

Entity Representations and Entity Ranking

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What is an Entity?

- Uniquely identifiable object or thing.
- Characterized by: Name(s), Type(s), Attributes, and Relationships to other entities.

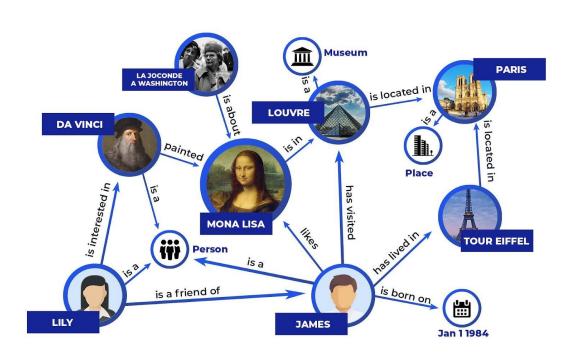


• Name: Food and Drug Organization

• **Type**: Organization

Relation: Located_In (USA)





Knowledge Graph

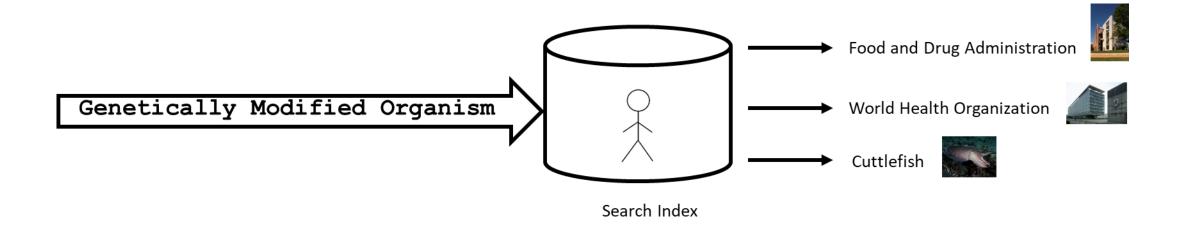
- Repository of entities.
- Nodes = entities and edges = relations.
- Contains: Types, Relations, Descriptions, etc.
- Examples: DBpedia, YAGO, Wikipedia, etc.

Picture credit: https://community.atlassian.com/t5/Confluence-questions/Knowledge-graph/qaq-p/1565284



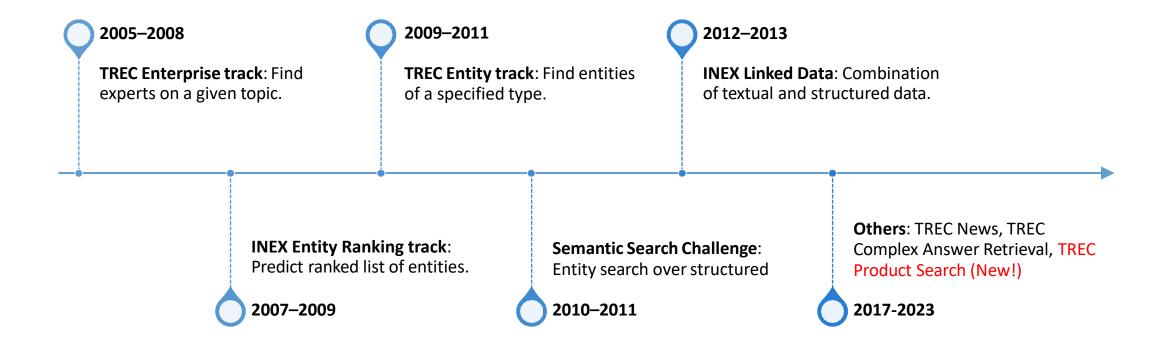
Task: Entity Ranking

Given a query and a KG, retrieve entities that are relevant to the query ordered by the relevance of each entity to the query.





Entity Ranking: Over the Years









Types of Entity Retrieval Models

- Drobabilistic Unstructured Models: Consider an entity as a single "document".
- ☐ Probabilistic Fielded Models: Consider an entity as a "document" with multiple fields.
- Learning-To-Rank Models: Use feature vectors of (query, entity) pairs to train a ML model.
- Semantically Enriched Models: Consider types and relations in KG for retrieval.
- Graph-embedding-based Models: Use graph embeddings for entity ranking.
- Transformer-based Models: Use Transformers (e.g., BERT) for entity ranking.

