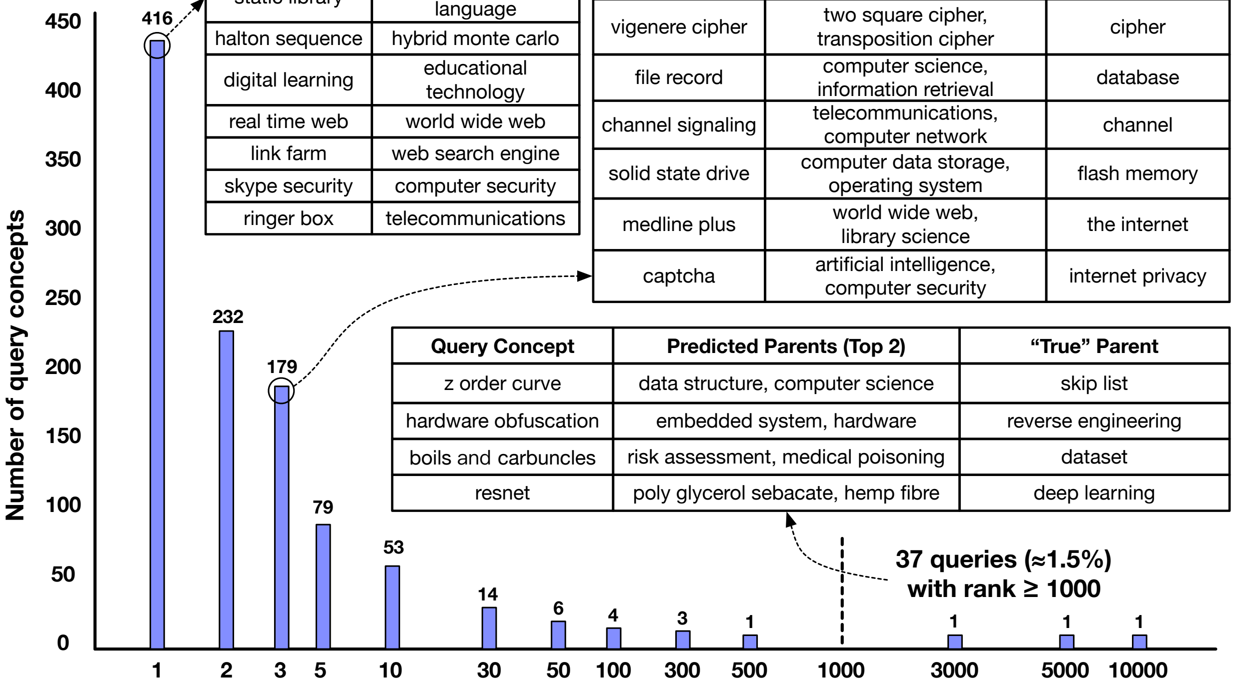
Leveraging Existing Taxonomy for Self-supervised Learning

- How to learn model parameters without relying on massive human-labeled data?
- An intuitive approach



