

Representation Learning on Hyper-Relational and Numeric Knowledge Graphs with Transformers



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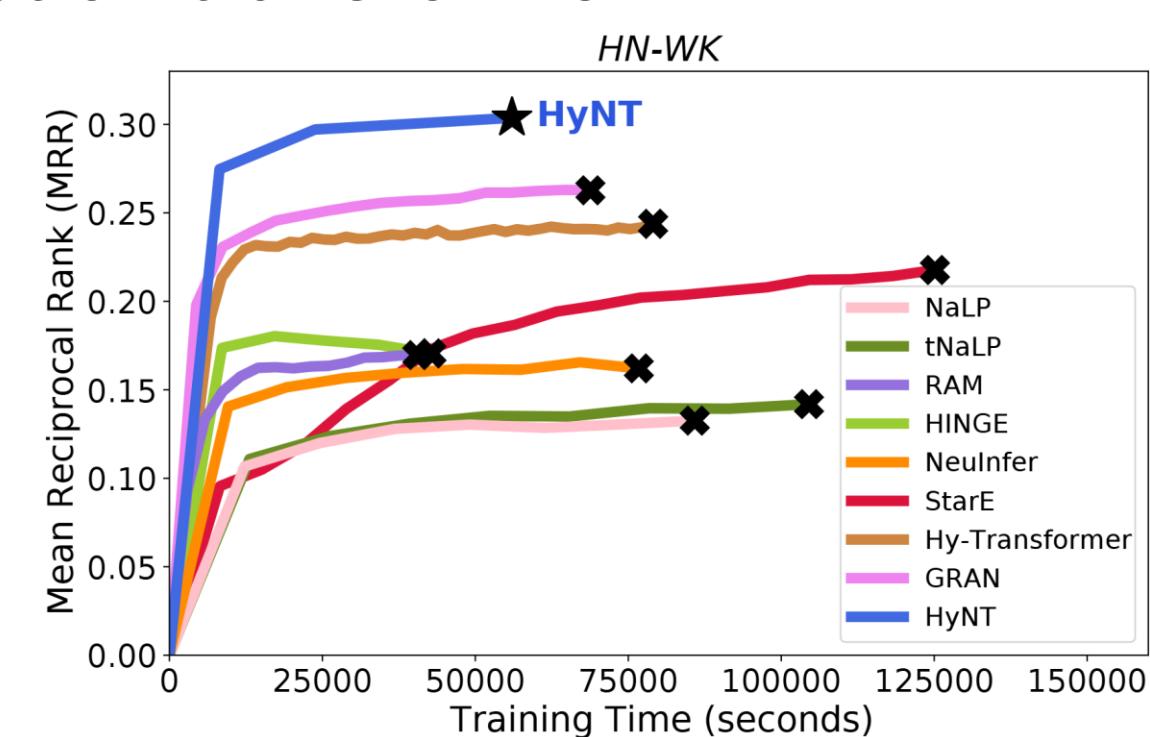
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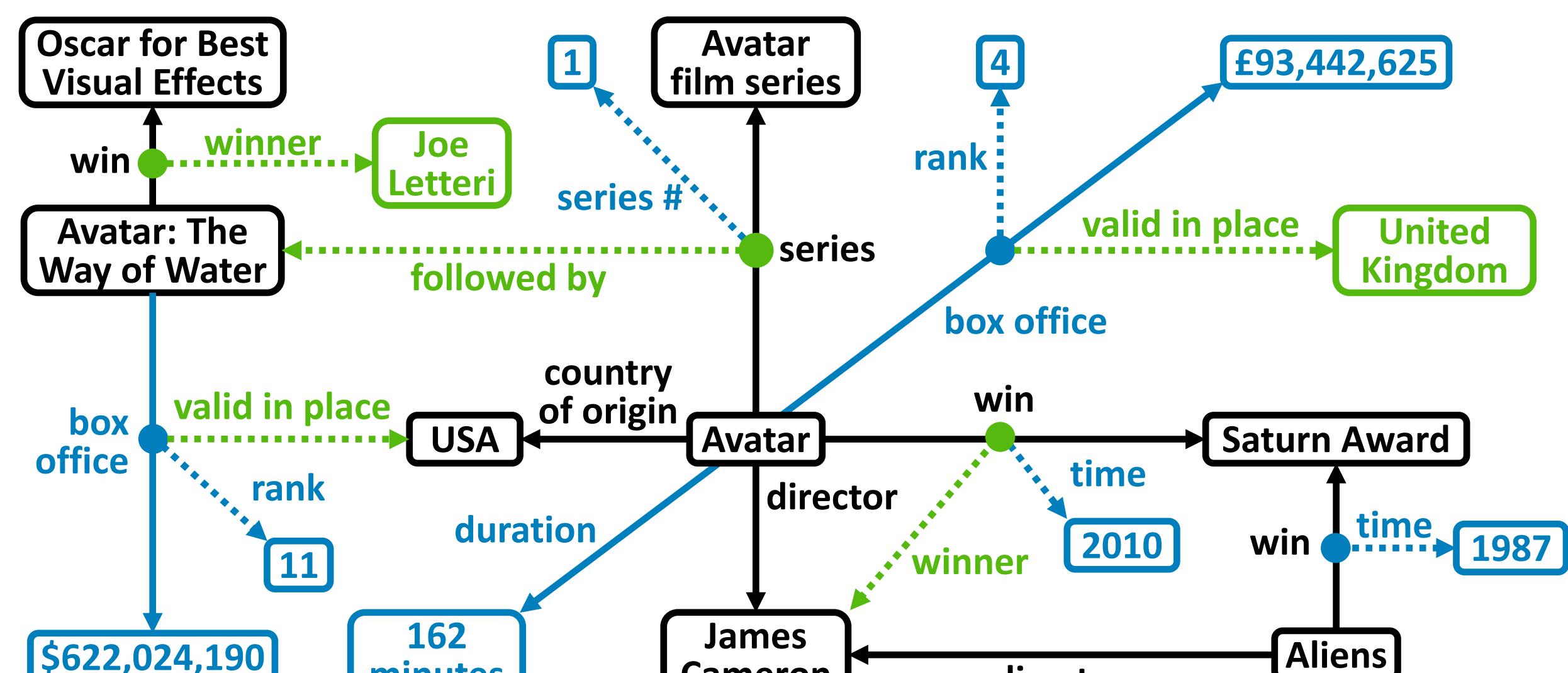
Main Contributions