"Traditional"/Non-Neural

Neural



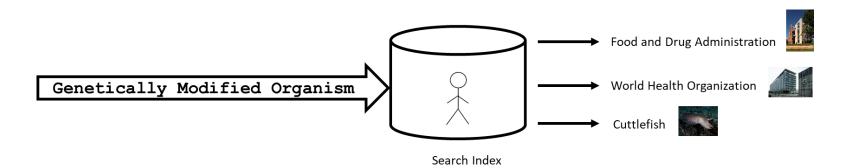
"Traditional"/Non-Neural Entity Ranking



How Do Systems Usually Retrieve Entities?

- Create a search index of all entities.
- Match query against representation of the entity.

One LM for whole entity

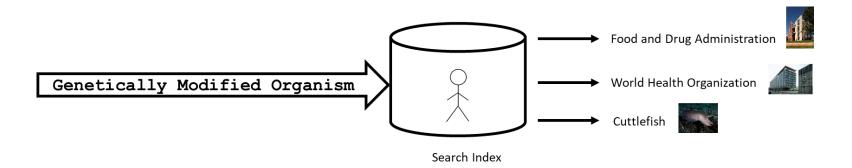




How Do Systems Usually Retrieve Entities?

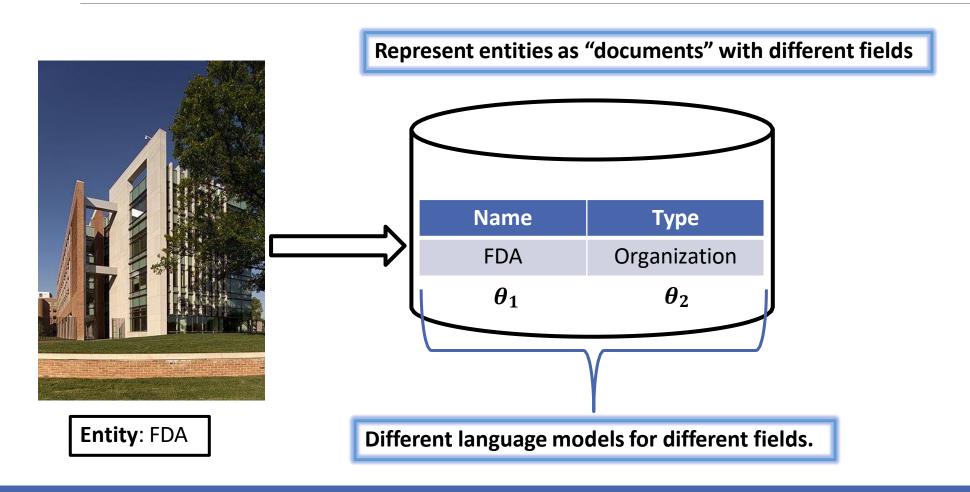
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Different LM for entity fields