TaxoExpan Framework Analysis

- Case studies on MAG-CS and MAG-Full datasets

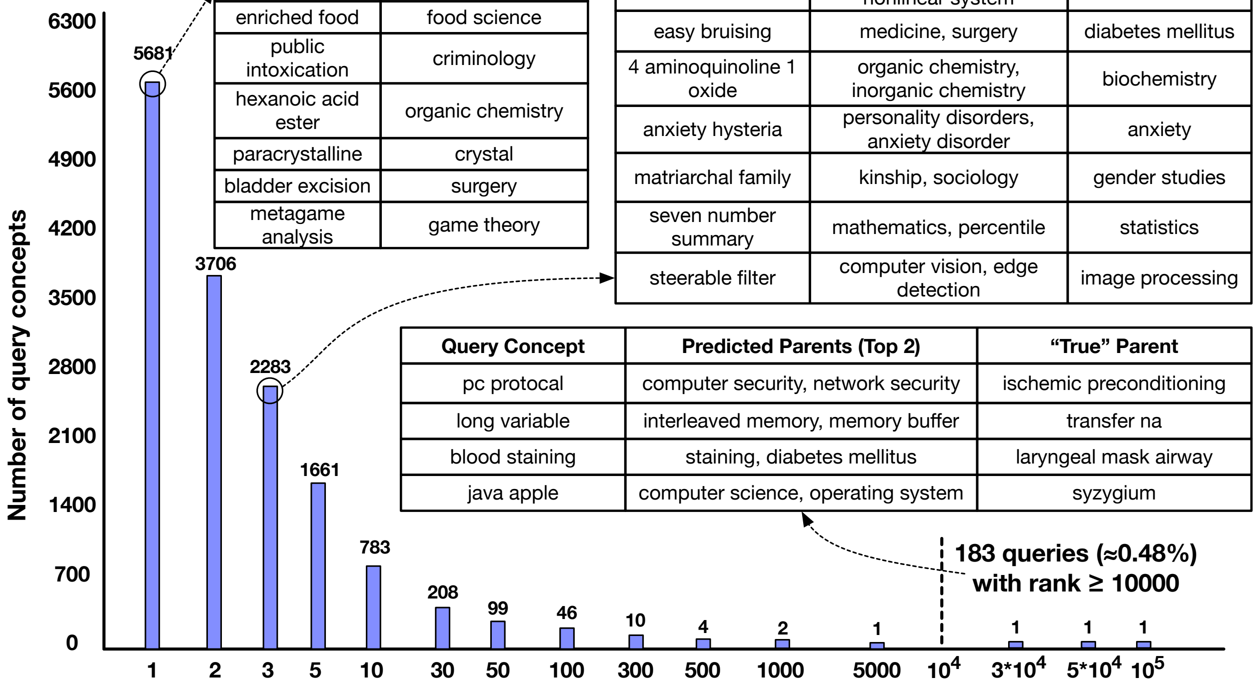


Query Concept	Predicted Parent = "True" Parent
archival science	library science
static library	programming language
halton sequence	hybrid monte carlo
digital learning	educational technology
real time web	world wide web
link farm	web search engine
skype security	computer security
ringer box	telecommunications

Query Concept	Predicted Parents (Top 2)	"True" Parent
email hacking	internet privacy, hacker	computer security
social graph	world wide web, the internet	social network
vigenere cipher	two square cipher, transposition cipher	cipher
file record	computer science, information retrieval	database
channel signaling	telecommunications, computer network	channel
solid state drive	computer data storage, operating system	flash memory
medline plus	world wide web, library science	the internet
captcha	artificial intelligence, computer security	internet privacy

Query Concept	Predicted Parents (Top 2)	"True" Parent
z order curve	data structure, computer science	skip list
hardware obfuscation	embedded system, hardware	reverse engineering
boils and carbuncles	risk assessment, medical poisoning	dataset
resnet	poly glycerol sebacate, hemp fibre	deep learning

(a) MAG-CS Dataset (totally 2450 query concepts)



Query Concept	Predicted Parent = "True" Parent
hindi language	linguistics
dyssodia	botany
enriched food	food science
public intoxication	criminology
hexanoic acid ester	organic chemistry
paracrystalline	crystal
bladder excision	surgery
metagame analysis	game theory

Query Concept	Predicted Parents (Top 2)	"True" Parent
syndactyla	ecology, biology	zoology
m matrix	symmetric matrix, nonlinear system	matrix
easy bruising	medicine, surgery	diabetes mellitus
4 aminoquinoline 1 oxide	organic chemistry, inorganic chemistry	biochemistry
anxiety hysteria	personality disorders, anxiety disorder	anxiety
matriarchal family	kinship, sociology	gender studies
seven number summary	mathematics, percentile	statistics
steerable filter	computer vision, edge detection	image processing

Query Concept	Predicted Parents (Top 2)	"True" Parent
pc protocal	computer security, network security	ischemic preconditioning
long variable	interleaved memory, memory buffer	transfer na
blood staining	staining, diabetes mellitus	laryngeal mask airway
java apple	computer science, operating system	syzygium

(b) MAG-Full Dataset (totally 37804 query concepts)