- Define **Hyper-relational and Numeric Knowledge Graphs (HN-KGs)**
 - Create 4 real-world HN-KG datasets
- Propose **HyNT**, Hyper-relational knowledge graph embedding with Numeric literals using Transformers
 - Define a context transformer and a prediction transformer
 - Reduce the cost by learning compact representations of triplets and qualifiers
- HyNT significantly outperforms 12 different state-of-the-art methods for **link prediction**, **numeric value prediction**, and **relation prediction**



Hyper-relational and Numeric Knowledge Graphs (HN-KGs)

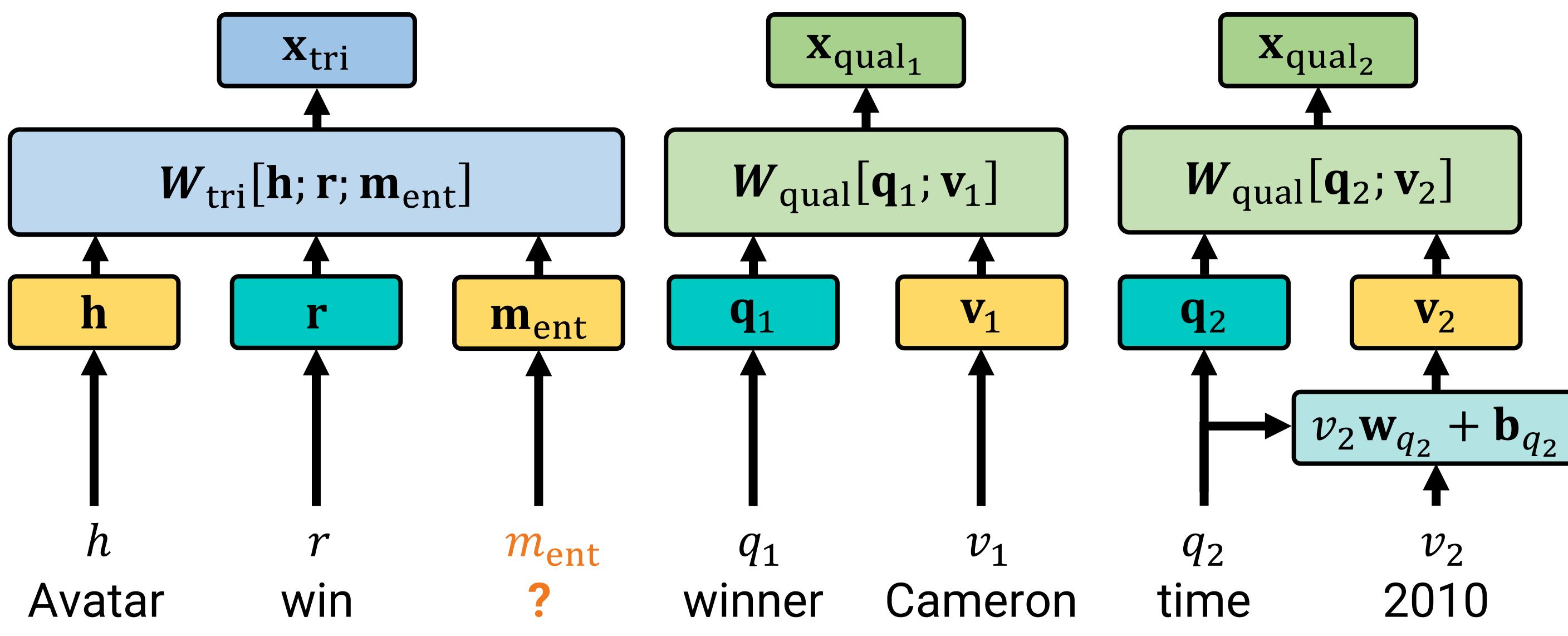
- Hyper-relational Knowledge Graphs**