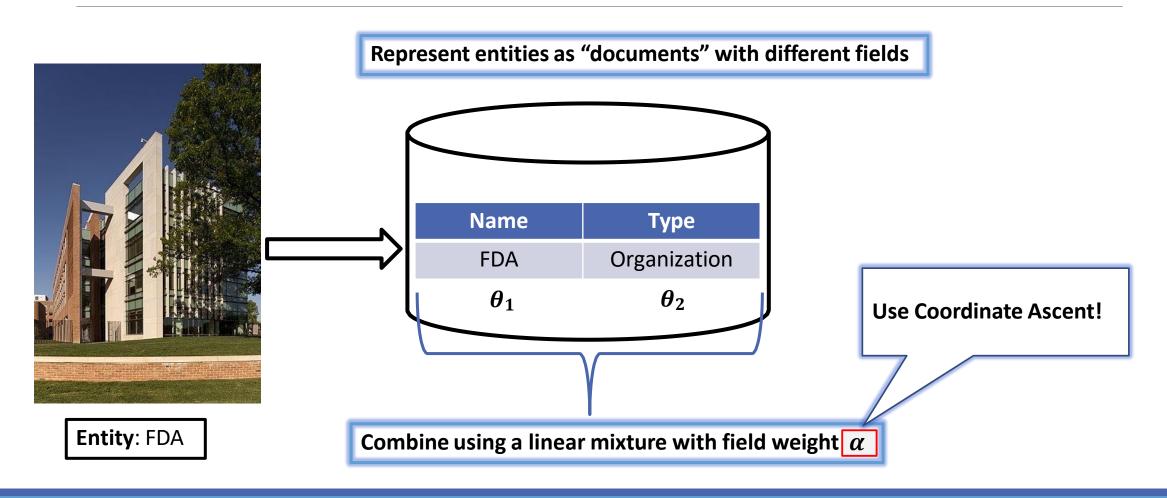


Different LM for Entity Fields





Different LM for Entity Fields

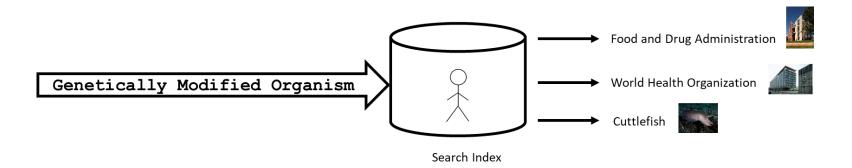




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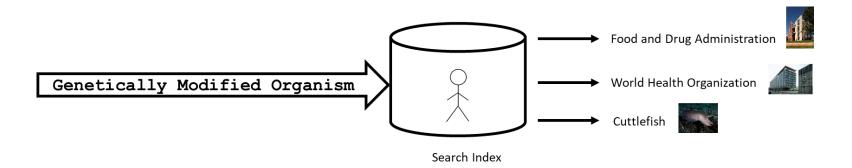
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How Do Systems Usually Retrieve Entities?

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Use features to train ML model.

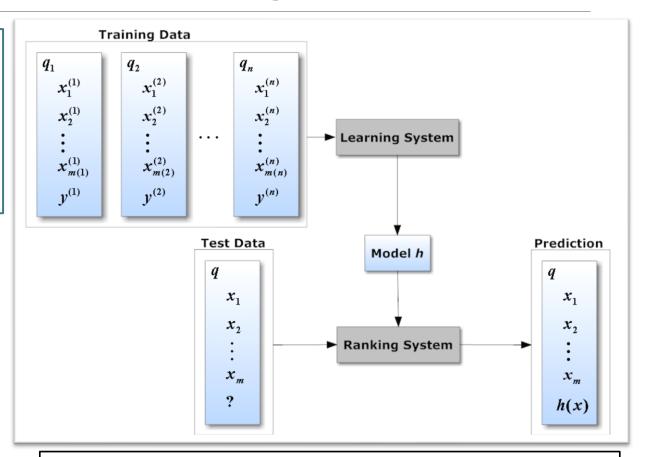




Use Features to Train ML model: Learning-To-Rank

Features:

- ☐ Entity retrieval from a KB using BM25+RM3.
- ☐Whether the candidate entity is contained in the query entities.
- ☐ Normalized Levenshtein Distance between the query and the mention.



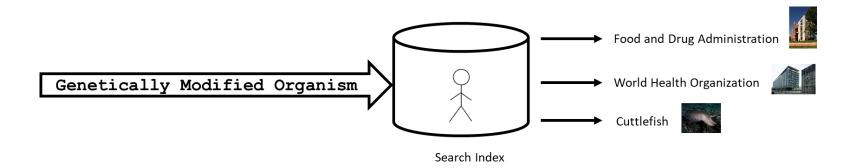
Picture credit: http://web.ist.utl.pt/~catarina.p.moreira/coursera.html



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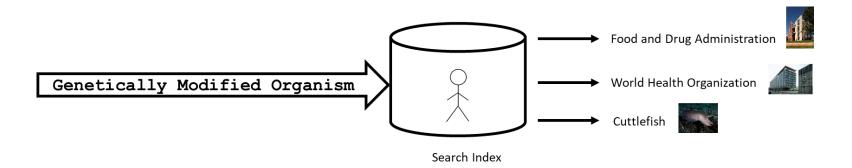




How Do Systems Usually Retrieve Entities?

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Use entity types from a KG.





Use Entity Types From a KG: Type-Aware Entity Retrieval

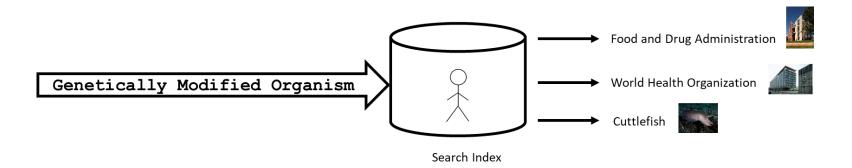
- ☐ Uses entity types from a type taxonomy (e.g., Wikipedia categories).
- Query enriched with types of entities in the query (called target types)
- ☐ Example [Balog et al., 2011]
- Learn a probability distribution over the query and entity types.
- Similarity = KL divergence between two distributions