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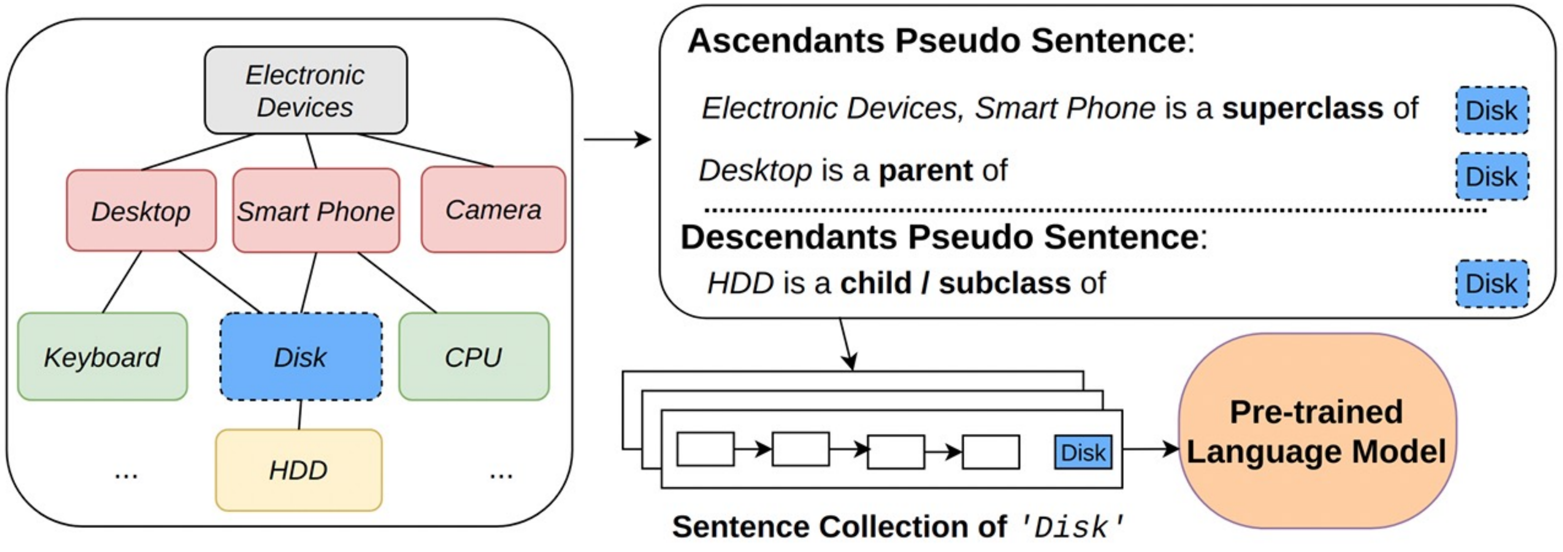
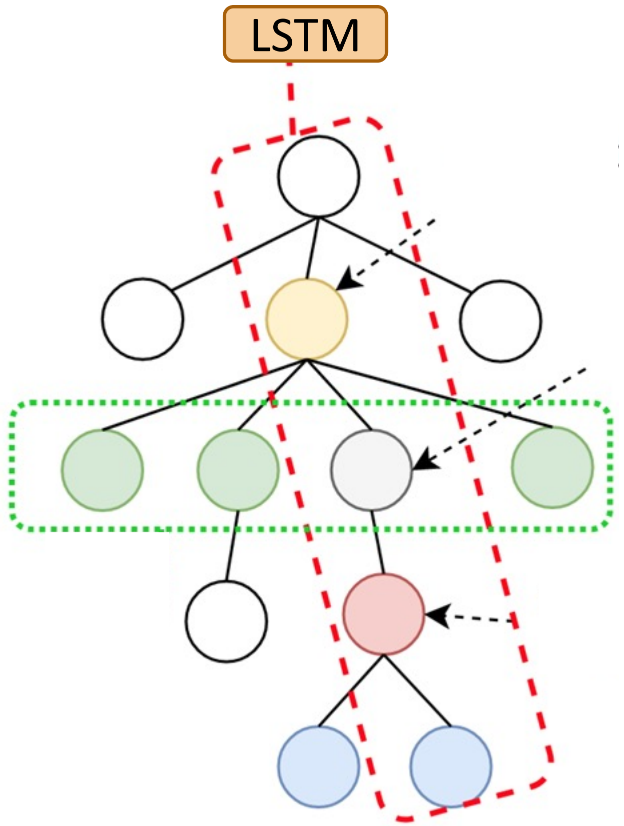
TaxoEnrich: Self-Supervised Taxonomy Completion via Structure-Semantic Representations [WWW'22]