 - Attach a set of **qualifiers** to a triplet to enrich information
 - Existing methods assume that all entities are **discrete** objects
- Hyper-relational and Numeric Knowledge Graphs**
 - Contain both hyper-relational facts and numeric values



- An example of a hyper-relational fact
 - ((Avatar, win, Saturn_Award), ((winner, James_Cameron), (time, 2010)))
 - Primary Triplet
 - Qualifier 1
 - Qualifier 2
- Predictions on HN-KGs
 - Link Prediction**: Predict a missing **discrete entity**
 - Numeric Value Prediction**: Predict a missing **numeric value**
 - Relation Prediction**: Predict a missing **relation**
 - The missing component can be in either a **primary triplet** or a **qualifier**

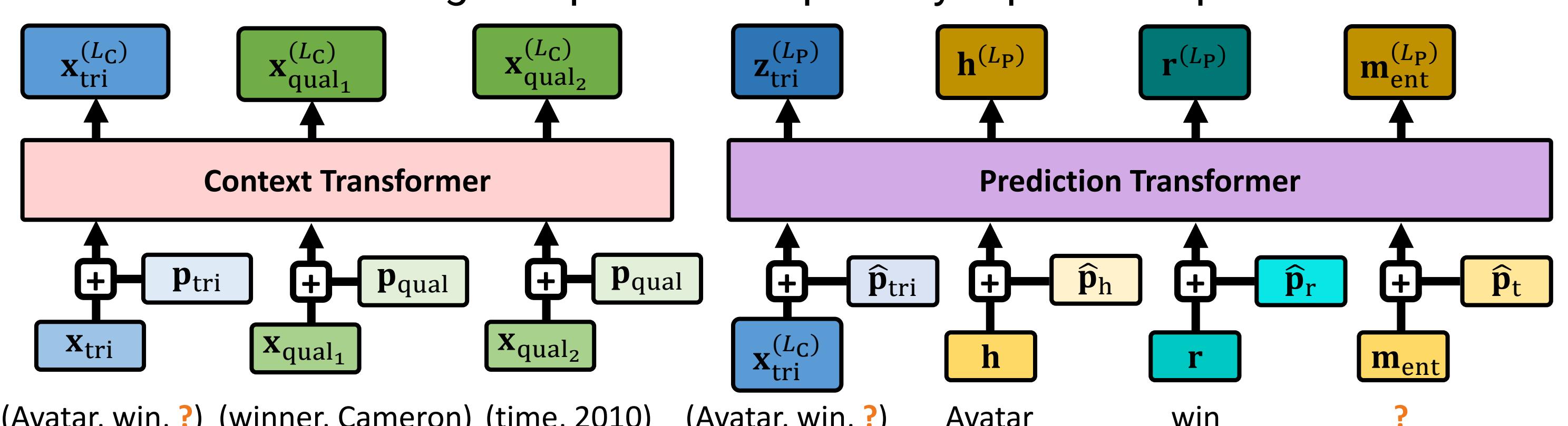
Triplet/Qualifier Encoding

- Convert a triplet/qualifier to a representation vector



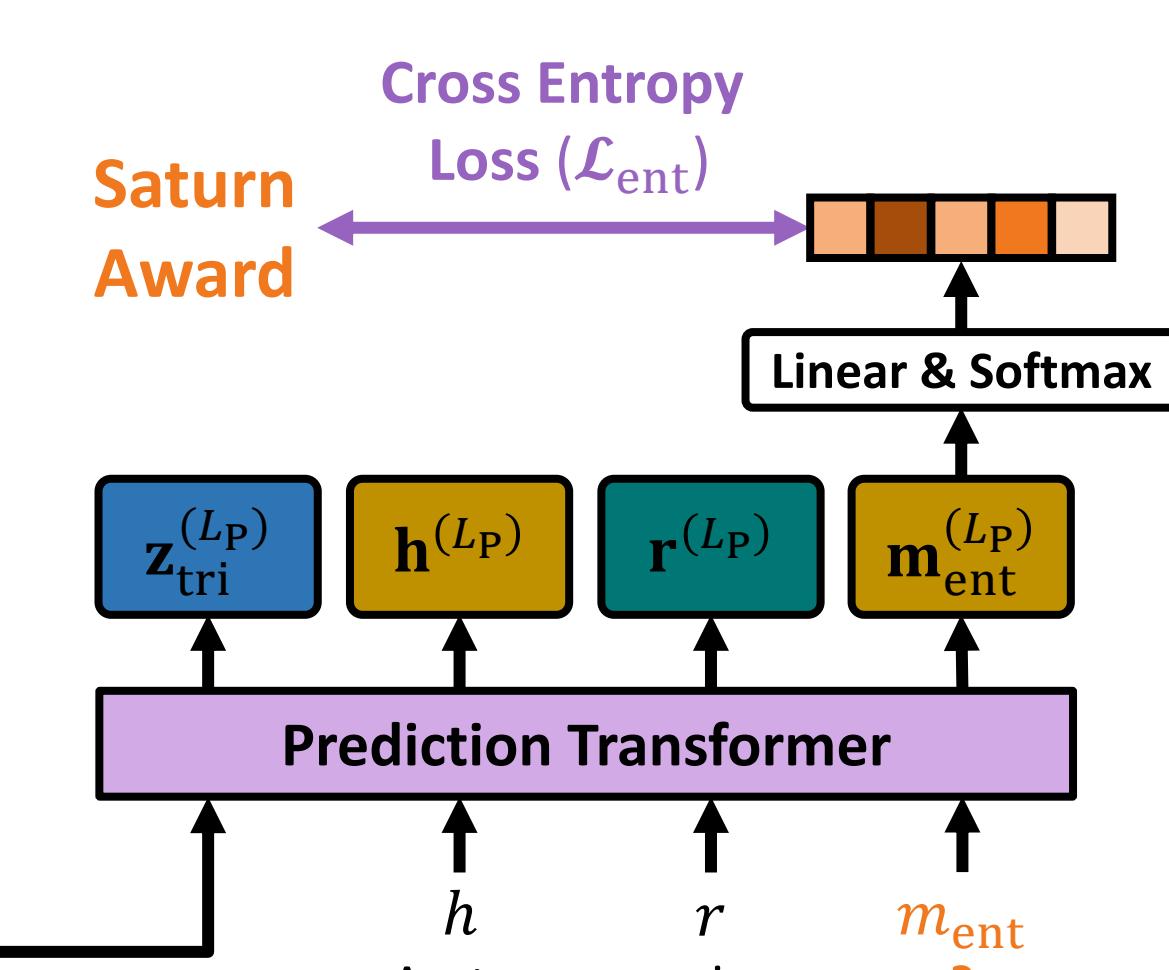
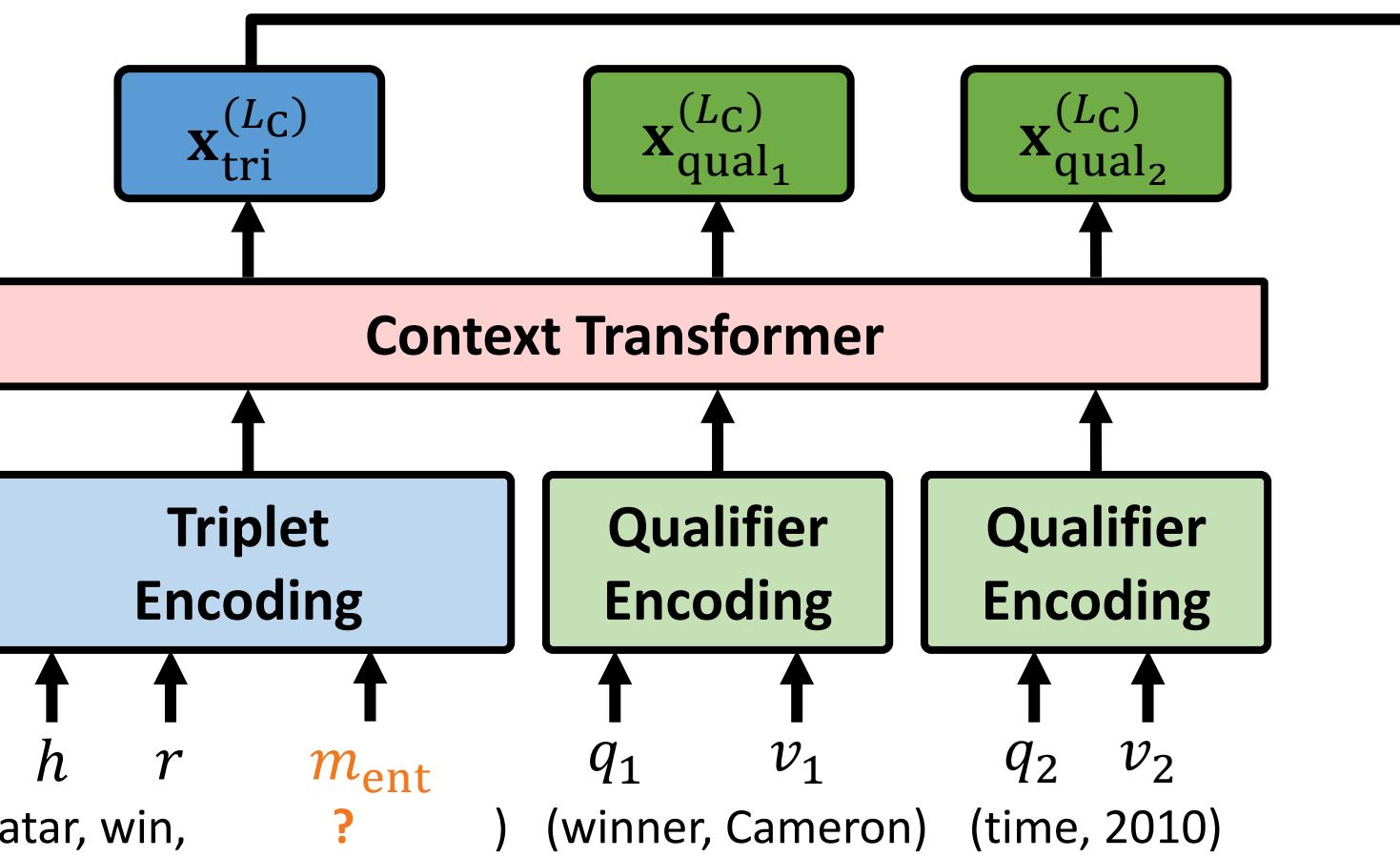
Context & Prediction Transformers