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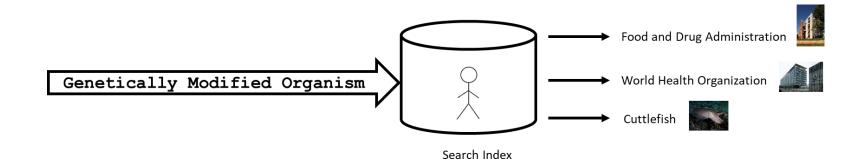


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Non-neural methods: Sparse

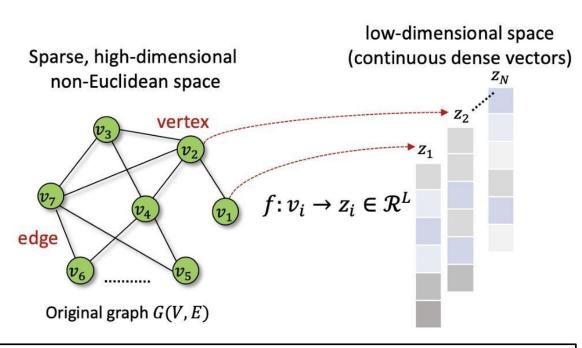
Neural methods: Dense





Neural Entity Ranking





Picture Credit: Mengjia Xu. Understanding Graph Embedding Methods and their Applications. 2020.

Graph Embeddings: Learning Dense Entity Representations

- ☐ Treat the knowledge repository as a KG.
- □Convert high-dimensional KG into low dimensional, dense and continuous vector spaces.
- ☐ Graph structure properties are maximally preserved.
- □ Examples: Wikipedia2Vec, TransE, TransR, etc.

Gerritse et al., 2020

GEEER: Using Wikipedia2Vec for Entity Ranking

- ☐ Re-ranks entities using Wikipedia2Vec.
- ☐ Shows that Wikipedia2Vec is useful for entity ranking.
- □ General Idea: Relevant entities for a given query are situated close (in graph embedding space) to the query entities identified by the entity linker.

■ Method:

Compute the embedding-based score for an entity:

$$Score_{emb}(E,Q) = \sum_{e \in Q} C(e) \cdot \cos(\vec{E}, \vec{e})$$

Final Score = interpolation of the embedding-based and retrieval scores.

$$Score_{final}(E,Q) = \lambda \cdot Score_{emb}(E,Q) + (1-\lambda) \cdot Score_{ret}(E,Q)$$

Gerritse et al., 2020

Confidence score of

entity linker.

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- Method:
 - Compute the embedding-based score for an entity:

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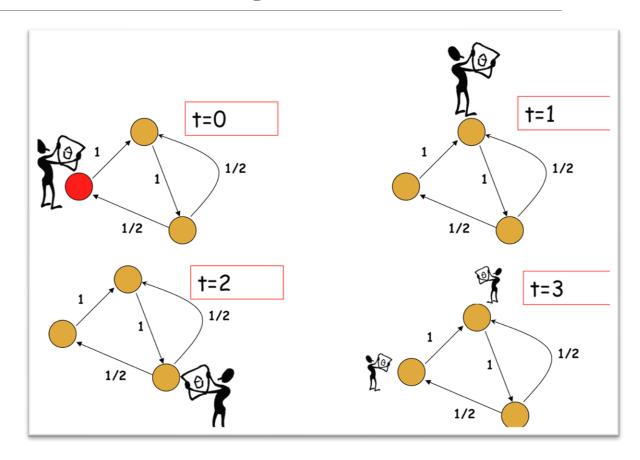
Use LTR optimized for NDCG@100.



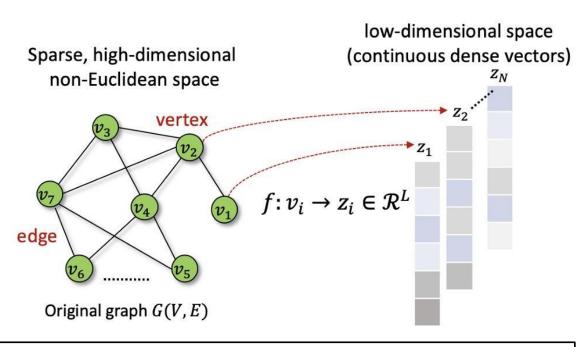
Nikolaev and Kotov., 2020

KEWER: Knowledge graph Entity and Word Embedding for Retrieval

- □ Joint embedding of entities and words (like Wikipedia2Vec).
- ☐ Uses: Entities, attributes, categories, KG structure.
- ☐ Method: Random walks over a KG.
 - Start from each entity.
 - Repeatedly follow directed edges
- ☐ Training: Skip-Gram-based model using generated random walks.
- Entity Ranking: Cosine similarity between query and entity embedding.







