Neuro-Symbolic Representations for IR
3.2 – Neuro Pseudo-Relevance-Feedback with Explainability

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2023

Tutorial Timetable

Part 1: Symbolic AI representations and tasks

- (Sub)symbolic AI, and representations
- Welcome/Purpose of this tutorial
- Question Answering on Knowledge Graphs

Part 2: Text-to-symbols and Ranking

- Neural Text and Graph Representations
- Text-Symbol Alignment and Semantic Annotations
- Entity Representations and Entity Ranking

Part 3: Neuro-symbolic representations for Reasoning

- Reasoning about Relevance
  ←You Are Here
- Neuro Pseudo-Relevance Feedback with Explainability

Part 4: Applications for Neuro-symbolic approaches

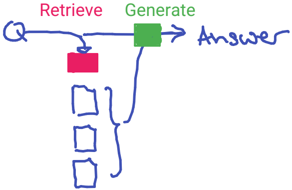
- Use Case: Knowledge Discovery
- Use Case: Task-based Assistance
- Panel & Discussion

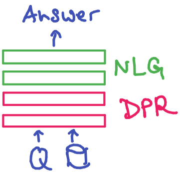
https://github.com/laura-dietz/neurosymbolic-representations-for-IR/

Retrieval-Augmented Generation Models

- Combines retrieval and generation to produce relevant summaries or responses to a given query with inter-dependent steps
- The typical retrieval-augmented generation model would:

  Retrieve top-k passages with Dense Retrieval Model
  Generate natural language answer from retrieval results
- Optionally: add few-shot learning





Both components are trained end-to-end.

Lewis, 2020. "Retrieval-augmented generation for knowledge-intensive nlp tasks."

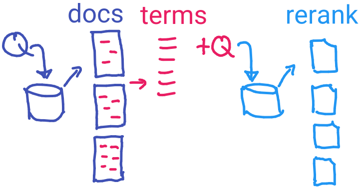
Reminds me of Pseudo-Relevance Feedback / RM3

Standard technique for Query Expansion Proceeds in three phases:

Given query,

- **Retrieve** documents, pretend they are relevant
- **Analyze** documents for frequently associated terms
- **Exploit** frequent terms to expand query (or to re-rank)

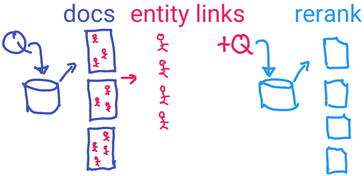
This part: closer look at these three phases in connection to Neuro-Symbolic approaches



Entity Link PRF

Best performing feature is "entity context model" Given query,

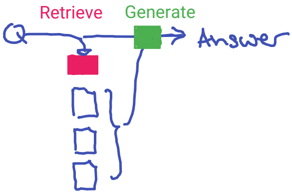
- **Retrieve** passages, which are annotated with entity links
- **Analyze** passages for frequently mentioned entities
- **Exploit** frequent entities, prefer documents which link to them

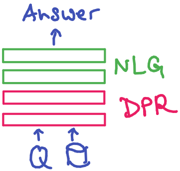


Exploit that symbols are less ambiguous and more meaningful

Dalton 2014, "Entity Query Feature Expansion "

Retrieval-augmented Generation





Given query,

- **Retrieve** passages (dense retrieval)
- **Analyze** —
- **Exploit** generate answers from passages

- Both components are trained end-to-end.
- Backpropagation will train retrieval model implicitly.
- No explicit retrieval benchmark needed!

Zamani, 2022. "Retrieval-Enhanced Machine Learning."

Comparison

	RAG	RM3	Entity Link PRF
Retrieve	trained end-to-end	heuristic (BM25)	heuristic (BM25)
Analyze		heuristic (RM)	heuristic (RM)
Exploit	trained	heuristic	trained (L2R)

Outline

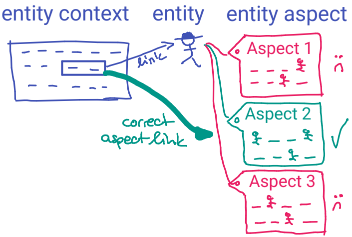
1. Guiding Entities
2. Coordinated Benchmarks
3. Exploiting Explainability in PRF
4. Retrieval-augmented Generation
5. Conclusion

Example Task: Entity Aspect Linking

Task:

- Given context passage with entity link
- given catalog of different aspect for this entity
- predict the most relevant aspect for the context

Ground truth harvested from hyperlinks to a Wikipedia section.



