

Logical Query Reasoning in Knowledge Graphs

CPSC483: Deep Learning on Graph-Structured Data

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Readings

- Readings are updated on the website (syllabus page)
- **Lecture 20 readings:**
 - [Neural Distance Embeddings](#)
 - [Hyperbolic Cone Embedding](#)
- **Lecture 21 readings:**
 - [Query2Box](#)
 - [Google PathQuery](#)
- NeurIPS 2022 Workshop ([Frontiers of Graph Learning](#))

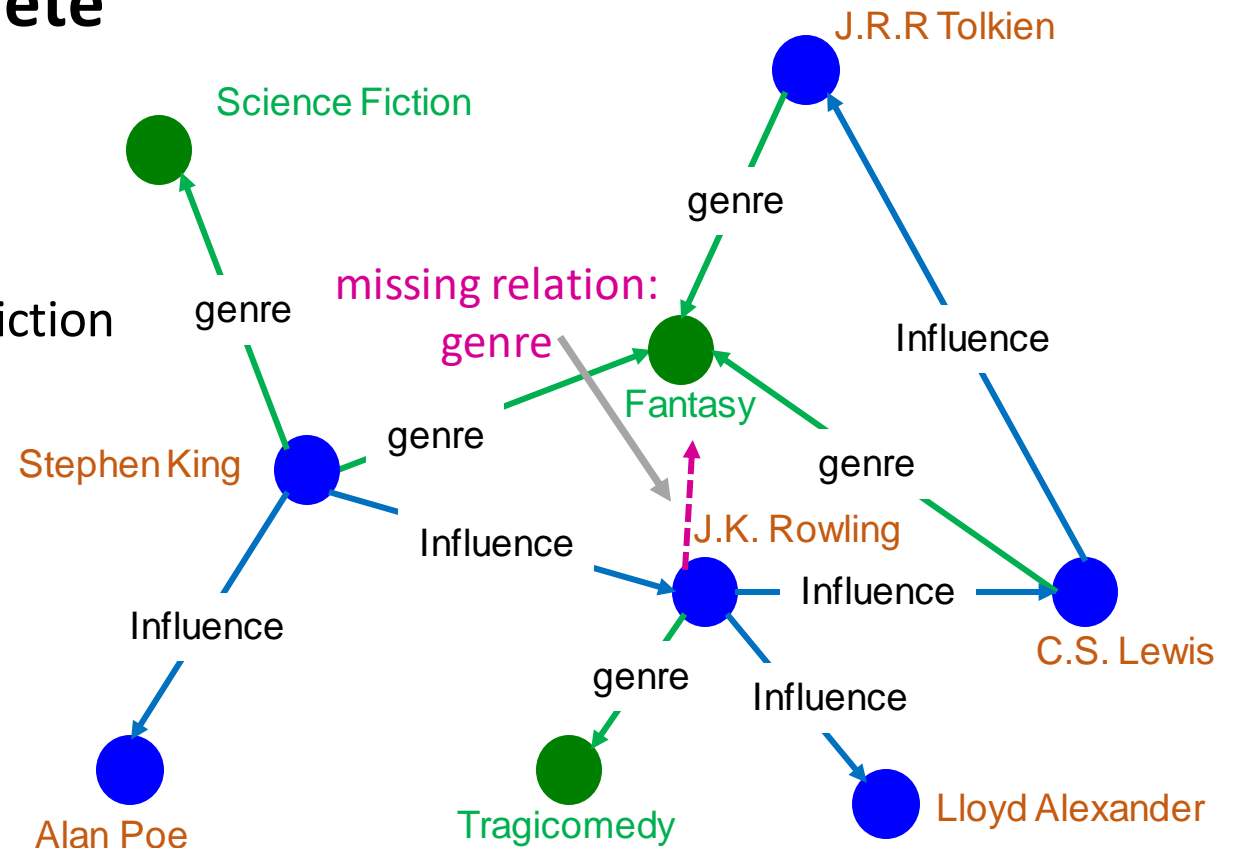
Recap: KG Completion Task

Given an enormous KG, can we complete the KG?

- For a given (**head**, **relation**), we predict missing **tails**.
 - (Note this is slightly different from link prediction task)

Example task: predict the “**Fantasy**” for (“**J.K. Rowling**”, “genre”)

- Today:** **multi-hop** reasoning over KG for complex queries



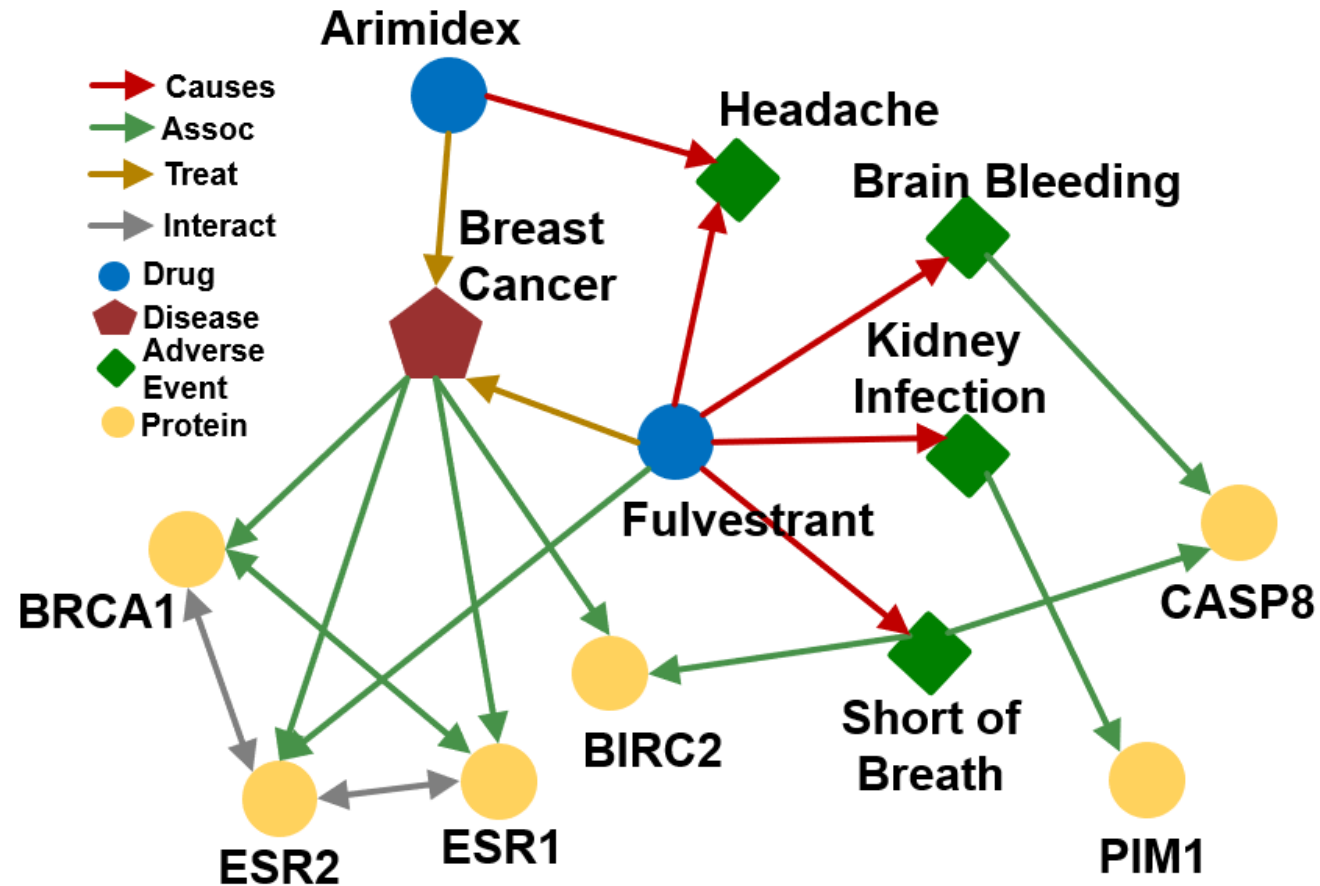
Outline of Today's Lecture

- **Queries on KG**
- **Traversing KG in Embedding Space**
- **Box Embeddings**

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Example KG: Biomedicine



Predictive Queries on KG

Can we do multi-hop reasoning, i.e., **answer complex queries** on an **incomplete, massive KG**?

Query Types	Examples: Natural Language Question , Query
One-hop Queries	What adverse event is caused by Fulvestrant? (e:Fulvestrant, (r:Causes))
Path Queries	What protein is associated with the adverse event caused by Fulvestrant? (e:Fulvestrant, (r:Causes, r:Assoc))
Conjunctive Queries	What is the drug that treats breast cancer and caused headache? ((e:BreastCancer, (r:TreatedBy)), (e:Migraine, (r:CausedBy)))

Inverse of (r:Treat)

Inverse of (r:Cause)

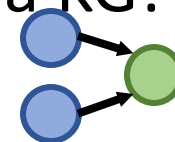
- In this lecture, we only focus on answering **queries** on a KG!



One-hop Queries



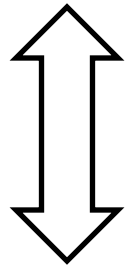
Path Queries



Conjunctive Queries

Predictive One-hop Queries

- We can formulate knowledge graph completion problems as answering one-hop queries.
- **KG completion**: Is link (h, r, t) in the KG?



- **One-hop query**: Is t an answer to query (h, r) ?
 - **For example**: What side effects are caused by drug **Fulvestrant**?

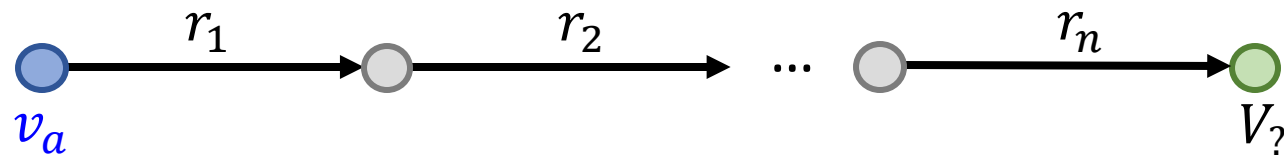
Path Queries

- Generalize one-hop queries to path queries by **adding more relations on the path**.
- An n -hop path query q can be represented by

$$q = (v_a, (r_1, \dots, r_n))$$

v_a is an “anchor” entity, answers are denoted by $\llbracket q \rrbracket_G$.

Query Plan of q :

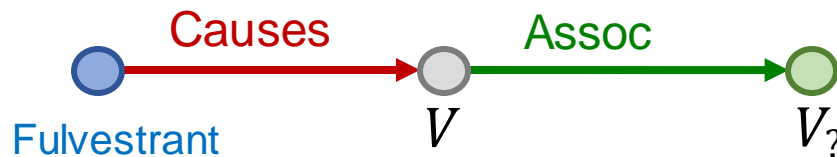


Query plan of path queries is a chain.

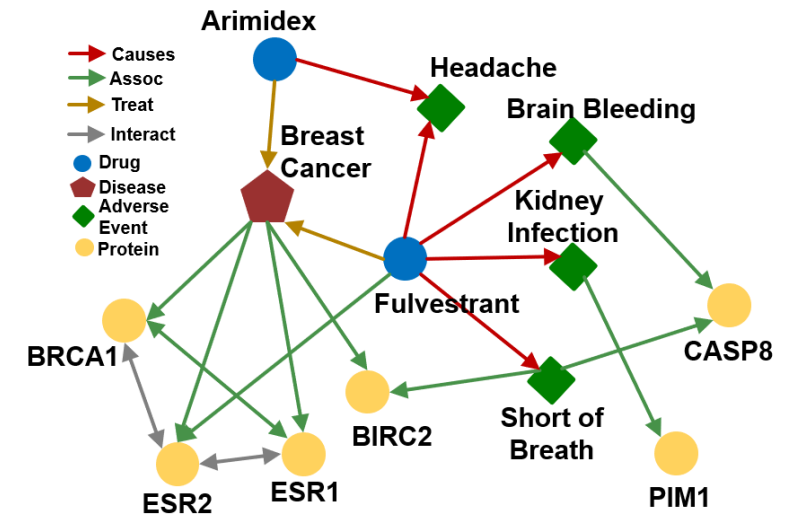
Path Queries: Example

“What proteins are **associated** with adverse events **caused** by **Fulvestrant**?”