Picture Credit: Mengjia Xu. Understanding Graph Embedding Methods and their Applications. 2020.

Graph Embeddings: Issues for IR

- ☐ IR: Considers explicit query.
- □ Current graph embedding methods: Not seen the query during training (query-agnostic!)



How About We Use BERT?



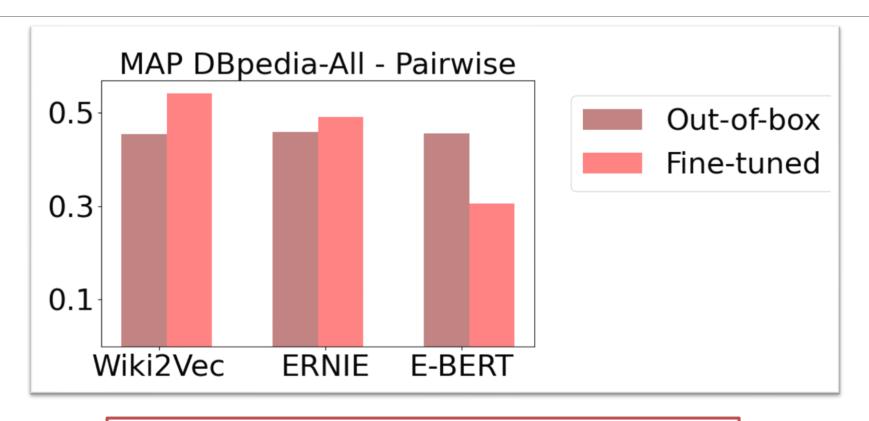
- BERT shown to be useful for document retrieval.
- **Question:** Can we use BERT for entity ranking?

Poerner et al., 2020

One Idea: E-BERT: Injecting Entity information into BERT

- ☐ Aligns Wikipedia2Vec entity vectors with BERT's native word piece vectors.
- □ Issue: BERT's word piece dictionary does not contain any entities!
- □ Solution: Use common words in the vocabulary of BERT and Wikipedia 2 Vec.
- ☐ Wikipedia2Vec embeds words and entities into the same vector space → Alignment learnt using words can also be applied to entities.

How Well Does BERT understand Entities?



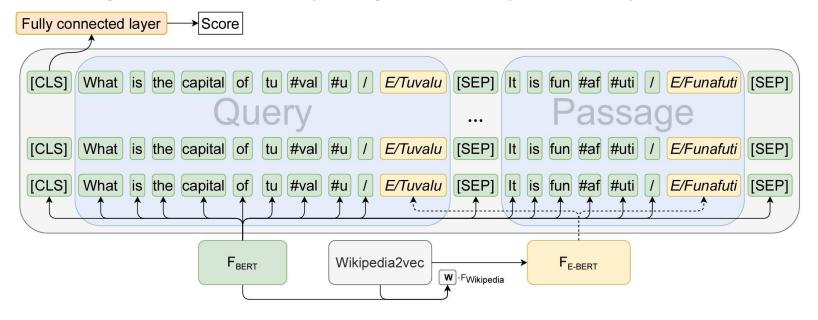
Results for GEEER with ERNIE and E-BERT. Dbpedia-Entity v2.



Gerritse et al., 2022

EM-BERT: Entity-enriched BERT for Entity Ranking

- □ Aligns Wikipedia2Vec entity vectors with BERT's native word piece vectors (as in E-BERT).
- Entity vectors used with entity mentions.
- ☐ Fine-tuning: First MS MARCO passages, then DBpedia-Entity v2.



Picture Credit: Gerritse et al. Entity-aware Transformers for Entity Search. 2022.

Figure 1: Illustration of the EM-BERT model. Entity annotated query and documents are tokenized and mapped to their corresponding vector representations using F_{BERT} and F_{E-BERT} functions.



Gerritse et al., 2022

EM-BERT: What do we learn?

- Substantial improvements over SOTA for entity ranking!
- ☐ Helps:
 - Complex natural language queries,
 - List search queries, and
 - Queries containing tail entities



One Idea: Injecting Entity information into BERT



Another Idea: Can we utilize existing knowledge in BERT?

- ☐ BERT has already seen a lot of the world (from books and Wikipedia).
- □ BERT can probably infer the connection between the query and entity from a term-based entity description.
- ☐ Term-based entity description = Introductory Wikipedia paragraph (most often).