[Oysters] influence ecosystems through nutrient cycling

- Anatomy
- Ecosystem Services
- As Food

Aspect catalog = sections of entity's Wiki article

Each section content has entity links!

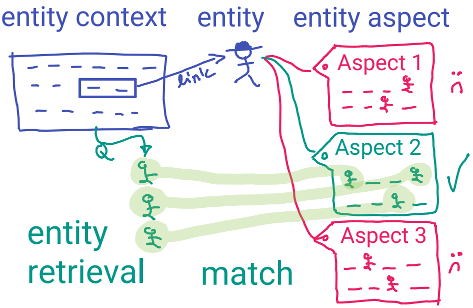
Nanni 2018. "Entity-aspect linking" - Ramsdell 2020. "A large test collection for entity asp

Entity Guides for Semantic Annotations

Given context (=query),

- **Retrieve** passages (heuristic)
- **Analyze** passages to predict relevant entities (trained)
- **Exploit** entities for semantic annotation task (trained)

Entity Ranking and Matching task are both trained individually, but on a **coordinated benchmark**.



Chatterjee 2022, "Predicting Guiding Entities for Entity Aspect Linking."

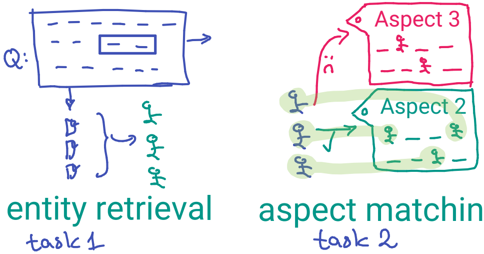
Coordinated Benchmarks for Joint Tasks

1. Task: Entity Retrieval

Query → Entity that is mentioned in the Section's content

2. Task: Aspect Matching

Query, Entities → Aspect (= Wikipedia Section)



Predicting with Entity Guides for Entity Aspect Linking

Prediction:

Given context passage with entity link

- **Retrieve** passages
- **Analyze** passages to rank entities (coordinated training)
- **Exploit** top entities to find right aspect (trained)

	Entity Ranking			Derived Aspect Ranking			LTR (Derived + Lexical)		
Entity Ranking Method	MAP@100	P@R	NDCG@100	P@1	MAP	NDCG@20	P@1	MAP	NDCG@20
BERT (PRF-Psg)*	**0.51***	**0.51***	**0.51***	**0.78***	**0.83***	**0.84***	**0.89***	**0.94***	**0.95***
BERT (LeadText)	0.33$^\blacktriangledown$	0.31$^\blacktriangledown$	0.57$^\blacktriangle$	0.35$^\blacktriangledown$	0.56$^\blacktriangledown$	0.66$^\blacktriangledown$	0.64$^\blacktriangledown$	0.78$^\blacktriangledown$	0.83$^\blacktriangledown$
Relatedness (Wikipedia2Vec [51])	0.30$^\blacktriangledown$	0.28$^\blacktriangledown$	0.53$^\blacktriangle$	0.35$^\blacktriangledown$	0.55$^\blacktriangledown$	0.65$^\blacktriangledown$	0.64$^\blacktriangledown$	0.78$^\blacktriangledown$	0.83$^\blacktriangledown$
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Article Generation

Task:

- Given query/topic
- generate a long-form article that informs about various aspects of the query

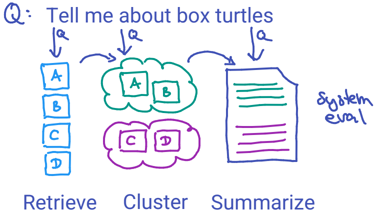
Idea:

1. Train to write Wikipedia articles
2. Read the web to produce articles for new topics.

Components for Article Generation

Given query/topic

- **Retrieve** relevant passages ← train/predict ↓
- **Cluster** passages into relevant sub-topics ← train/predict ↓
- **Summarize** text and remove redundancy ← train/predict ↓
- **Stitch** all text parts together ← System eval

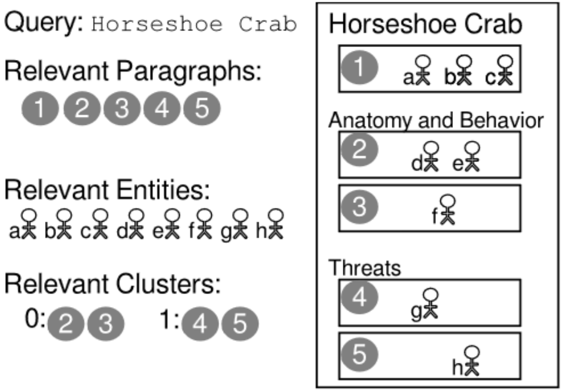


Train with Wikimarks Benchmarks

Dietz 2022 "Wikimarks: Harvesting Relevance Benchmarks from Wikipedia."