- v_a is **e:Fulvestrant**
- (r_1, r_2) is (**r:Causes**, **r:Assoc**)
- Query: (**e:Fulvestrant**, (**r:Causes**, **r:Assoc**))

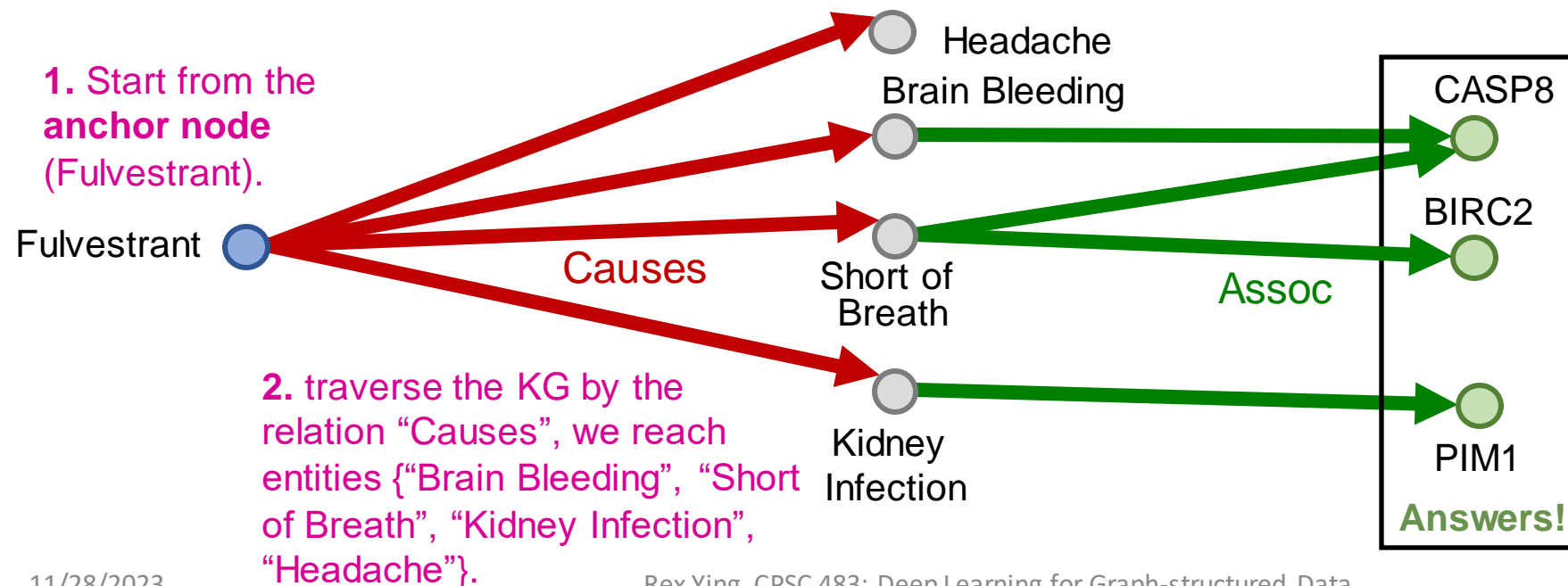


Given a KG, **how to answer a path query?**



Traversing Knowledge Graphs

- Answer path queries by traversing the KG: “What proteins are **associated** with adverse events **caused** by **Fulvestrant**?”
- Query: (e:Fulvestrant, (r:Causes, r:Assoc))

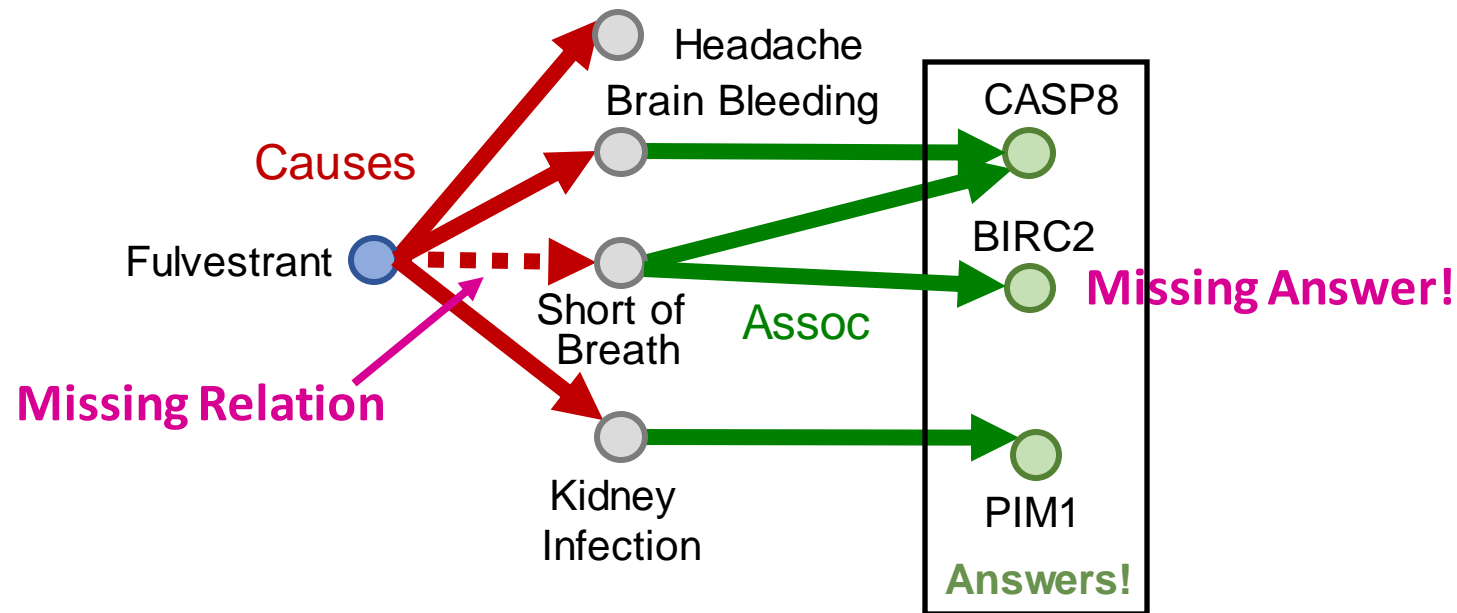


KGs are incomplete

- **Answering queries seems easy: Just traverse the graph.**
- **However, KGs are notoriously incomplete:**
 - Many relations between entities are missing or are incomplete
 - For example, we lack all the biomedical knowledge
 - Enumerating all the facts takes non-trivial time and cost, we cannot hope that KGs will ever be fully complete
- **Due to KG incompleteness, one is not able to identify all the answer entities**

Example: Incomplete KG

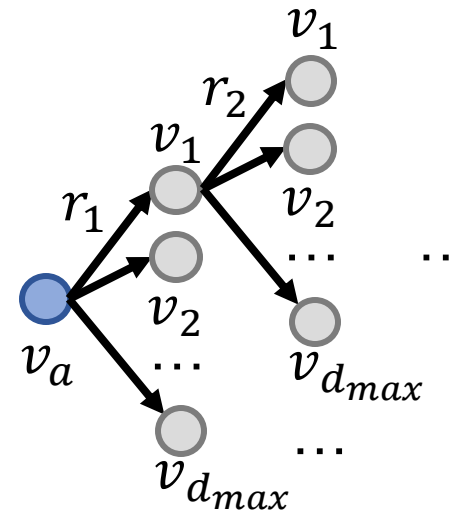
- Answer path queries by traversing the KG: “What proteins are **associated** with adverse events **caused** by **Fulvestrant**?”
- Query: (e:Fulvestrant, (r:Causes, r:Assoc))



Can KG Completion Help?

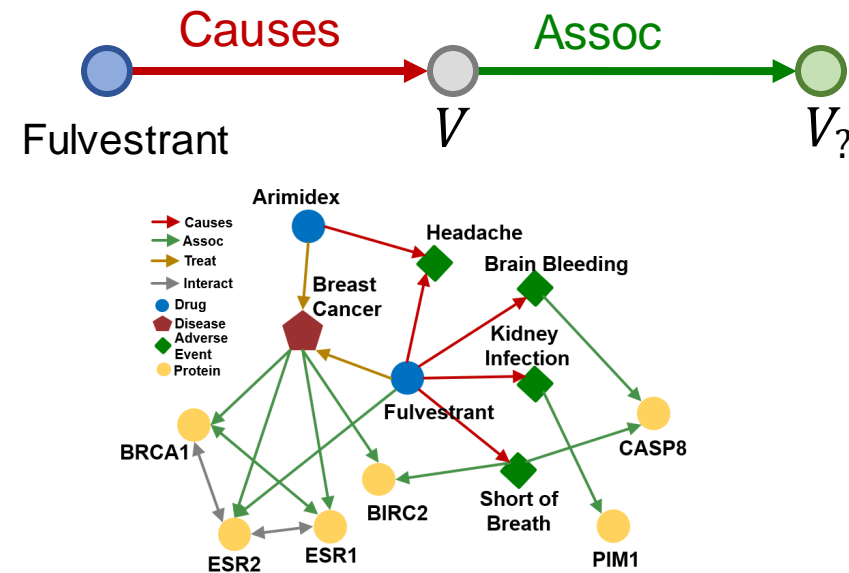
Can we first do KG completion and then traverse the completed (probabilistic) KG?

- **It's difficult.** The “completed” KG is a **dense graph**!
 - Most (h, r, t) triples (edge on KG) will have some non-zero probability.
- Time complexity of traversing a dense KG is exponential as a function of the path length L : $O(d_{max}^L)$



Task: Predictive Queries

- We need a way to answer path-based queries over an incomplete knowledge graph.
- We want our approach to implicitly impute and account for the incomplete KG.
- **Task: Predictive queries**
 - Want to be able to answer arbitrary queries while implicitly imputing for the missing information
 - **Generalization of the link prediction task**



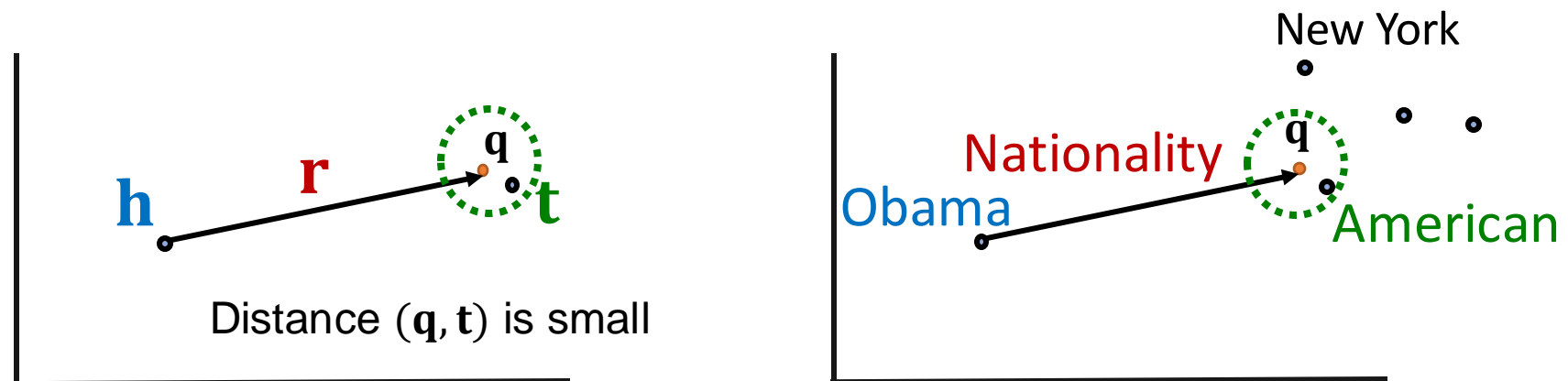
Outline of Today's Lecture

- Queries on KG
- **Traversing KG in Embedding Space**
- Box Embeddings

Idea: Traversing KG in Embedding Space

- **Key idea: Embed queries!**

- Generalize **TransE** to multi-hop reasoning.
- **Recap: TransE:** Translate **h** to **t** using **r** with score function $f_r(h, t) = -||\mathbf{h} + \mathbf{r} - \mathbf{t}||$.
- Another way to interpret this is that:
 - **Query embedding:** $\mathbf{q} = \mathbf{h} + \mathbf{r}$ (**Note** that **q** is the **embedding** of q)
 - Goal: **query embedding** **q** is **close** to the **answer embedding** **t**
 $f_q(t) = -||\mathbf{q} - \mathbf{t}||$

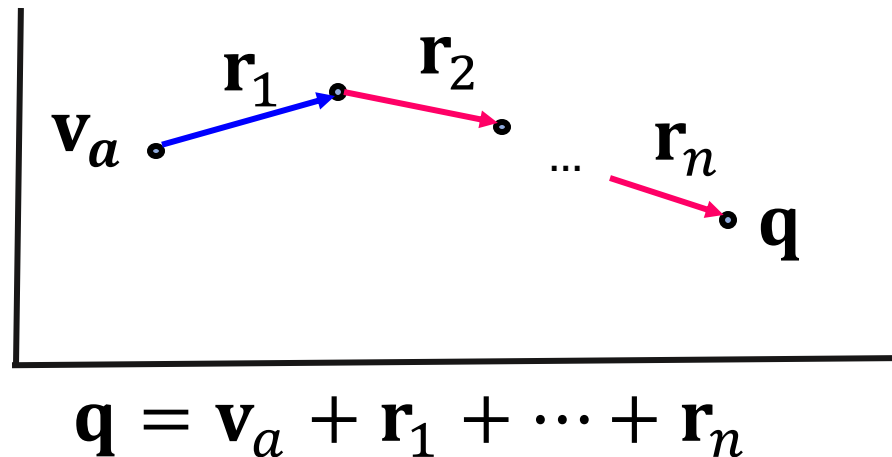


Traversing KG in Embedding Space

- **Key idea: Embed queries!**

- Generalize **TransE** to multi-hop reasoning.

Given a path query $q = (v_a, (r_1, \dots, r_n))$,



- The embedding process **only involves vector addition**, **independent of # entities** in the KG!

Traversing KG in Embedding Space: Example

Embed path queries in vector space.

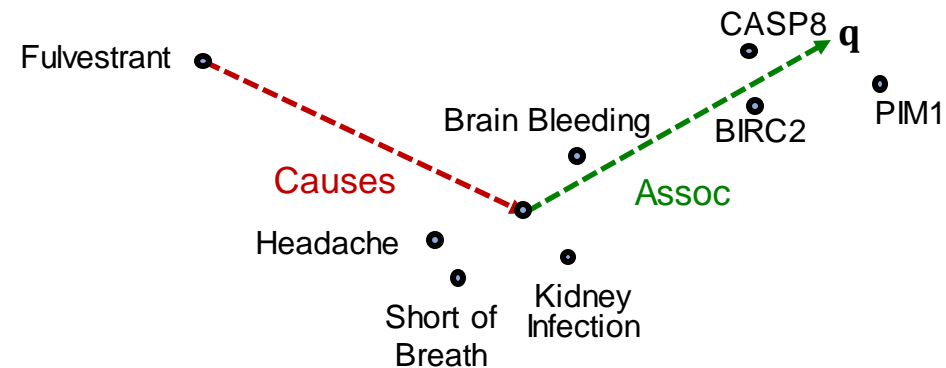
- “What proteins are **associated** with adverse events **caused** by **Fulvestrant**?”
- (e:Fulvestrant, (r:Causes , r:Assoc))

Follow the query plan:

Query Plan



Embedding Process



Traversing KG in Embedding Space: Insights

Insights:

- We can train **TransE** to optimize knowledge graph completion objective (Lecture 18)
- Since **TransE** can naturally handle **composition relations**, it can handle path queries by translating in the latent space **for multiple hops using addition of relation embeddings**.