Query: Genetically Modified Organism

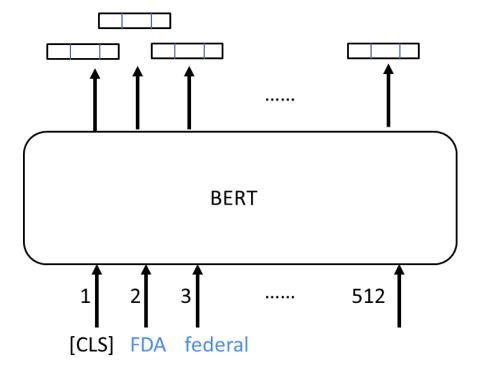
Relevant Entity: Food and Drug Administration



Lead Text

Food and Drug Administration

The United States **Food and Drug Administration** (**FDA** or **USFDA**) is a federal agency of the Department of Health and Human Services. The FDA is responsible for protecting and promoting public health through the control and supervision of <u>food safety</u>, tobacco products, dietary supplements, prescription and over-the-counter pharmaceutical drugs (medications), vaccines, biopharmaceuticals, blood transfusions, medical devices, electromagnetic radiation emitting devices (ERED), cosmetics, animal foods & feed^[3] and veterinary products.

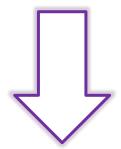


- Lead Text = Static entity description
- No knowledge of the query!
- Static entity embeddings.

Query: Genetically Modified Organism

Relevant Entity: Food and Drug Administration

FDA regulates most human and animal food, including GMO foods. In doing so, FDA makes sure that foods that are GMOs or have GMO ingredients meet the same strict safety standards as all other foods. FDA sets and enforces food safety standards [...]



What if we had this text instead of lead text?

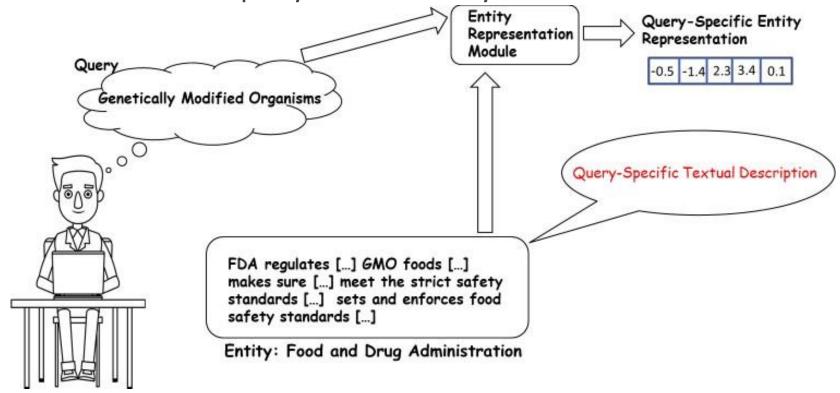


Clarifies the connection between the query and entity.

Chatterjee and Dietz., 2022

BERT-ER: Query-Specific Entity Descriptions

Query-specific entity descriptions \rightarrow descriptions that mention relevant connections between the query and the entity.



The United States Food and Drug Administration (FDA or USFDA) is a federal agency of the Department of Health and Human Services. The FDA is responsible for protecting and promoting public health through the control and supervision of food safety, tobacco products, dietary supplements, prescription and over-the-counter pharmaceutical drugs (medications), vaccines, biopharmaceuticals, blood transfusions, medical devices, electromagnetic radiation emitting devices (ERED), cosmetics, animal foods & feed^[3] and veterinary products.

- 1 Organizational structure
- 2 Location
- 3 Scope and funding
- 4 Regulatory programs
- 5 Science and research programs
- 6 Data management
- 7 History

Aspects = Top-Level Sections

Query-Specific Entity Descriptions: Alternative 1

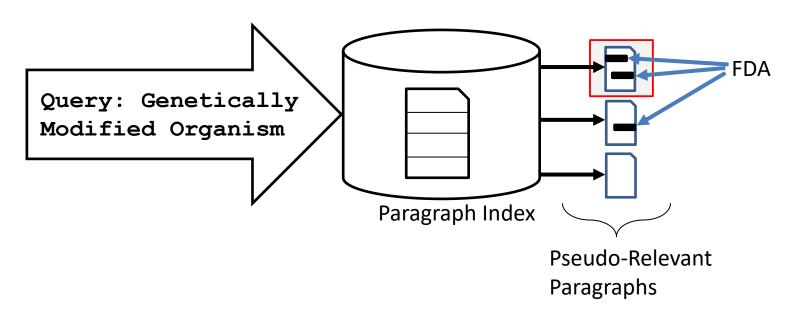
- ☐ Using Wikipedia: Top-Level Sections
 ☐ Identify relevant top-level sections from the
- Wikipedia page. (Why? —because the lead text is does not elaborate the relevance!)
- ☐ Use catalog of top-level sections (aspects)
- from Ramsdell et al., 2020.
- ☐ Downside: Wikipedia articles often do not contain all relevant information!