Trained on Wikimarks: Coordinated Benchmark

"Puzzle": (1) Take articles apart, (2) train to re-assemble



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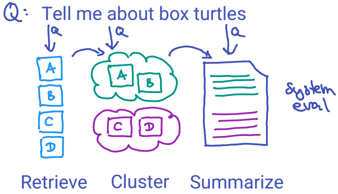
Components for Article Generation



Method	MAP
BM25-Section	**0.1566**
BM25-All	0.1429
BM25-Title	0.1010

Method	ARI
QS3M Mean	**0.3002**
QS3M Lead	0.2983
QS3M Title	0.2891
SBERT Euclid	0.2631
SBERT Cosine	0.2585

Retrieval	Clustering	Precision
BM25-All	QS3M Lead	▲0.533
	QS3M Mean	0.537
	QS3M Title	▲**0.548**
	SBERT Cosine	0.530
	SBERT Euclid	▲0.541
BM25-Section	QS3M Lead	▲0.535
	*QS3M Mean	*0.525
	QS3M Title	0.530
	SBERT Cosine	0.516
	SBERT Euclid	0.529
BM25-Title	QS3M Lead	0.519
	QS3M Mean	0.512
	QS3M Title	0.523
	SBERT Cosine	▼0.494
	SBERT Euclid	▼0.507
Manual	Manual	▼0.409

Coordinated benchmarks,
For each component:

- train each method
- select best method

+ System-level evaluation

Comparison (2)

	RAG	RM3	Entity Link PRF
Retrieve	trained end-to-end	heuristic (BM25)	heuristic (BM25)
Analyze	—	heuristic (RM)	heuristic (RM)
Exploit	trained (backprop)	heuristic	trained (L2R)

	Entity Guides	Article Generation
Retrieve	heuristic	heuristic
Analyze	coord training	coordinated training
Exploit	training	coordinated training

End-to-end $\rightarrow$ Compromise? $\leftarrow$ Coordinated Training

Multi-objective Coordinated Training

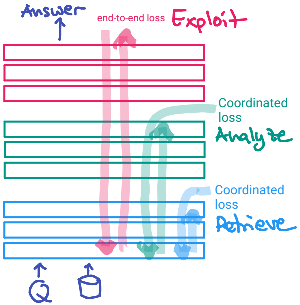
Standard approach: end-to-end training for task objective

- Costly (time + data)
- Issues propagating deep

Coordinated Training Objectives

- Directly train lower layers
- Also train to serve the task

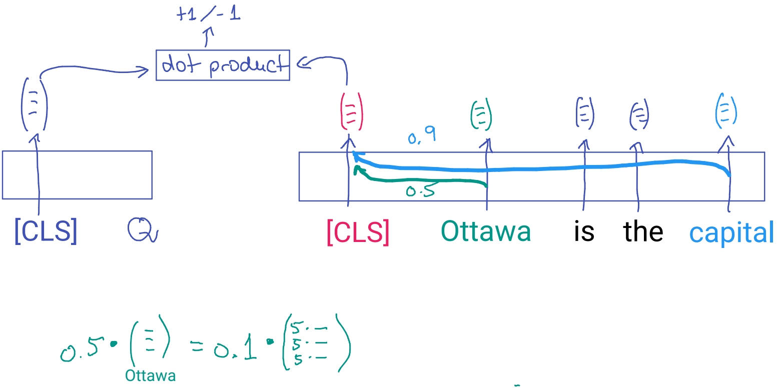
Variant: initialization with layer-block pre-training



Outline

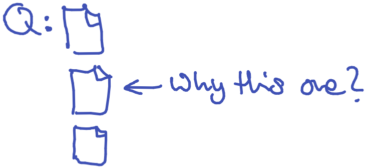
Attention $\neq$ Relevance

- Common idea: Parts with high attention are more relevant
- Sadly, this is not confirmed by empirical evaluations
  - Overparametrization = Different weights lead to same results.
  - Attention weigths can be absorbed in representation.