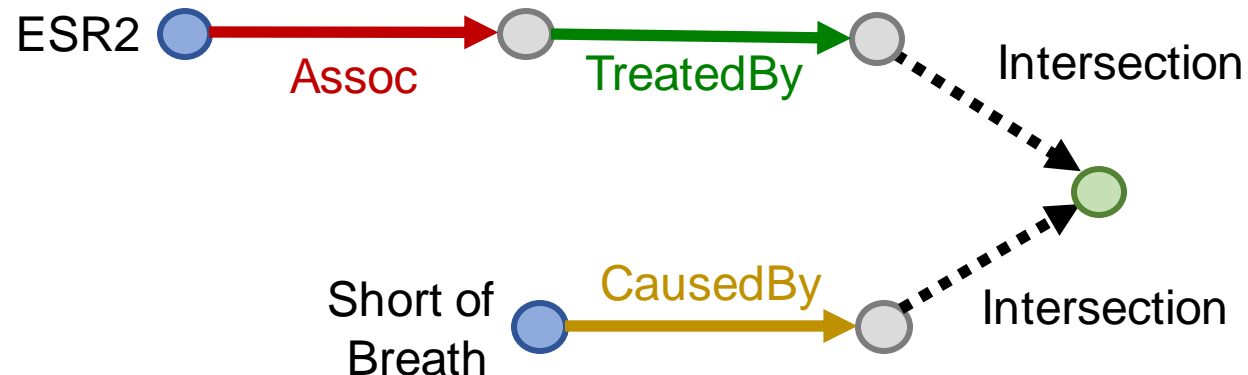
Conjunctive Queries (1)

Can we answer more complex queries with **conjunction (AND) operation**?

- **Conjunctive Queries:** “What are drugs that **cause** Short of Breath and **treat** diseases **associated** with protein ESR2?”

$((e:ESR2, (r:Assoc, r:TreatedBy)), (e:Short\ of\ Breath, (r:CausedBy)))$

Query plan:

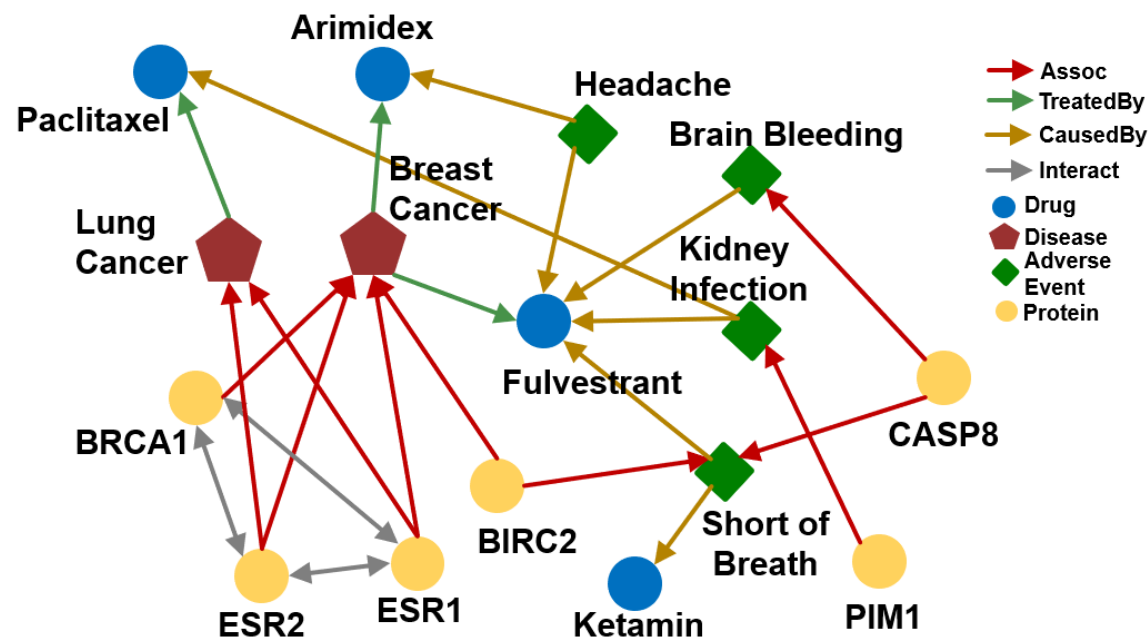


Conjunctive Queries (2)

- “What are drugs that **cause** Short of Breath and **treat** diseases **associated** with protein ESR2?”

$((e:ESR2, (r:Assoc, r:TreatedBy)), (e:Short\ of\ Breath, (r:CausedBy)))$

How do we answer the question by KG traversal?

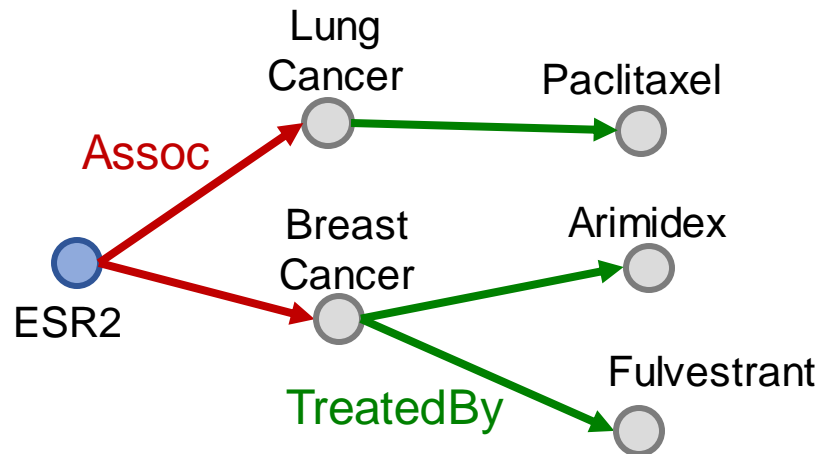


Traversing KG for Conjunctive Queries (1)

- “What are drugs that **cause** Short of Breath and **treat** diseases **associated** with protein ESR2?”

$((e:ESR2, (r:Assoc, r:TreatedBy)), (e:Short\ of\ Breath, (r:CausedBy)))$

Traverse KG from **anchor nodes**: ESR2 and Short of Breath:



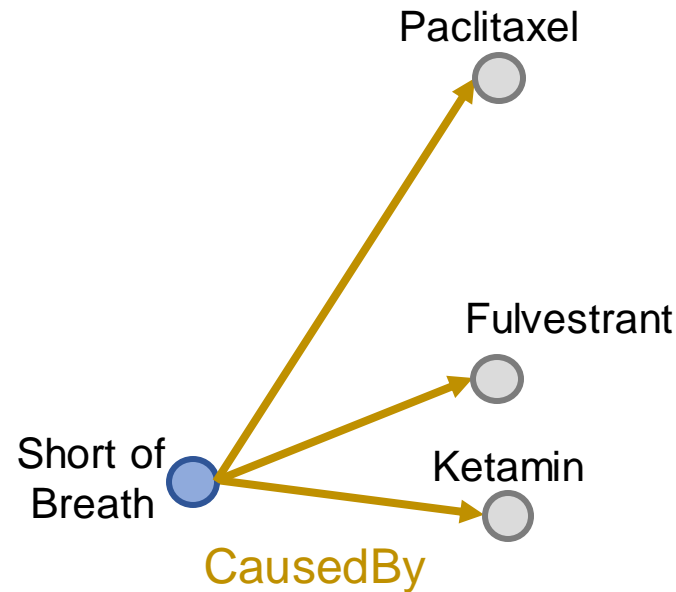
Traversing from a set of entities {“Lung Cancer”, “Breast Cancer”} by relation TreatedBy, we achieve a set of entities: {“Paclitaxel”, “Arimidex”, “Fulvestrant”}

Traversing KG for Conjunctive Queries (2)

- “What are drugs that **cause** Short of Breath and **treat** diseases **associated** with protein ESR2?”

$((e:ESR2, (r:Assoc, r:TreatedBy)), (e:Short\ of\ Breath, (r:CausedBy)))$

Traverse KG from anchor nodes: **ESR2** and **Short of Breath**:



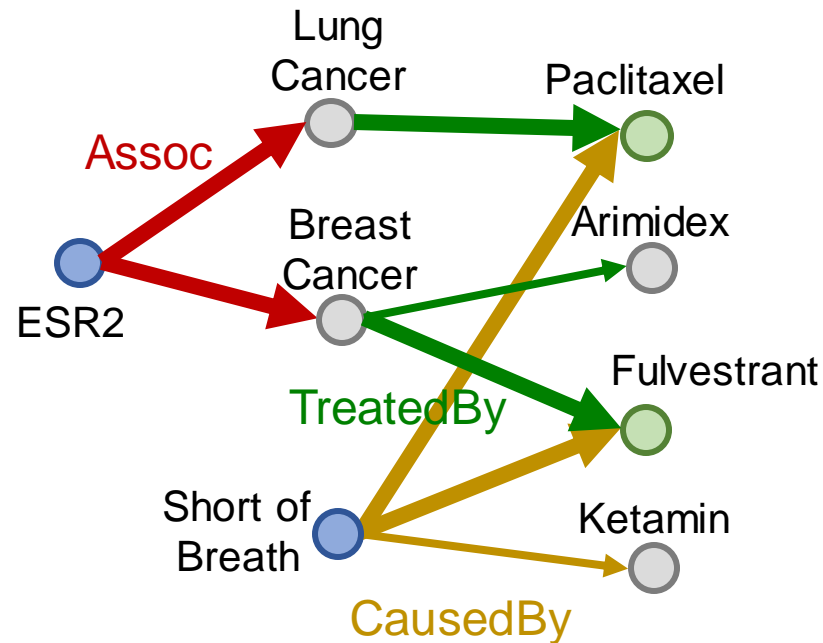
Traverse from the second anchor “Short of Breath” by relation “CausedBy”, we achieve a set of entities: {“Fulvestrant”, “Ketamin”, “Paclitaxel”}

Traversing KG for Conjunctive Queries (3)

- “What are drugs that **cause** Short of Breath and **treat** diseases **associated** with protein ESR2?”

$((e:ESR2, (r:Assoc, r:TreatedBy)), (e:Short\ of\ Breath, (r:CausedBy)))$

Traverse KG from **anchor nodes**: **ESR2** and **Short of Breath**:



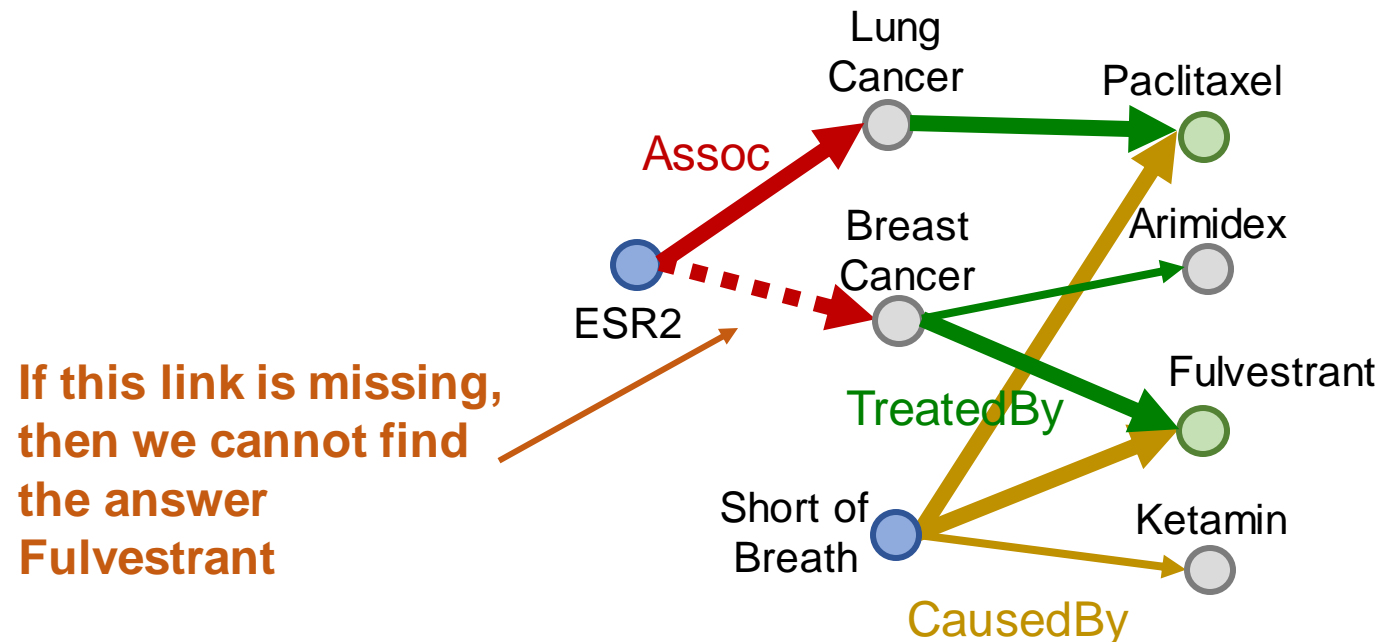
We take intersection between the two sets and arrive at the answers {"Fulvestrant", "Paclitaxel"}

Traversing KG for Conjunctive Queries (4)

- “What are drugs that **cause** Short of Breath and **treat** diseases **associated** with protein ESR2?”