Query-Specific Entity Descriptions: Alternative 2

Chatterjee and Dietz., 2022

☐ Using Paragraph Collection: PRF Passages



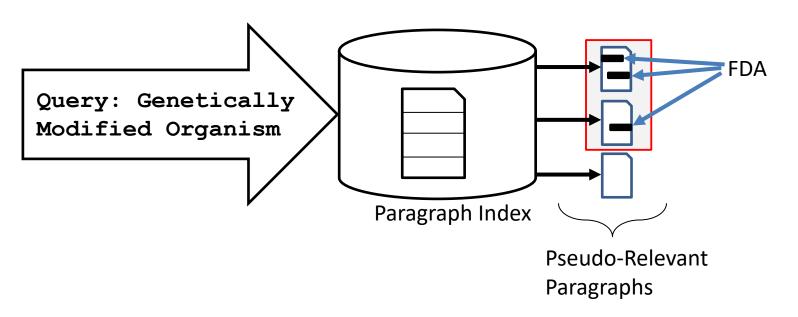
☐ Downside: Entity may not be central to the discussion in the text!



Query-Specific Entity Descriptions: Alternative 3

Chatterjee and Dietz., 2022

☐ Using Paragraph Collection: Entity-Support Passages



- ☐ Re-rank these documents.
- ☐ Two criteria:
- 1. How many relevant connections between query and entity?
- 2. Are the relevant connections central to the discussion in the text?

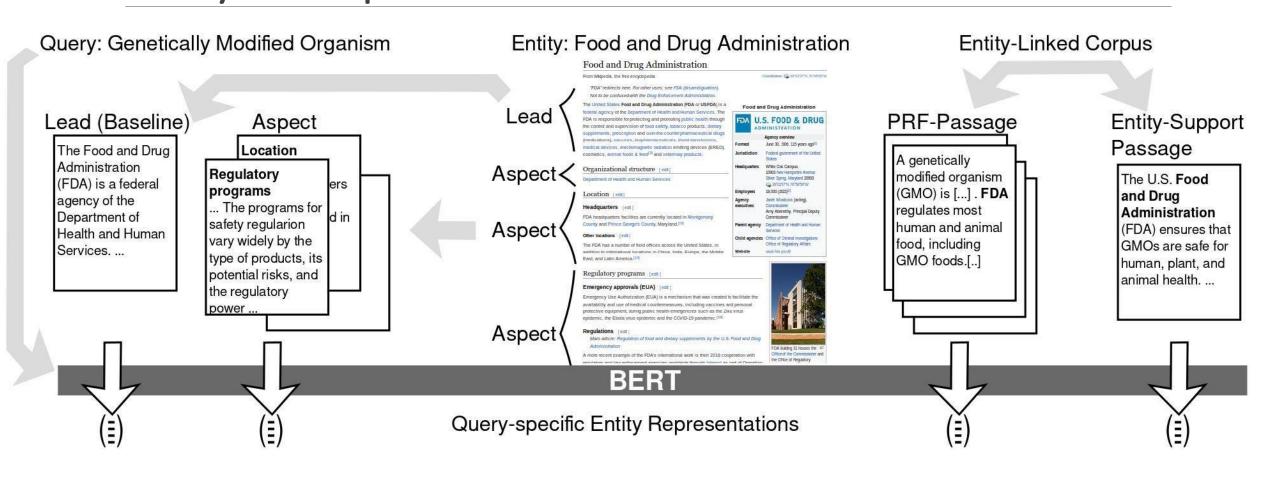
Entity-Support Passages: *Chatterjee and Dietz, ICTIR 2019.*