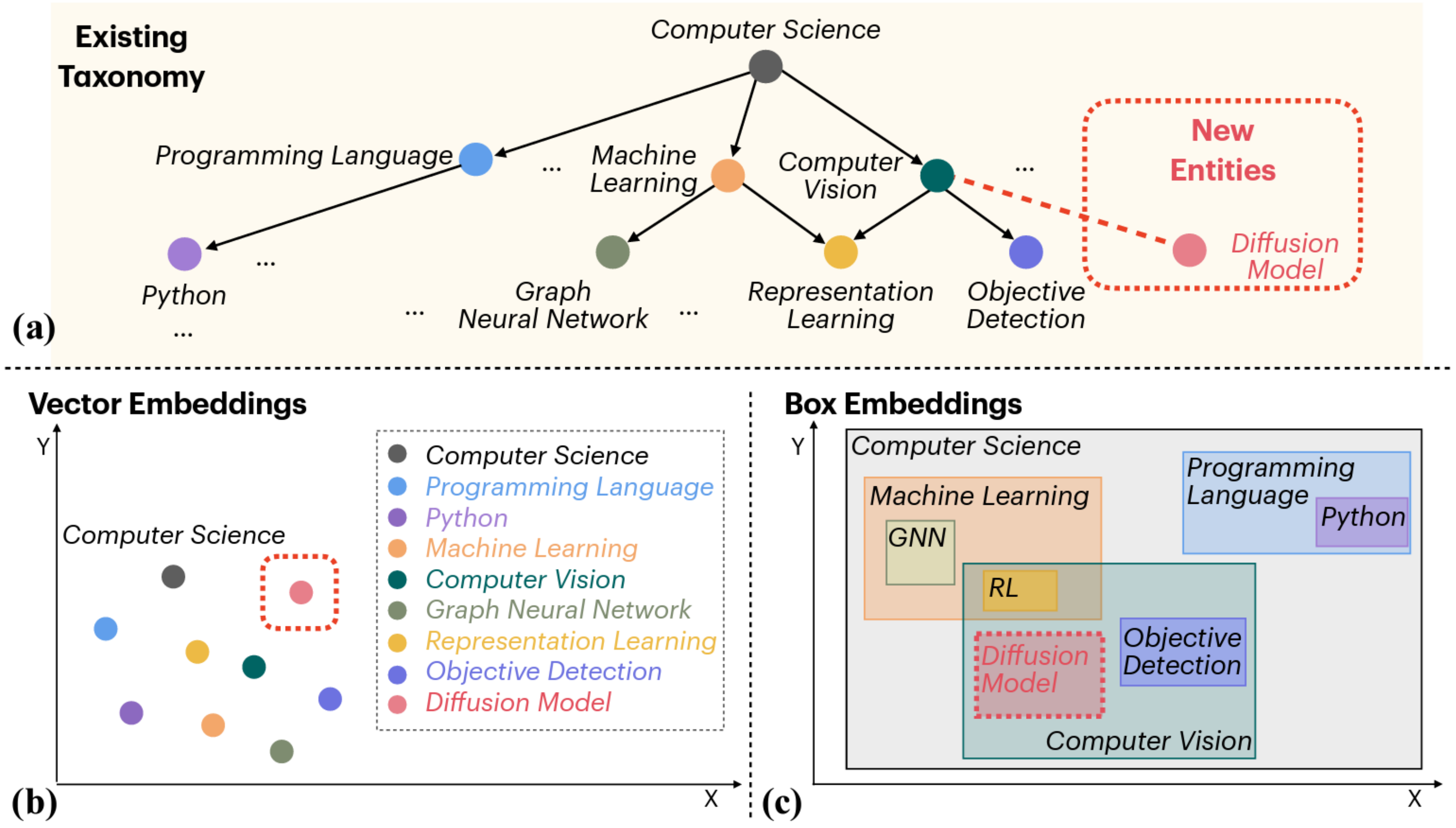
- Extra semantic information
  - Taxonomy-contextualized embedding
  - Layer-aware representation