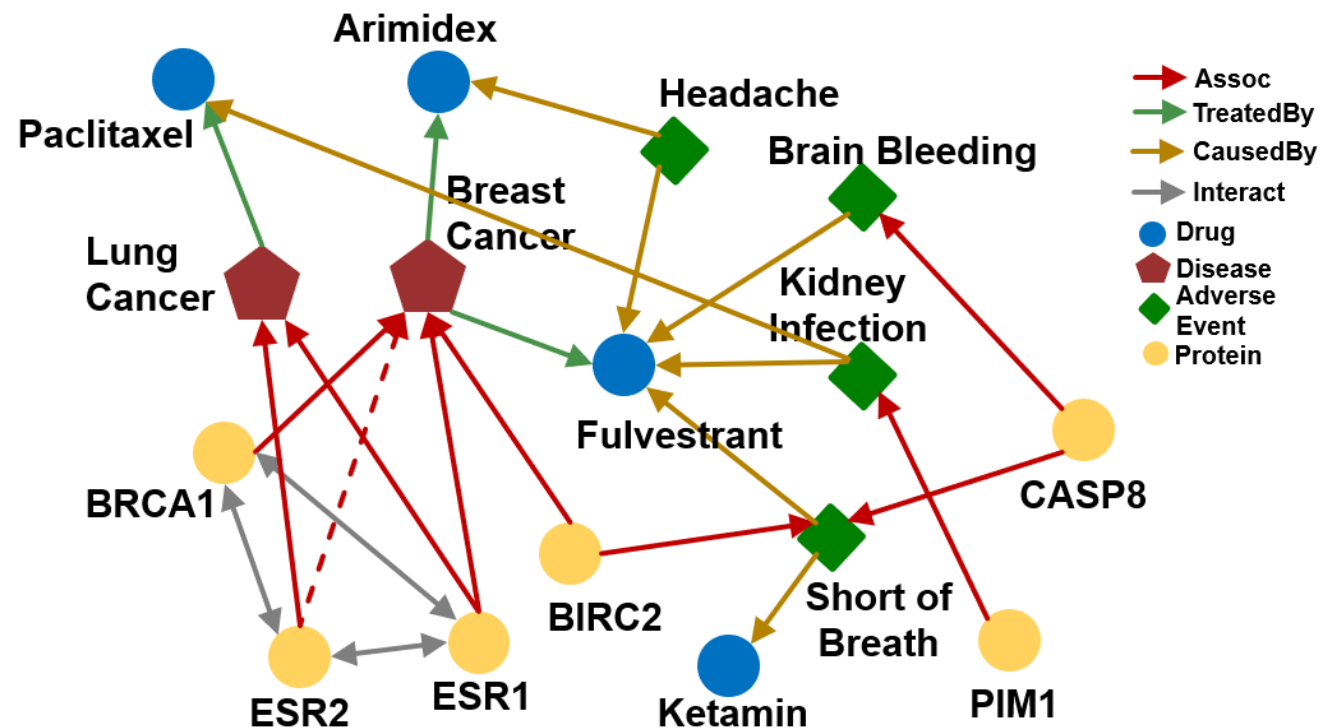
$((e:ESR2, (r:Assoc, r:TreatedBy)), (e:Short\ of\ Breath, (r:CausedBy)))$

Traverse KG from anchor nodes: **ESR2** and **Short of Breath**:



Traversing KG for Conjunctive Queries (5)

- How can we use embeddings to implicitly impute the **missing (ESR2, Assoc, Breast Cancer)**?
- **Intuition:** ESR2 interacts with both **BRCA1** and **ESR1**. Both proteins are associated with **breast cancer**.

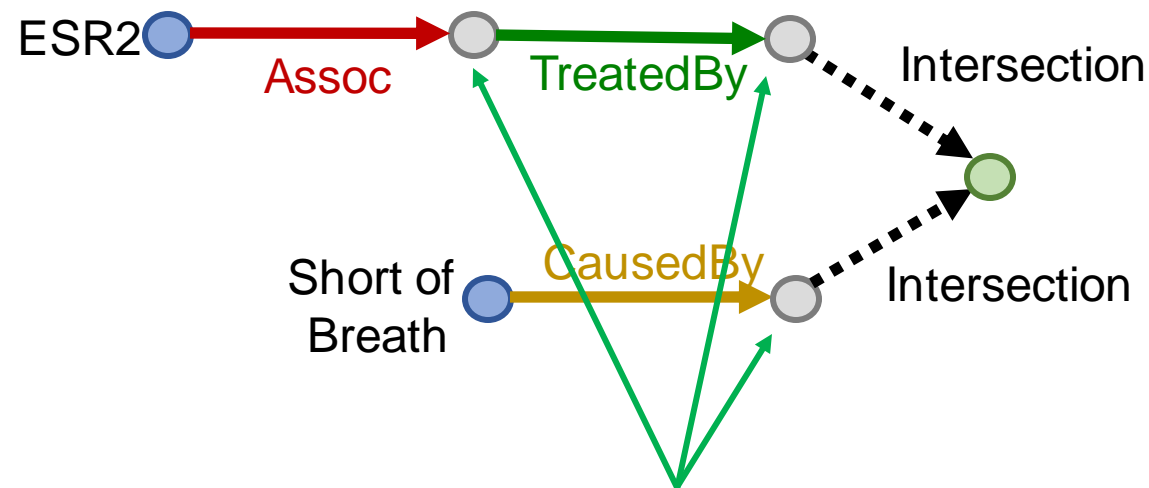


Represent a set of Entities (1)

- “What are drugs that **cause** Short of Breath and **treat** diseases **associated** with protein ESR2?”

$((e:ESR2, (r:Assoc, r:TreatedBy)), (e:Short\ of\ Breath, (r:CausedBy)))$

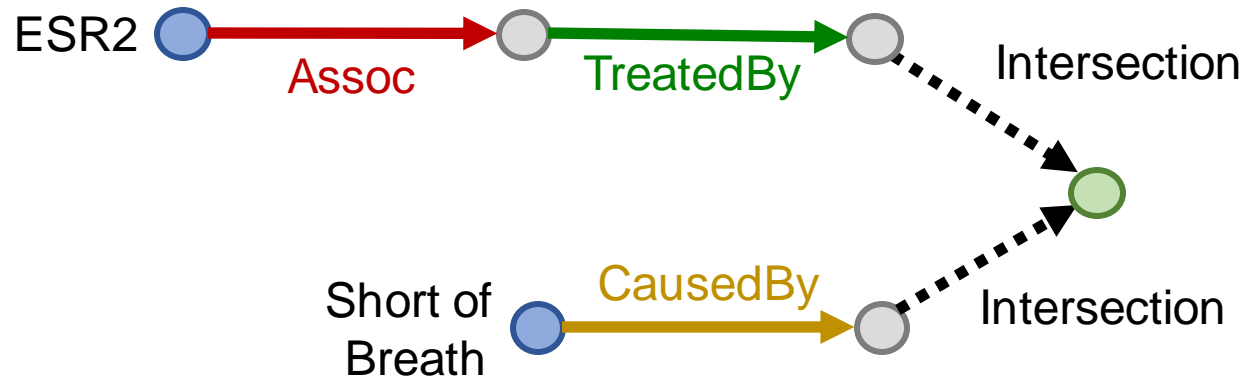
Query plan:



Each intermediate node represents a set of entities, how do we represent it? How do we define the intersection operation in the latent space?

Represent a set of Entities (2)

How can we answer **more complex queries** with **logical conjunction operation**?



- (1) Each intermediate node represents a set of entities, how do we represent it?
- (2) How do we define the intersection operation in the latent space?

Outline of Today's Lecture

- Queries on KG
- Traversing KG in Embedding Space

- **Box Embeddings**

[Query2box: Reasoning over Knowledge Graphs in Vector Space Using Box Embeddings](#). H. Ren*, W. Hu*, J. Leskovec. *International Conference on Learning Representations (ICLR)*, 2020.

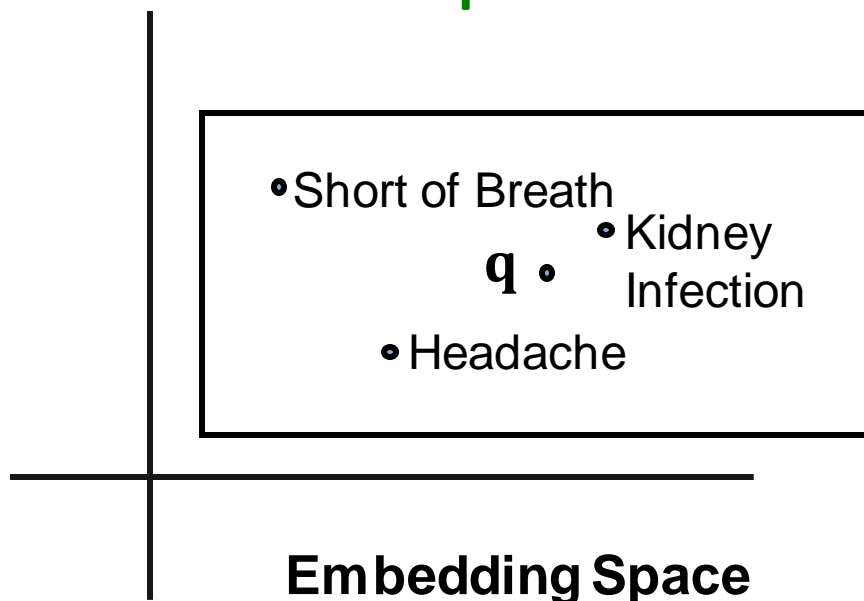
Box Embeddings

- Embed queries with **hyper-rectangles (boxes)**

$$\mathbf{q} = (\text{Center}(\mathbf{q}), \text{Offset}(\mathbf{q}))$$

position

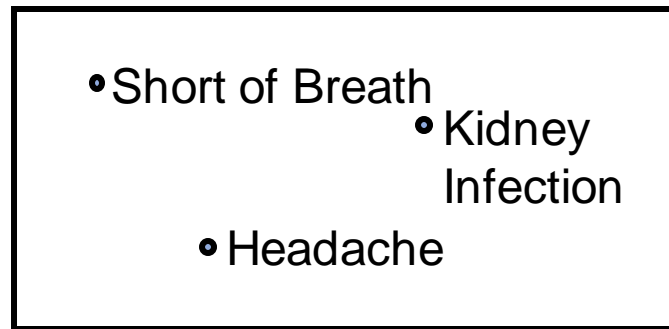
size



For example, we can embed the adverse events of Fulvestrant with **a box that enclose all the answer entities.**

Key Insight: Intersection

- **Intersection of boxes is well-defined!**
- When we traverse the KG to find the answers, each step produces a set of reachable entities.
- **How can we better model these sets?**
 - Boxes are a **powerful abstraction**, as we can project the center and control the offset to model the set of entities enclosed in the box



Embed with Box Embedding (1)

Things to figure out:

- **Entity embeddings** (# params: $d|V|$):
 - Entities are seen as zero-volume boxes
- **Relation embeddings** (# params $2d|R|$)
 - Each relation takes a box and produces a new box
- **Intersection operator:**
 - New operator, inputs are boxes and output is a box
 - Intuitively models intersection of boxes

Projection Operator

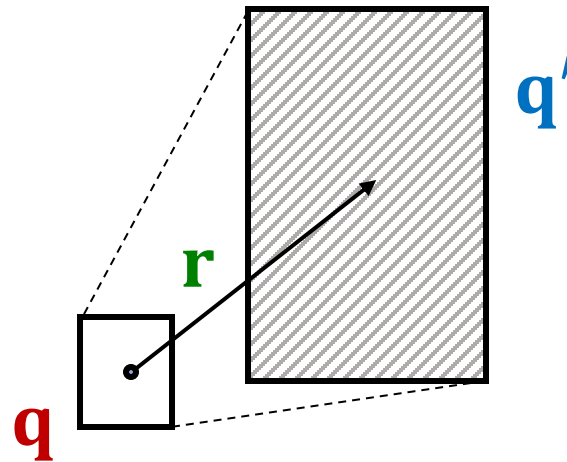
- **Projection Operator** \mathcal{P}

- **Intuition:**

- Take the current box as input and use the **relation embedding** to **project and expand** the box!

- $\mathcal{P} : \text{Box} \times \text{Relation} \rightarrow \text{Box}$

$$\begin{aligned}\text{Cen}(\mathbf{q}') &= \text{Cen}(\mathbf{q}) + \text{Cen}(\mathbf{r}) \\ \text{Off}(\mathbf{q}') &= \text{Off}(\mathbf{q}) + \text{Off}(\mathbf{r})\end{aligned}$$



Embed with Box Embedding (2)

“What is the drug that **causes** Short of Breath and **treats** disease **associated** with protein ESR2?”

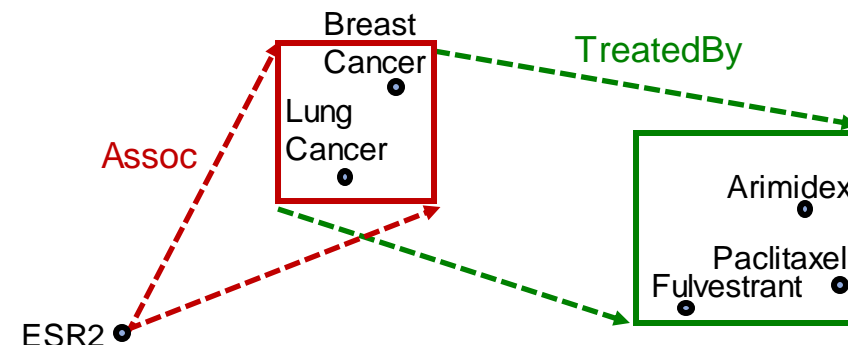
$((e:ESR2, (r:Assoc, r:TreatedBy)), (e:Short\ of\ Breath, (r:CausedBy)))$

- Use **projection operator** again following the query plan.

Query Plan



Embedding Space



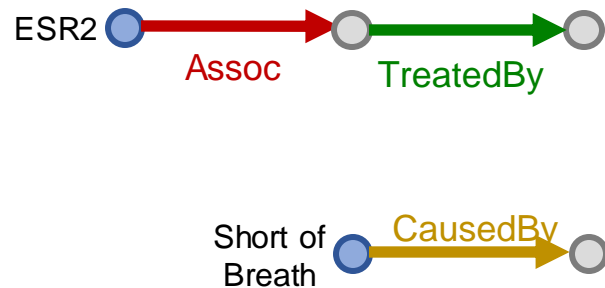
Embed with Box Embedding (3)

“What is the drug that **causes** Short of Breath and **treats** disease **associated** with protein ESR2?”