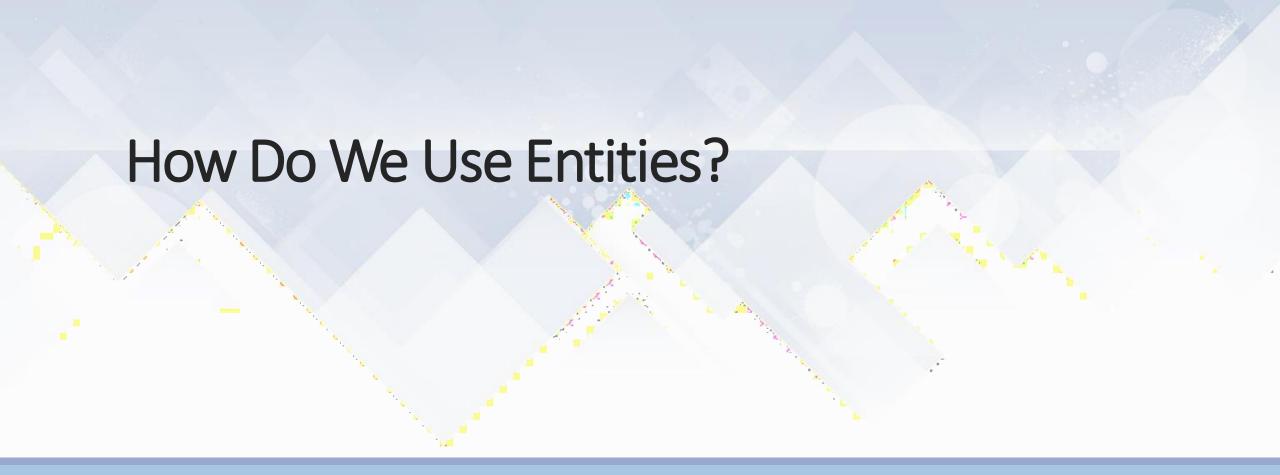
BERT-ER: Alternative Approaches for Query-Specific

Entity Description s

Chatterjee and Dietz, SIGIR 2022





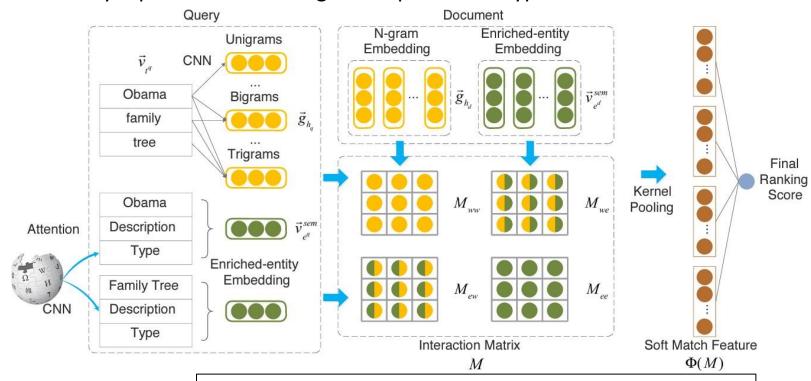




Entity-Duet Neural Ranking Model

Liu et al., 2018

- ☐ Incorporates entities in interaction-based neural ranking models.
- ☐ Learns entity representations using: descriptions and types.



Picture Credits: Liu et al. Entity-Duet Neural Ranking. 2018.



Dense Retrieval With Entity Views

Tran and Yates, 2022

- ☐ Enrich query/document representation with entity representations.
- \square Cluster entities \rightarrow Entity embeddings using clusters \rightarrow Clusters act as "views" of the document.

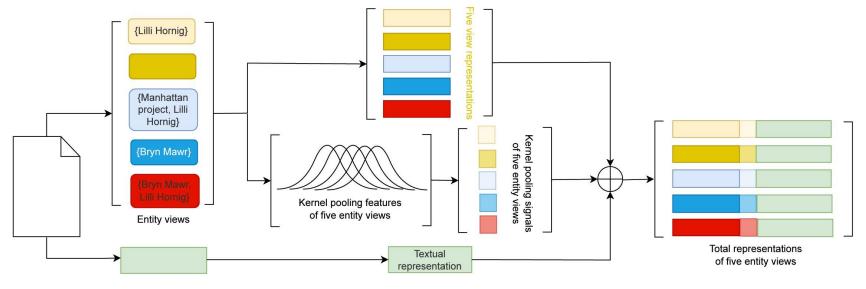


Figure 1: Overview of EVA with multiple representations. Entity clusters such as {Lilli Hornig}, {Manhattan project}, {Manhattan project, Lilli Hornig}, {Bryn Mawr} and {Bryn Mawr, Lilli Hornig} can be understood as different entity views of the passage. EVA generates one total representation for each view, which enriches a textual representation with the entities present.

Picture Credits: Tran and Yates. Dense Retrieval with Entity Views. 2022.