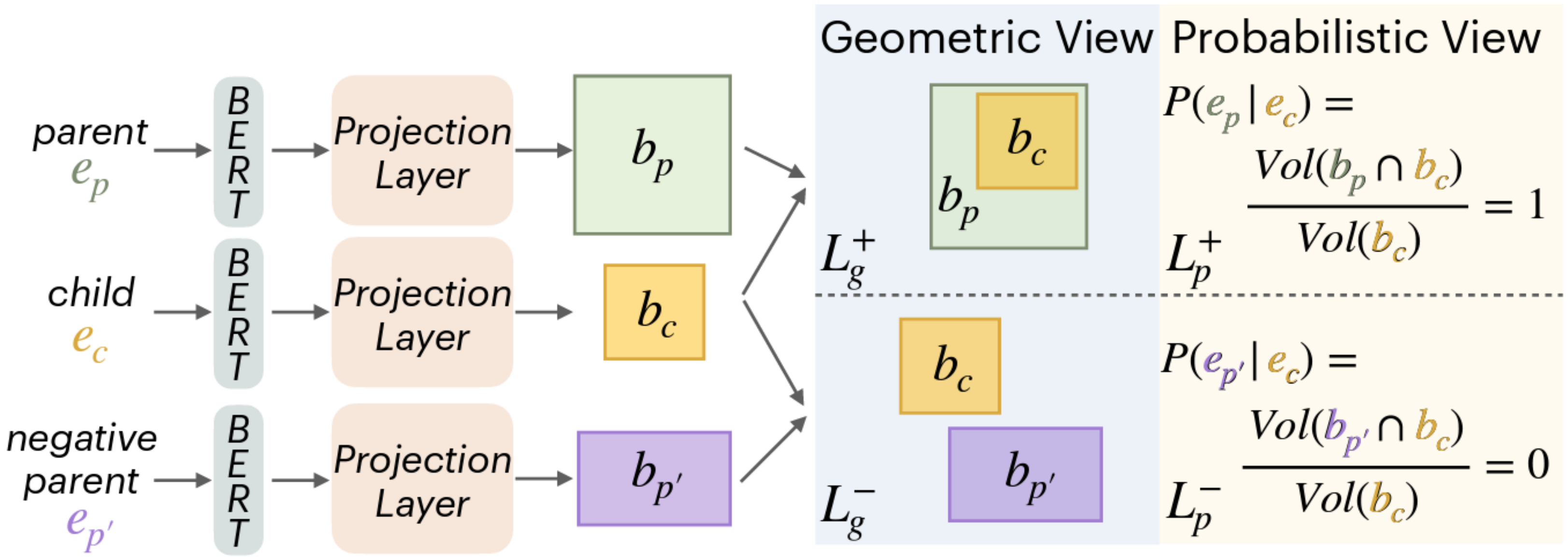
A Single Vector Is Not Enough: Taxonomy Expansion via Box Embeddings [WWW'23]

- Vector embeddings can only represent similarity/dissimilarity
- Box embeddings can represent entailment relations



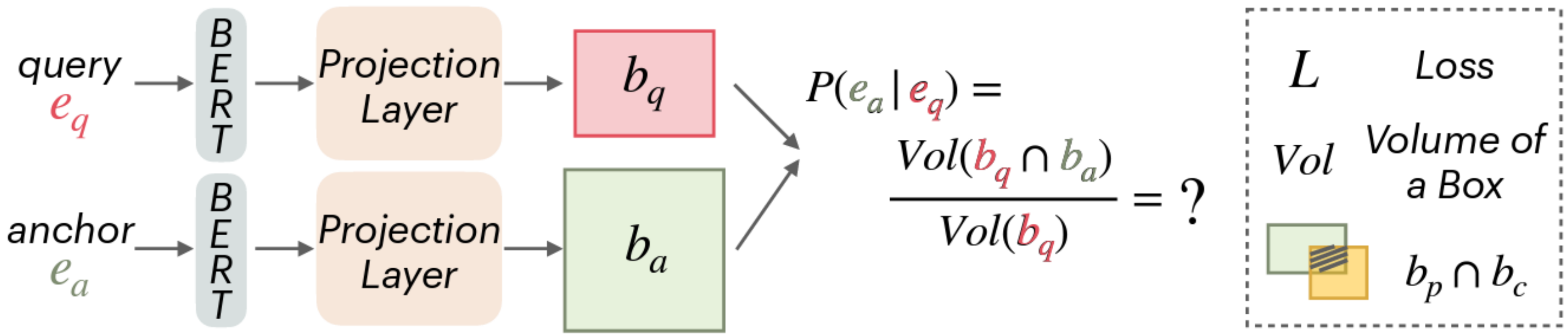
Box Training

- Training: the box embeddings are optimized to accurately represent the taxonomic hierarchies.



Inference with Box

- Inference: check whether a query's box is enclosed by the candidate anchor's box in a probabilistic way.