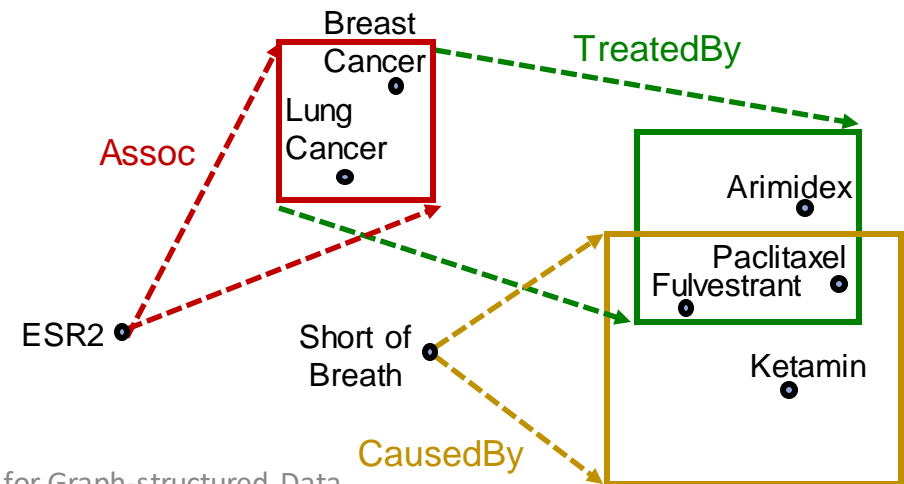
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- Use **projection operator** again following the query plan.

Query Plan



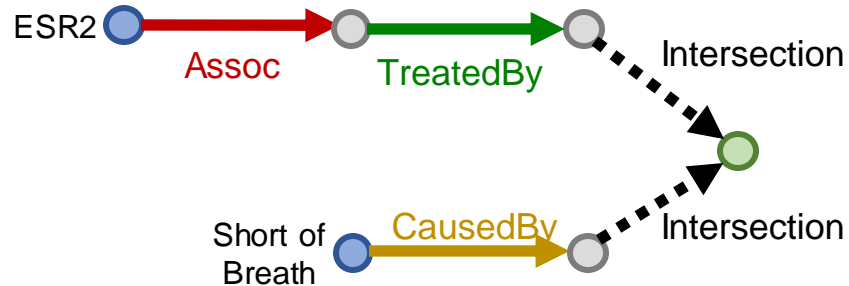
Embedding Space



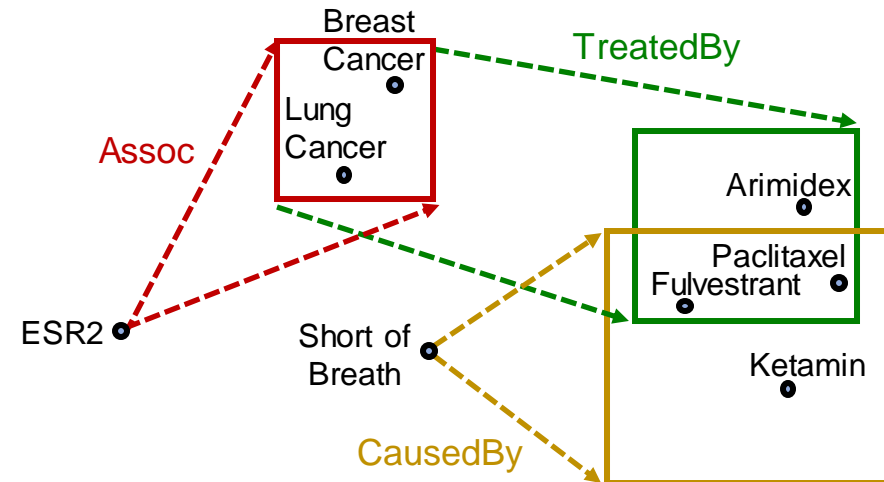
Embed with Box Embedding (4)

How do we take intersection of boxes?

Query Plan



Embedding Space



Note: One possible choice here would be to directly take set intersection, however, using richer learnable parameterization (will be introduced next) is more expressive and robust.

Intersection Operator (1)

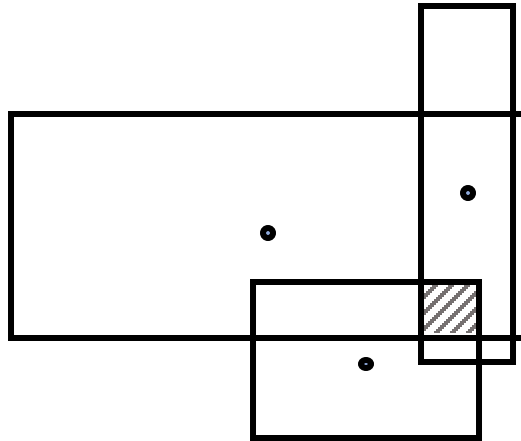
- **Geometric Intersection Operator \mathcal{I}**

- Take multiple boxes as input and produce the intersection box

- **Intuition:**

- The center of the new box should be “close” to the centers of the input boxes
- The offset (box size) should **shrink** (since the size of the intersected set is **smaller** than the size of all the input set)

- $\mathcal{I} : \text{Box} \times \cdots \times \text{Box} \rightarrow \text{Box}$



Intersection Operator (2)

- **Geometric Intersection Operator** \mathcal{I}

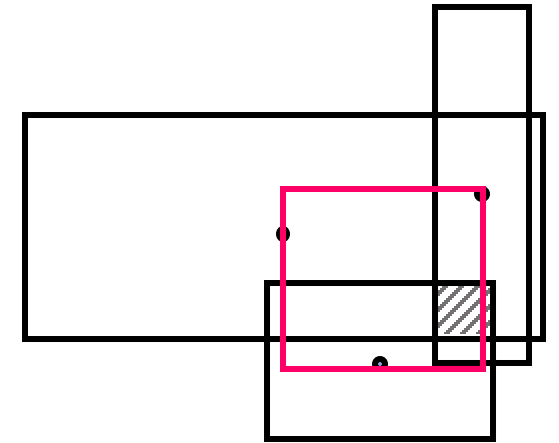
- $\mathcal{I} : \text{Box} \times \cdots \times \text{Box} \rightarrow \text{Box}$

$$\text{Cen}(\mathbf{q}_{\text{inter}}) = \sum_i \mathbf{w}_i \odot \text{Cen}(\mathbf{q}_i)$$

Hadamard product
(element-wise product)

$$\mathbf{w}_i = \frac{\exp(f_{\text{cen}}^i(\text{Cen}(\mathbf{q}_i)))}{\sum_j \exp(f_{\text{cen}}(\text{Cen}(\mathbf{q}_j)))} \quad \begin{array}{l} \text{Cen}(\mathbf{q}_i) \in \mathbb{R}^d \\ \mathbf{w}_i \in \mathbb{R}^d \end{array}$$

- **Intuition:** The center should be in the **red** region!
- **Implementation:** The center is a **weighted sum** of the input box centers
- $\mathbf{w}_i \in \mathbb{R}^d$ is calculated by a neural network f_{cen} (with trainable weights)
- \mathbf{w}_i **represents a “self-attention” score for the center of each input** $\text{Cen}(\mathbf{q}_i)$.



Intersection Operator (3)

- **Geometric Intersection Operator** \mathcal{I}

- $\mathcal{I} : \text{Box} \times \dots \times \text{Box} \rightarrow \text{Box}$

$$\text{Off}(\mathbf{q}_{inter}) = \min(\text{Off}(\mathbf{q}_1), \dots, \text{Off}(\mathbf{q}_n)) \odot \sigma(f_{\text{off}}(\text{Off}(\mathbf{q}_1), \dots, \text{Off}(\mathbf{q}_n)))$$

- **Intuition:** The offset should be smaller than the offset of the input box
- **Implementation:** We first **take minimum** of the offset of the input box, and then we make the model more expressive by introducing a new function f_{off} to extract the **representation** of the input boxes with a **sigmoid function** to **guarantee shrinking**.

guarantees shrinking

Sigmoid function:
squashes output in (0,1)

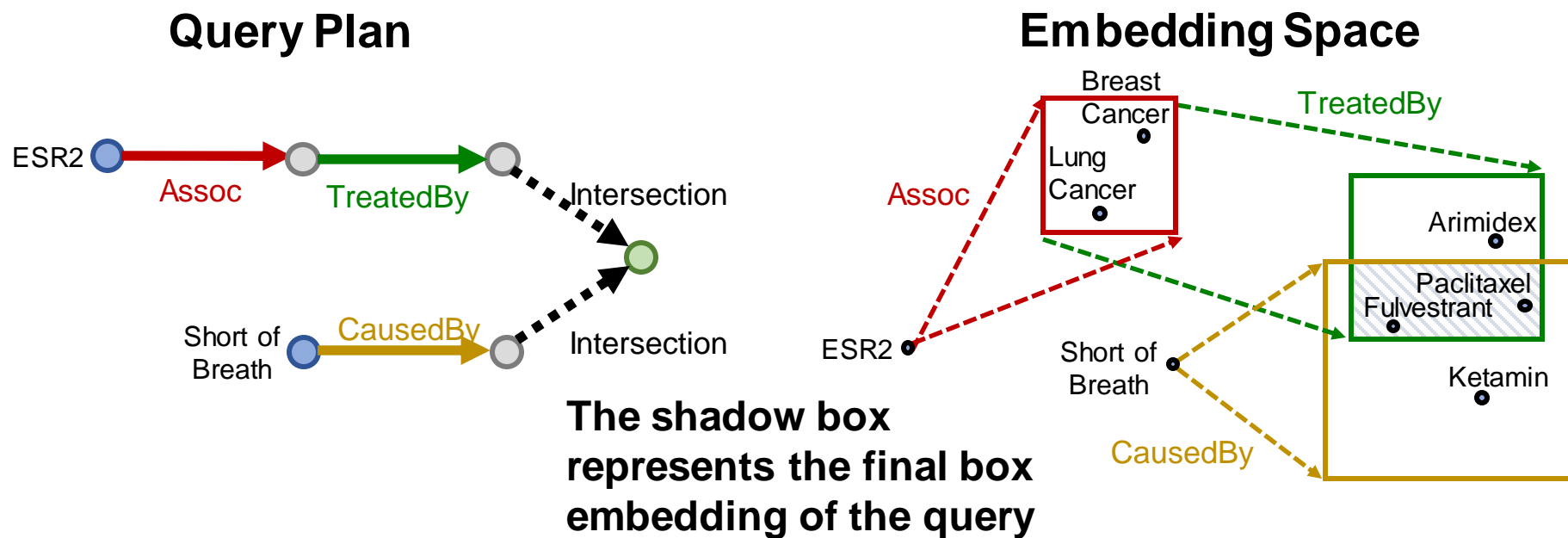
f_{off} is a neural network (with trainable parameters) that extracts the representation of the input boxes to increase expressiveness

Embed with Box Embedding (5)

“What is the drug that **causes** Short of Breath and **treats** disease **associated** with protein ESR2?”

((e:ESR2, (r:Assoc, r:TreatedBy)), (e:Short of Breath, (r:CausedBy)))

- Use box intersection operator



Entity-to-Box Distance

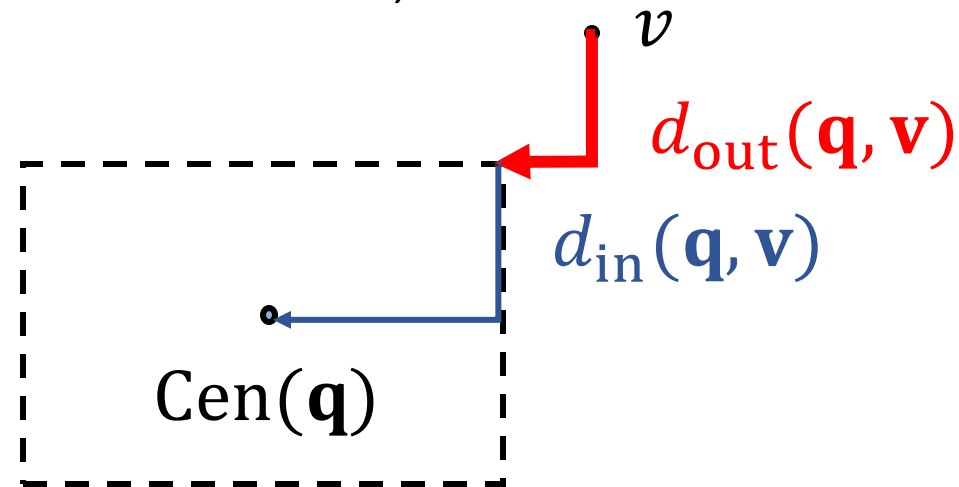
- How do we define the score function $f_q(v)$ (negative distance)?
($f_q(v)$ captures inverse **distance** of a node v as answer to q)

- Given a query box \mathbf{q} and entity embedding (box) \mathbf{v} ,

$$d_{\text{box}}(\mathbf{q}, \mathbf{v}) = d_{\text{out}}(\mathbf{q}, \mathbf{v}) + \alpha \cdot d_{\text{in}}(\mathbf{q}, \mathbf{v})$$

where $0 < \alpha < 1$.

- **Intuition**: if the point is enclosed in the box, the distance should be **downweighted**.
- $f_q(v) = -d_{\text{box}}(\mathbf{q}, \mathbf{v})$



Extending to Union Operation

- Can we embed complex queries with **union**?
E.g.: “*What drug can treat breast cancer **or** lung cancer?*”
- **Conjunctive queries + disjunction** is called **Existential Positive First-order (EPFO)** queries.
We’ll refer to them as **AND-OR** queries.
- Can we also design a disjunction operator and embed **AND-OR** queries in low-dimensional vector space?