Explainability, Saliency, or Rationale Models

- Explainability method for neural networks
- Which input features are most important for the model's predictions?



WHY is based on gradients of prediction w.r.t input features.

Anand 2022 "Explainable Information Retrieval: A Survey"

Exploiting Explainability in Retrieve-Analyze-Exploit

Retrieve Use Dense Retrieval model (DPR)

- Dense retrieval model
  $\text{score} = \texttt{proj}\left(\mathbf{q}\right) \cdot \texttt{proj}\left(\mathbf{d}\right)$

Analyze with explainability methods to derive "WHY"

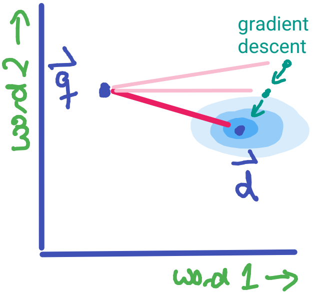
- will identify important terms
- use gradients of the DR model

Exploit important terms within Relevance Feedback framework

- query expansion to expand retrieved set
- use to find relevant symbols
  use symbols for better results

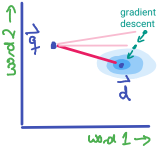
Explainability for Neural Networks

- Model: Dense retrieval $\quad\quad \text{score} = \texttt{proj}(\mathbf{q}) \cdot \texttt{proj}(\mathbf{d})$
- Features are embedded words in retrieved documents
- Prediction is the relevance score



Take gradient ∇ of predicted output, w.r.t the input words
High magnitude of gradient indicates the
words need to change the least to affect the prediction the most?

Different Explainability Methods



Gradients $\nabla_{input}(output)$
of the model's output w.r.t. the input features

- **Saliency Maps**
  - absolute value of the gradients $\nabla_{input}(output)$
- **Gradient * Input**
  - Consider Signed gradients and magnitude of input features
  - Input features $\odot \quad \nabla_{input}(output)$
- **Integrated Gradients**
  - Computes the integral of gradients $\nabla_{input}(output)$ along a path from a "bad" baseline input to the actual input
- Attention mechanisms in NLP models (e.g., BiDAF)
- Layer-wise relevance propagation (LRP) for text-based models

Simonyan 2013 Saliency Maps - Shrikumar 2017 Gradient * Input - Sundararajan 2017 Integ

Note: No Ground Truth Required

- Saliency methods can be applied without knowledge of the ground truth
- Asks: Why did the model find this passage/symbol relevant?
- Methods: Trade-off accuracy and computational cost

We should do more research to explore the combination of Explainability, DPR, and PRF

Outline

RAG - With Grounded Hypotheses

How to combine across retrieved documents to generate answer?

Concatenate Issue: Input too large to process
also: needs to refresh when retrieved docs change

FiD (Izacard & Grave 2020): Generate latent representation of each document, fuse, then generate

RetGen/MoE (Zhang 2022,Cho 2020): From each document, generate a hypothesis (at token level)
then integrate with Max Mutual Information

Generated hypotheses are "grounded" in words.

Question: Why not grounded in entities or facts?

Zhang 2022 "Joint Retrieval and Generation Training for Grounded Text Generation.

Neuro-Symbolic Q/A: Facts-as-Experts

- Transformer-based Masked Language Model
- Mask out entities, predict correct one
- To predict maked entities
  1. use context (the usual transformer)
  2. make use of external fact representations (memory)
- Only consider facts that are mentioned in the remaining text.