Summary & Future Directions

KDD 2023 Tutorial

Pretrained Language Representations for Text Understanding: A Weakly-Supervised Perspective

Yu Meng, Jiaxin Huang, Yu Zhang, Yunyi Zhang, Jiawei Han

Computer Science, University of Illinois Urbana-Champaign

Aug 9, 2023

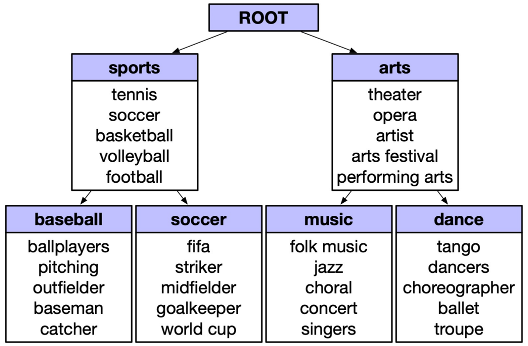
Tutorial Website:

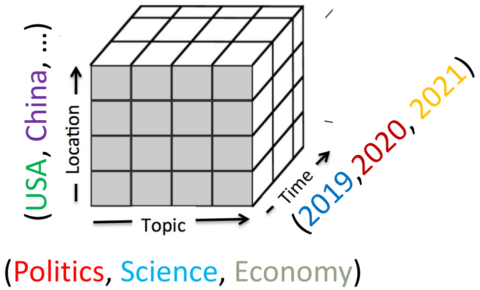
Our Roadmap of This Tutorial

Text Corpus

Language Foundation Models

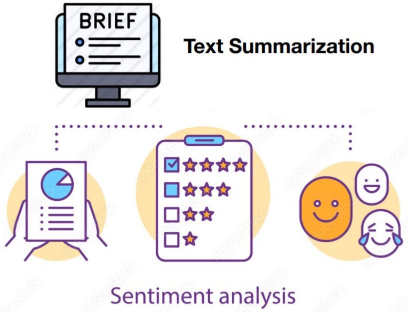
Topic Discovery





Weakly-Supervised Text Classification

Knowledge Base Construction (Entity, Relation & Event)



Advanced Text Mining Applications

Summary: from Unstructured Text to Knowledge

- Leverage the Power of Text Embedding and Language Models to Transform Unstructured Text into Structured Knowledge
- Mining Structures from Massive Unstructured Text (Texts → Structures)
  - Automated Text Representation Learning
  - Automated Multi-Faceted Taxonomy Construction
  - Automated Topic Mining
  - Automated Text Classification for Document Assignment
  - Automated Comparative Summarization in Multidimensional Text Cube
- Still a lot of work to do from unstructured text to structured knowledge

Our Journey: From Big Data to Big Structures & Knowledge

Han, Kamber and Pei, Data Mining, 3rd ed. 2011

Yu, Han ... Link...

... Information Networks, 2012

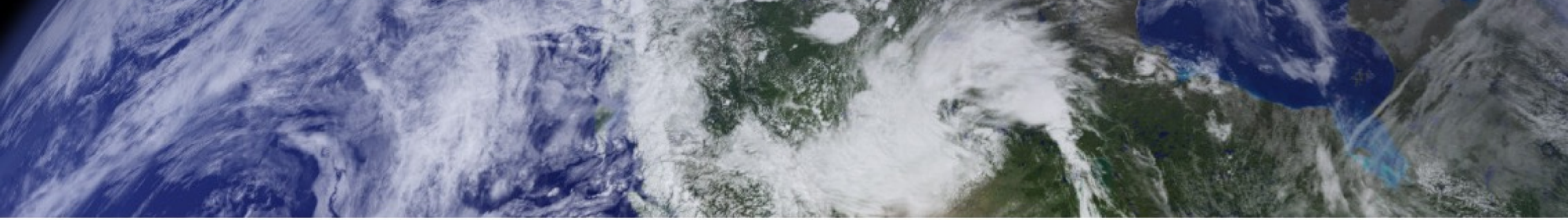
Y. Sun: SIGKDD'13 Dissertation Award

...g and Han, Mining Latent Entity Structures, 2015

... Wang: SIGKDD'15 Dissertation Award

Acknowledgement

- Thanks for the research support from: ARL/NSCTA, NIH, NSF, DHS, ARO, DTRA



Thank you !
Q&A