Embedding AND-OR Queries (1)

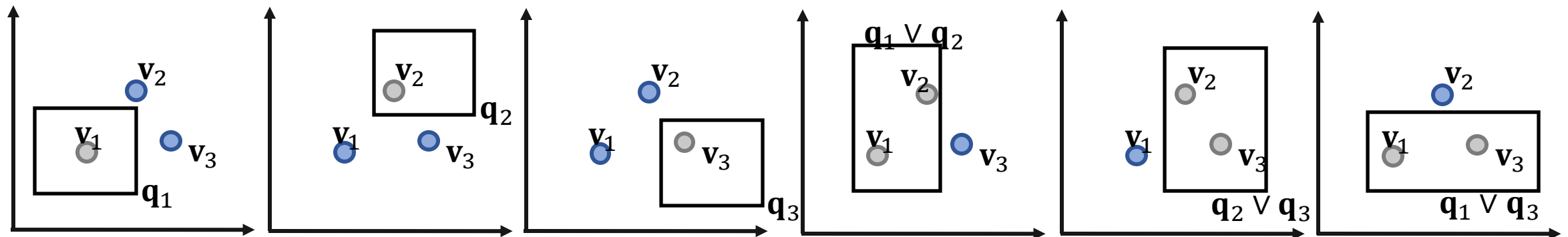
- Can we embed AND-OR queries in a low-dimensional vector space?
- No! Intuition: Allowing **union** over **arbitrary queries** requires **high-dimensional** embeddings!
- Example:
 - Given 3 queries q_1, q_2, q_3 , with answer sets:
 - $\llbracket q_1 \rrbracket = \{v_1\}, \llbracket q_2 \rrbracket = \{v_2\}, \llbracket q_3 \rrbracket = \{v_3\}$
 - If we allow union operation, can we embed them in a **two-dimensional** plane?

Embedding AND-OR Queries (2)

- **Example 1:**

- Given 3 queries q_1, q_2, q_3 , with answer sets:
- $\llbracket q_1 \rrbracket = \{v_1\}$, $\llbracket q_2 \rrbracket = \{v_2\}$, $\llbracket q_3 \rrbracket = \{v_3\}$
- If we allow union operation, can we embed them in a **two-dimensional** plane?

We want grey dots (answers) to be in the box while the blue dots (negative answers) to be outside the box

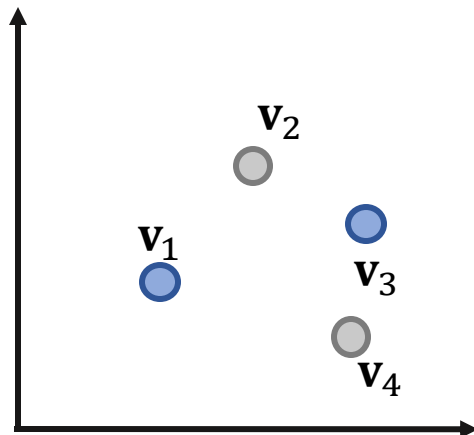


- For 3 points, 2-dimension is okay! **How about 4 points?**

Embedding AND-OR Queries (3)

- **Example 2:**

- Given 4 queries q_1, q_2, q_3, q_4 with answers:
- $\llbracket q_1 \rrbracket = \{v_1\}, \llbracket q_2 \rrbracket = \{v_2\}, \llbracket q_3 \rrbracket = \{v_3\}, \llbracket q_4 \rrbracket = \{v_4\},$
- If we allow union operation, can we embed them in two-dimensional plane?



We cannot design a box embedding for $q_2 \vee q_4$, that only v_2 and v_4 are in the box but v_1 and v_3 are outside the box.

Embedding AND-OR Queries (4)

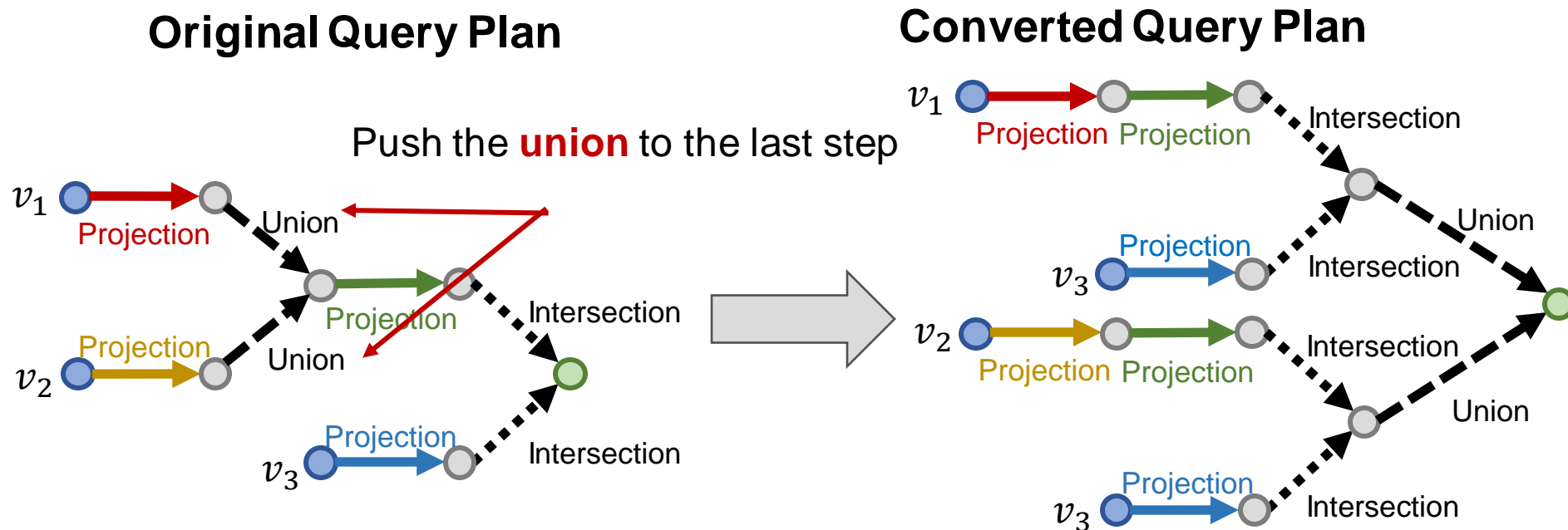
Can we embed AND-OR queries in low-dimensional vector space?

- **Conclusion:** Given any M conjunctive queries q_1, \dots, q_M with **non-overlapping** answers, we need dimensionality of $\Theta(M)$ to handle all OR queries.
 - For real-world KG, such as FB15k, we find $M \geq 13,365$, where $|V| = 14,951$.
 - Remember, this is for arbitrary OR queries.
- Find the formal theorem and proof in [Query2box: Reasoning over Knowledge Graphs in Vector Space Using Box Embeddings](#), Appendix A.

Embedding AND-OR Queries (5)

Since we **cannot embed** AND-OR queries in low-dimensional space, can we still handle them?

- **Key idea:** take all unions out and only do union **at the last step!**



Disjunctive Normal Form

Disjunctive Normal Form

- Any **AND-OR query** can be transformed into equivalent DNF, i.e., **disjunction of conjunctive queries**.
- Given any AND-OR query q ,
$$q = q_1 \vee q_2 \vee \cdots \vee q_m$$
where q_i is a **conjunctive query**.
- Now we can first embed all q_i and then “**aggregate**” at the last step!

Distance Between q and an Entity (1)

- **Distance** between entity embedding and a DNF $q = q_1 \vee q_2 \vee \dots \vee q_m$ is defined as:

$$d_{\text{box}}(\mathbf{q}, \mathbf{v}) = \min(d_{\text{box}}(\mathbf{q}_1, \mathbf{v}), \dots, d_{\text{box}}(\mathbf{q}_m, \mathbf{v}))$$

- **Intuition:**

- As long as v is the answer to one conjunctive query q_i , then v should be the answer to q
- As long as v is close to one conjunctive query q_i , then v should be close to q **in the embedding space**

Distance Between q and an Entity (2)

- **Distance** between entity embedding and a DNF $q = q_1 \vee q_2 \vee \dots \vee q_m$ is defined as:

$$d_{\text{box}}(\mathbf{q}, \mathbf{v}) = \min(d_{\text{box}}(\mathbf{q}_1, \mathbf{v}), \dots, d_{\text{box}}(\mathbf{q}_m, \mathbf{v}))$$

- **The process of embedding any AND-OR query q**
 1. Transform q to **equivalent DNF** $q_1 \vee \dots \vee q_m$
 2. **Embed** q_1, \dots, q_m do get $\mathbf{q}_1, \dots, \mathbf{q}_m$
 3. Calculate the (box) distance $d_{\text{box}}(\mathbf{q}_i, \mathbf{v})$
 4. Take the **minimum** of all distance
 5. **The final score** $f_q(v) = -d_{\text{box}}(\mathbf{q}, \mathbf{v})$

Training Overview

- **Overview and Intuition** (similar to KG completion):
 - Given a query q , maximize the score $f_q(v)$ for answers $v \in \llbracket q \rrbracket$ and minimize the **scoring function** $f_q(v')$ for negative answers $v' \notin \llbracket q \rrbracket$
- **Trainable parameters**:
 - Entity embeddings with $d|V|$ # params
 - Relation embeddings with $2d|R|$ # params
 - Intersection operator
- **How to achieve a query, its answers, its negative answers from the KG to train the parameters?**
- **How to split the KG for query answering?**

Training Pipeline

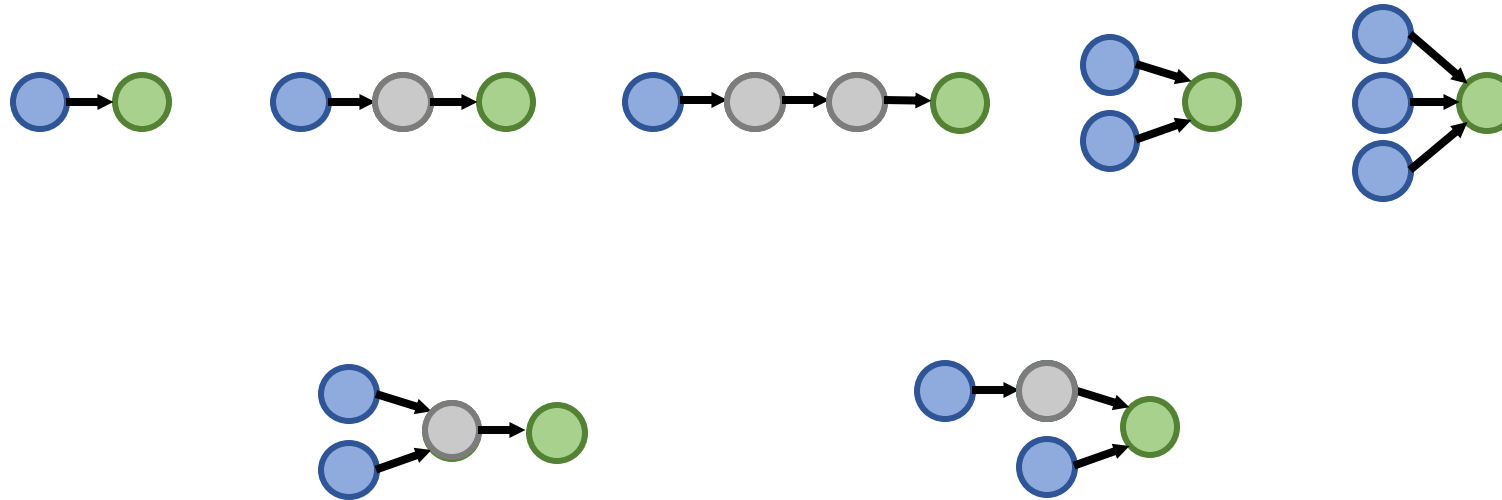
- **Training:**

1. Randomly sample a query q from the training graph G_{train} , answer $v \in \llbracket q \rrbracket_{G_{\text{train}}}$, and a negative sample $v' \notin \llbracket q \rrbracket_{G_{\text{train}}}$.
 - Negative sample: Entity of same type as v but not answer.
2. Embed the query q to \mathbf{q} .
3. Calculate the **scoring function** $f_q(v)$ and $f_q(v')$.
4. Optimize the loss ℓ to maximize $f_q(v)$ while minimize $f_q(v')$:

$$\ell = -\log \sigma \left(f_q(v) \right) - \log(1 - \sigma(f_q(v')))$$

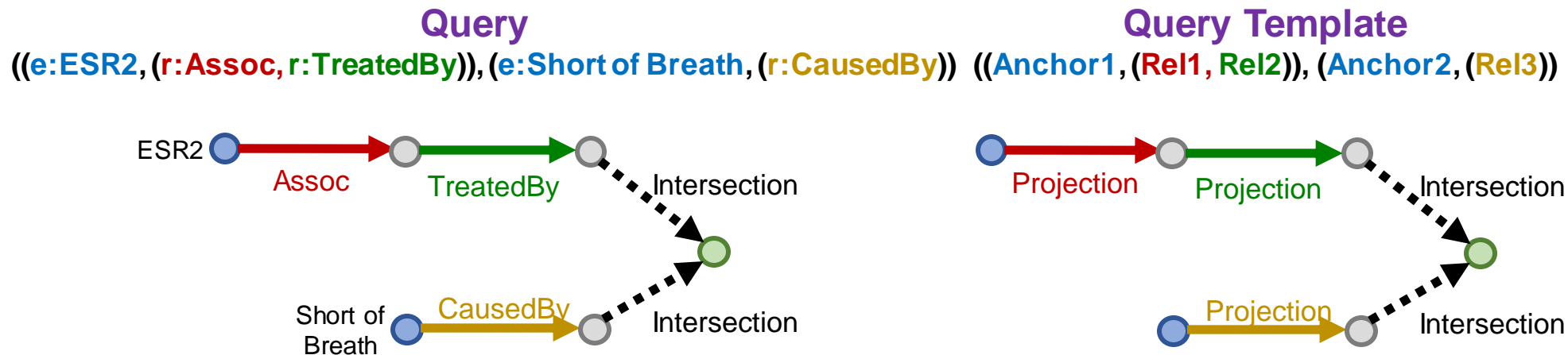
Query Generation from Templates (1)

- Generate queries from multiple query templates:



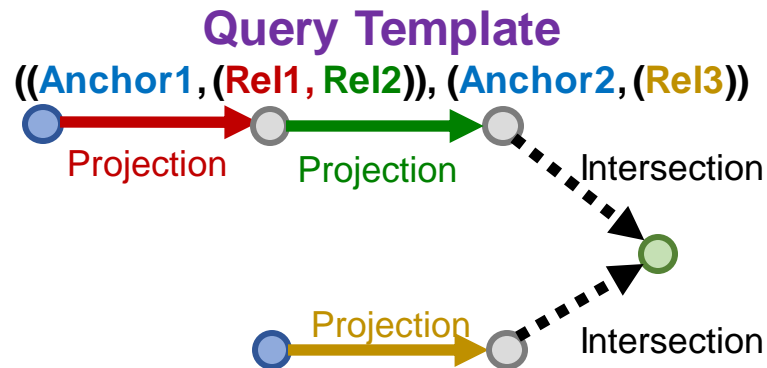
Query Generation from Templates (2)

- How can we generate a **complex query**?
- We start with a **query template**
- **Query template** can be viewed as an abstraction of the query
- We generate a query by instantiating every variable with a concrete entity and relation from the KG
 - E.g., instantiate **Anchor1** with **ESR2** (a node on KG)
 - E.g., instantiate **Rel1** with **Assoc** (an edge on KG)
- **How to instantiate query template given a KG?**



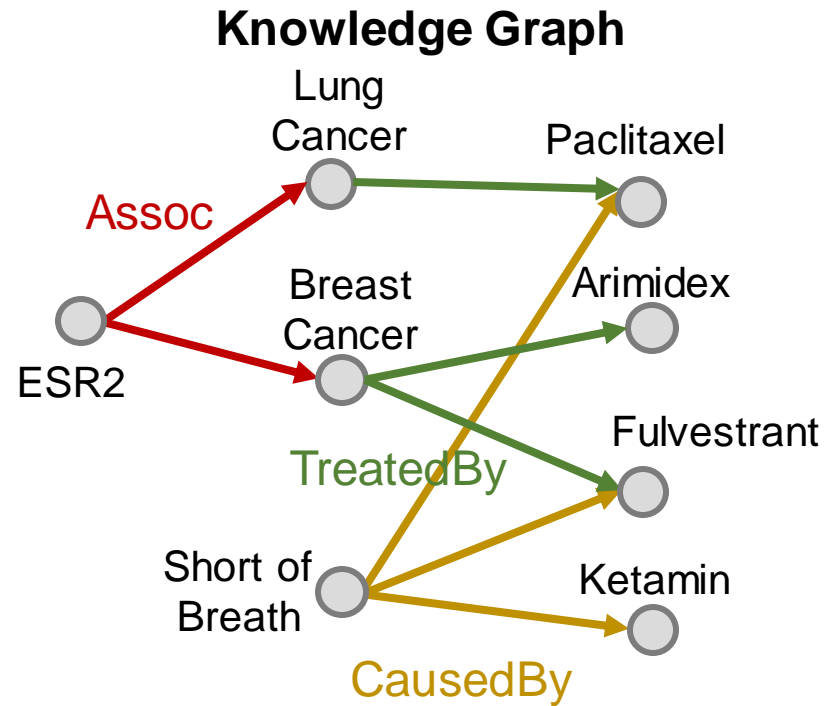
Query Generation from Templates (3)

- How to instantiate a query template given a KG?



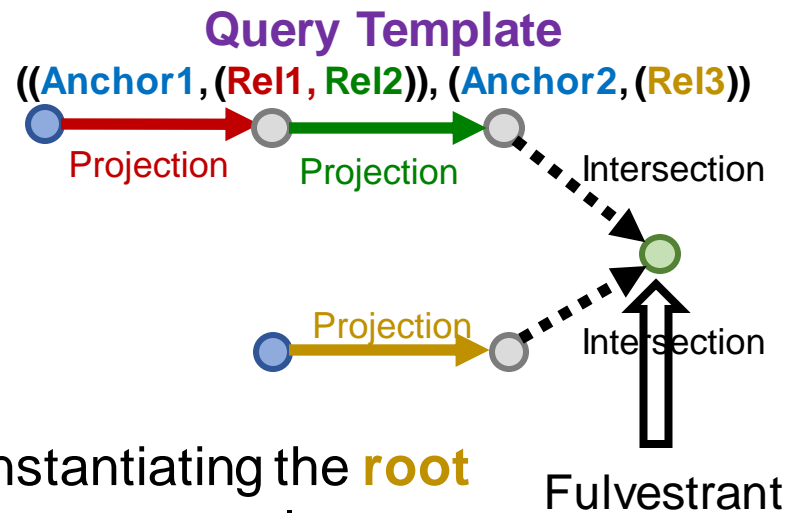
Overview:

Start from instantiating the **answer node** of the query template and then iteratively instantiate the other edges and nodes until we ground **all the anchor nodes**

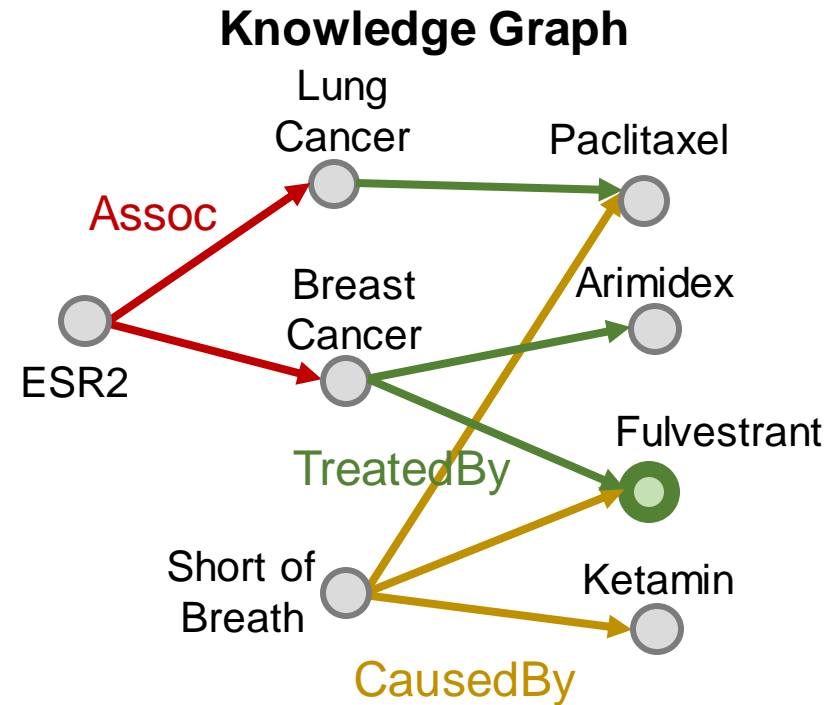


Query Generation from Templates (4)

- How to instantiate a query template given a KG?

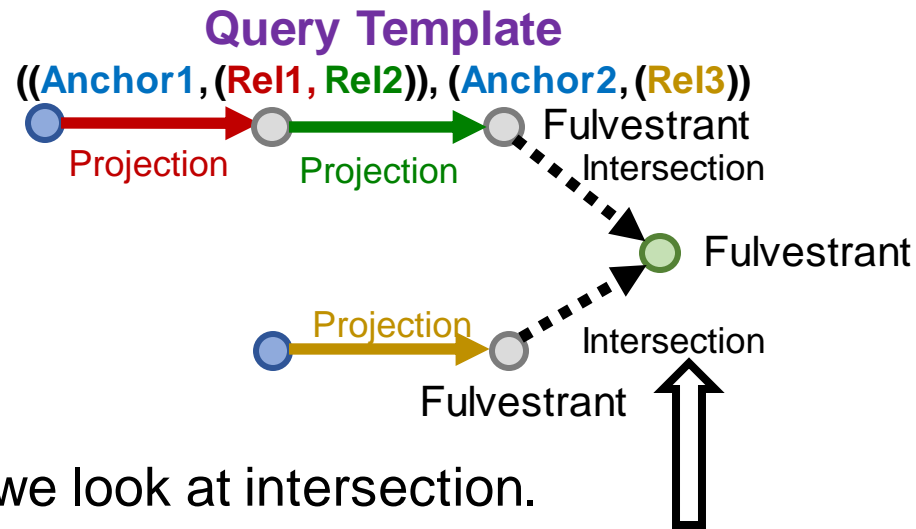


Start from instantiating the **root node** of the query template. Randomly pick one entity from KG as the root node, e.g., we pick **Fulvestrant**.

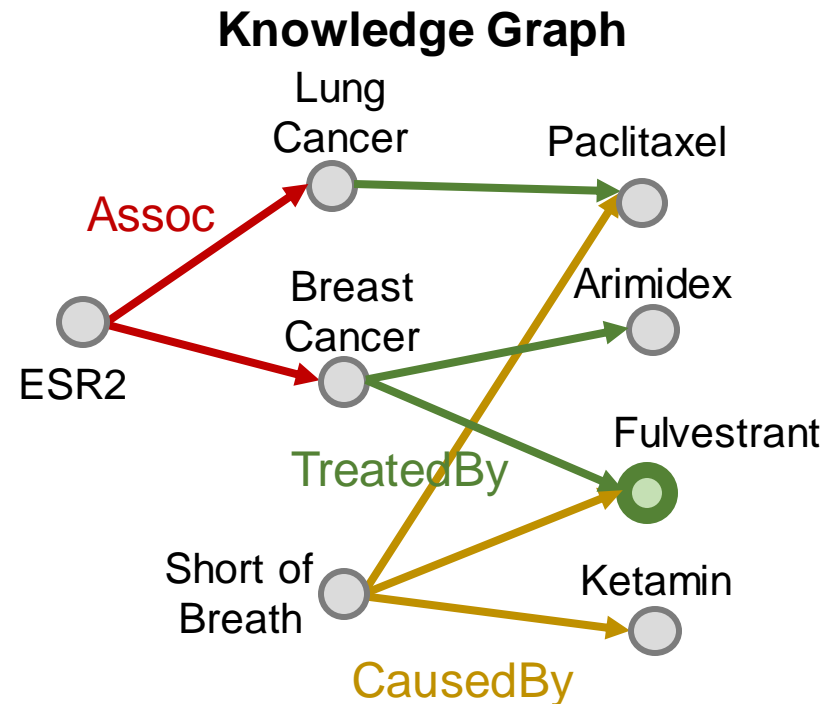


Query Generation from Templates (5)

- How to instantiate a query template given a KG?

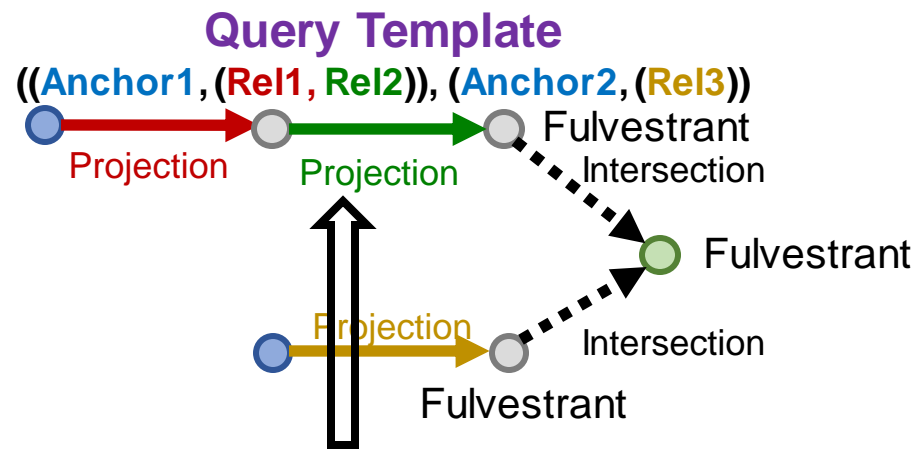


Now we look at intersection.
What we have is that the
intersection of the sets of entities
is **Fulvestrant**, then naturally the
two sets should also contain
Fulvestrant.

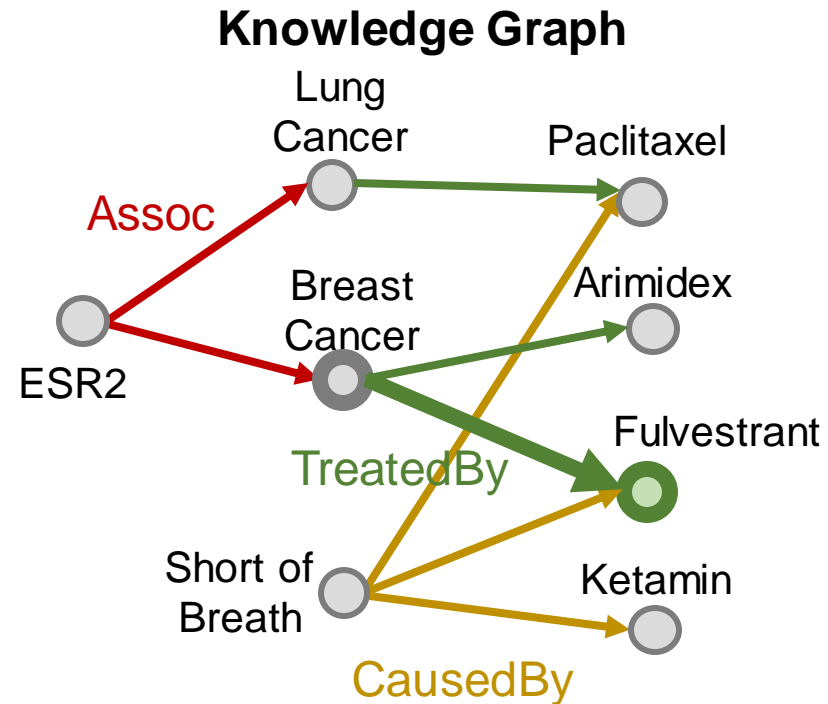


Query Generation from Templates (6)

- How to instantiate a query template given a KG?