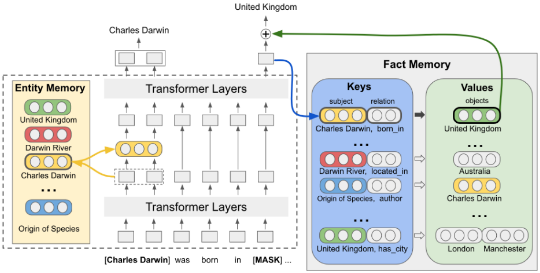
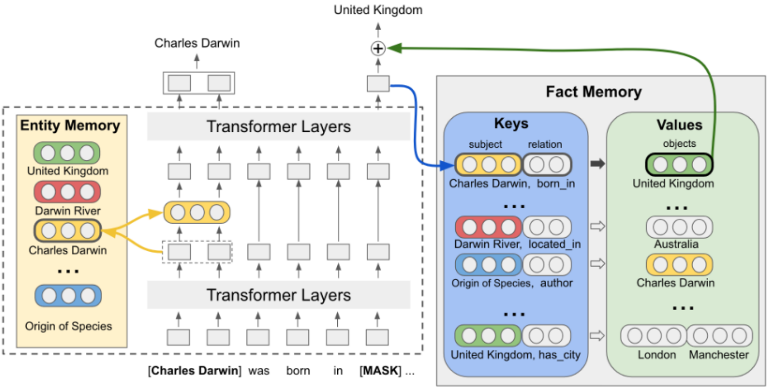


Figure 1: **Fact Injected Language Model architecture.** The model takes a piece of text (a question during fine-tuning or arbitrary text during pre-training) and first contextually encodes it with an entity enriched transformer.

Verga 2021. "Adaptable and interpretable neural memoryover symbolic knowledge."

Neuro-Symbolic Q/A: Facts-as-Experts



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Results on Open Domain Q/A

	Model	WebQuestionsSP				TriviaQA			
		Full Dataset		Wikidata Answer		Full Dataset		Wikidata Answer	
		Total	No Overlap	Total	No Overlap	Total	No Overlap	Total	No Overlap
Closed-book	**FILM**	**54.7**	**36.4**	**78.1**	**72.2**	**29.1**	**15.6**	**37.3**	**28.4**
	EaE	47.4	25.1	62.4	42.9	19.0	9.1	24.4	17.1
	T5-11B	49.7	31.8	61.0	48.5	–	–	–	–
	BART-Large	30.4	5.6	36.7	8.3	26.7	0.8	30.6	1.0
Open-Book	RAG	**50.1**	**30.7**	**62.5**	**45.1**	56.8	29.2	64.9	45.2
	DPR	48.6	34.1	56.9	45.1	57.9	31.6	66.3	48.8
	FID	–	–	–	–	**67.6**	**42.8**	**76.5**	**64.5**
	EmQL†	75.5	-	74.6	-	-	-	-	-

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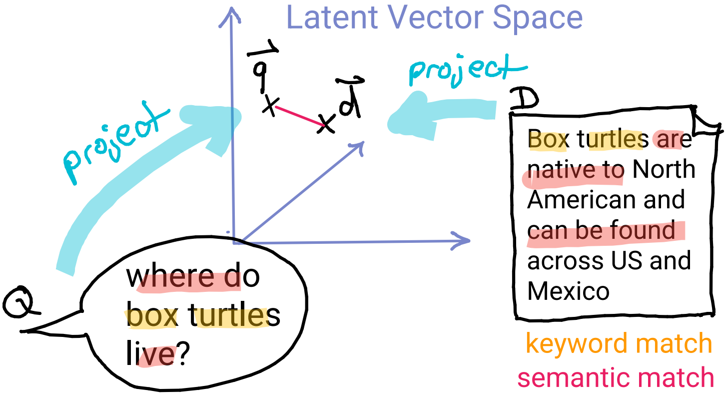
SOTA: ad hoc Text Ranking

Dense Retrievel Approach:



Latent space and projections are trained, so that **q** and **d** are close whenever documents are relevant for the query.

Opportunities of Neuro-Symbolic Approaches

- Explainability and interpretability:
  - promising direction to exploit "model knowledge"
  - symbolic logic providing insights into the reasoning process
  - make it easier for users to trust the generated results
- Robustness to noise and ambiguity:
  - Use symbolic reasoning to when neural components struggle
  - more reliable for relevance and topics
  - dealing with incomplete or noisy data
- Transfer learning and generalization:
  - Leverage compositional nature of symbolic representation
  - Generalize to unseen queries or domains
  - Exploit known knowledge — rather than learning first principles

Opportunities for IR

Query Processing Improve the interpretation of user queries

- Expand the query with semantically related terms/symbols
- Decide what is not relevant
- Guess where to find non-obvious relevant info

Matching Improve the relevance of retrieved documents

- Identify similarity of semantically related information
- Reason about which connections are meaningful

Ranking Relative ordering of retrieved documents

- Capture the importance and relevance of entities to the query and the document
- Provide explanations and relevant background
- Fill knowledge graps in retrieved results