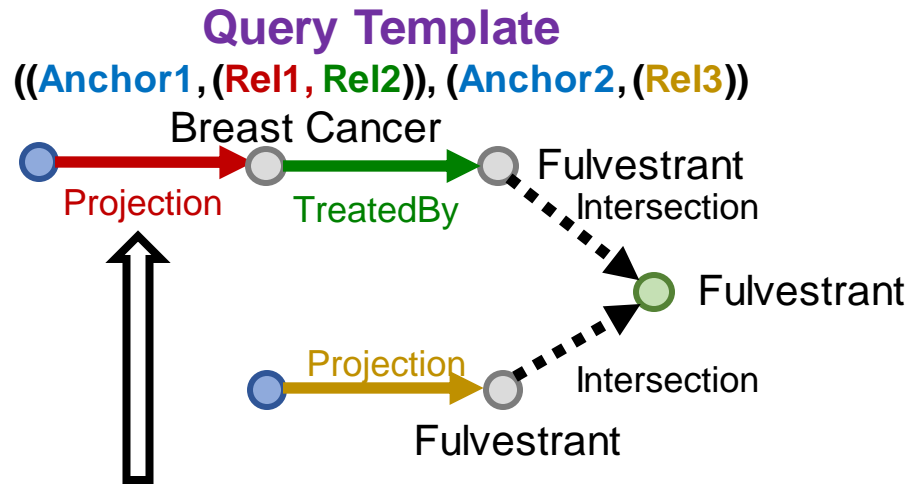


We instantiate the **Projection edge** in the template by randomly sample one relation associated with the current entity **Fulvestrant**. For example, we may select relation **TreatedBy**, and check what entities are connected to **Fulvestrant** with **TreatedBy**: {**Breast Cancer**}.

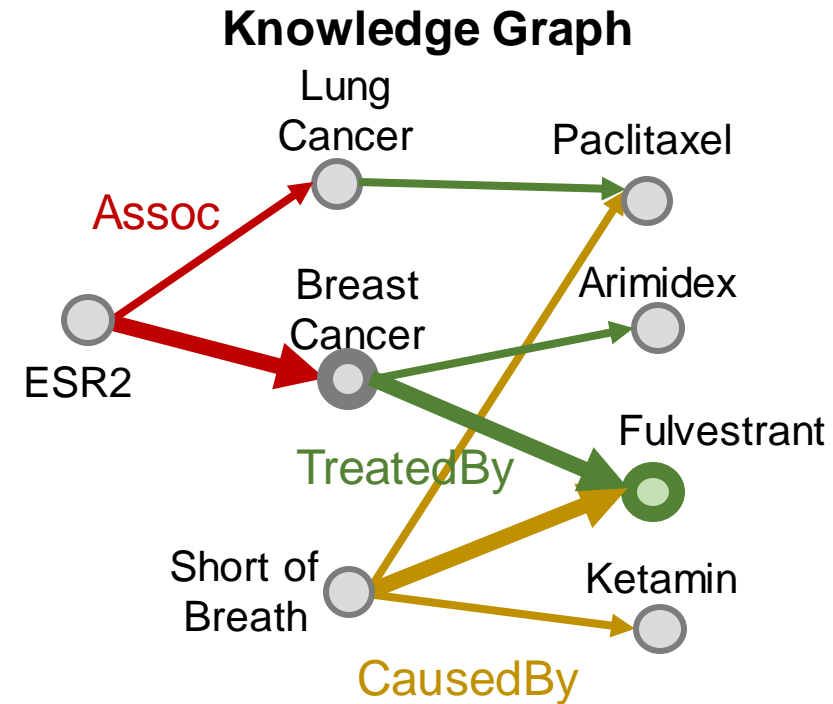


Query Generation from Templates (7)

- How to instantiate a query template given a KG?



We first look at one branch and ground the **Projection edge** with the relation associated with **Breast Cancer**, e.g., **Assoc**. Then we check what entities are connected to **Breast Cancer** with **Assoc**: {**ESR2**}.

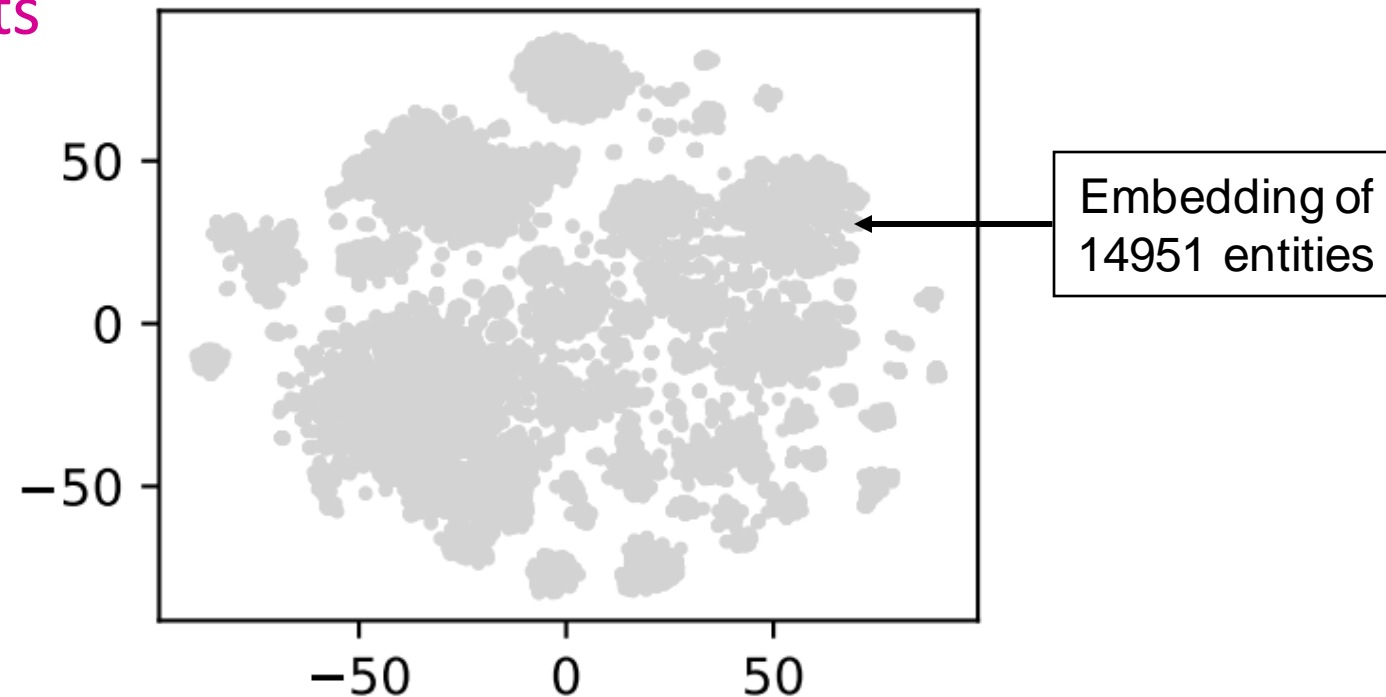
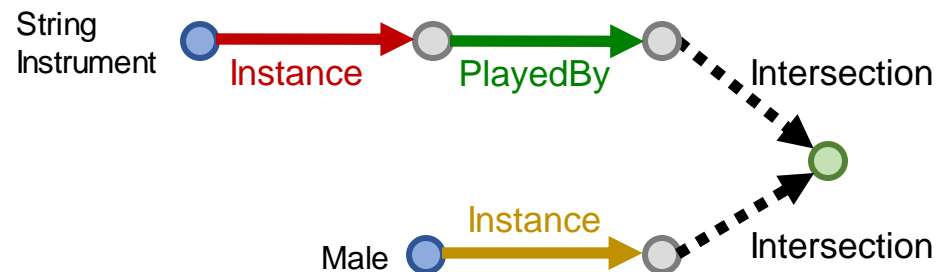


Visualization of Box Embeddings (1)

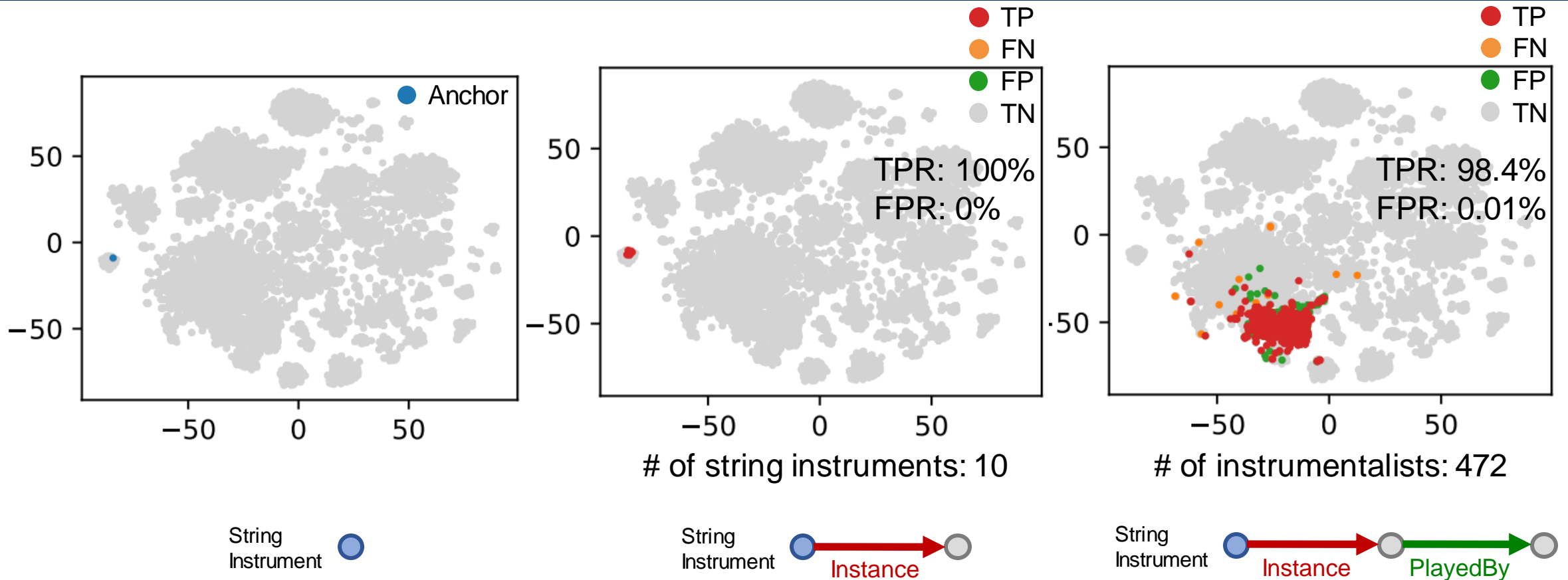
- What do box embeddings actually learn?

Example: “List *male instrumentalists* who *play* string instruments”

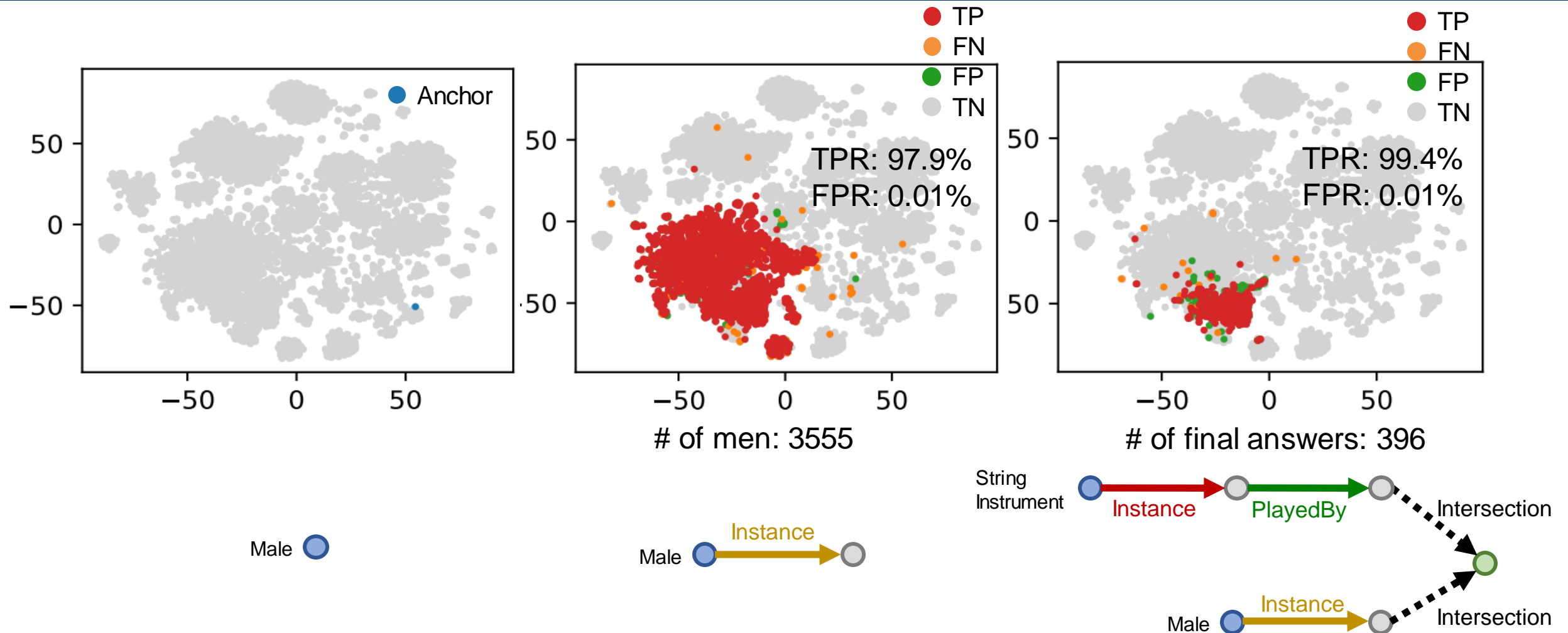
- We use **t-SNE** to reduce the embedding space to a 2-dimensional space, in order to **visualize the query results**



Visualization of Box Embeddings (2)



Visualization of Box Embeddings (3)



Summary

- Queries on KG
 - One-hop queries, Path queries, Conjunctive queries
- Traversing KG in the embedding space
 - We embed the query by composing learned operators (e.g. **TransE**)
 - Embedding of the query is **close** to its answers in the embedding space
- Query2Box
 - **Box Embeddings** to represent a set of entities
 - Embed **AND-OR** queries by transforming them into their equivalent Disjunctive Normal Form (DNF).