- Context Transformer**
 - Learn the representations of a primary triplet and the qualifiers
- Prediction Transformer**
 - Predict a missing component in a primary triplet or a qualifier

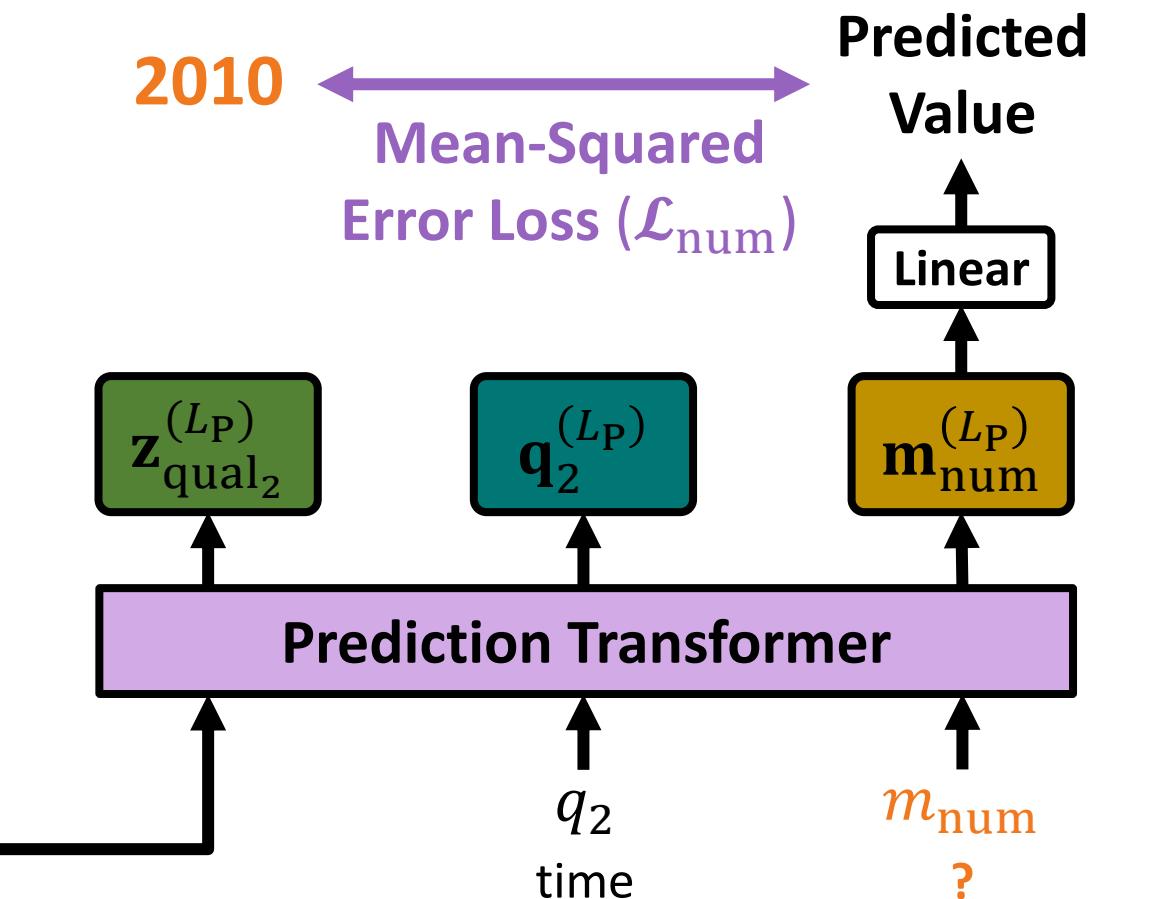
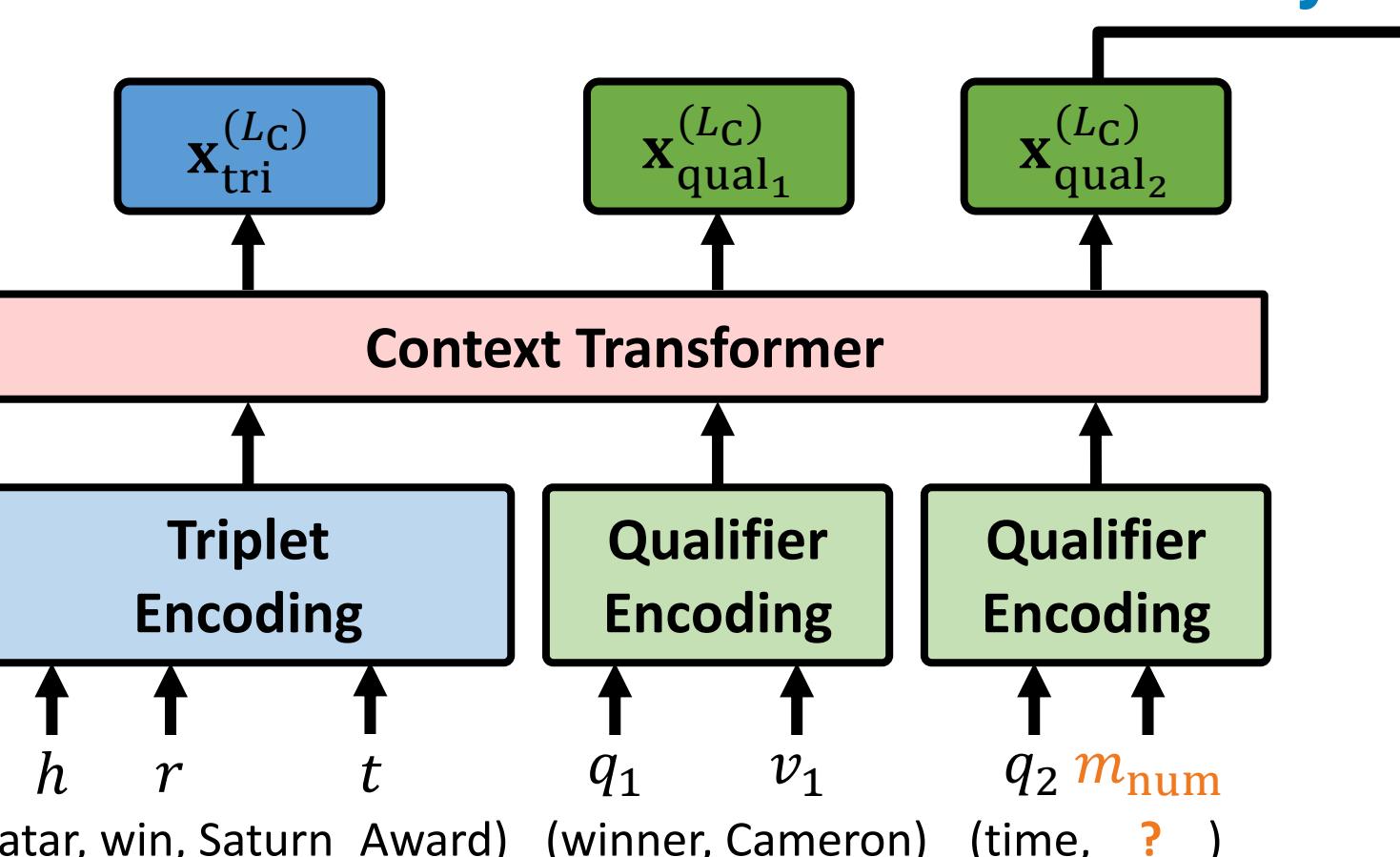


Training & Predictions of HyNT

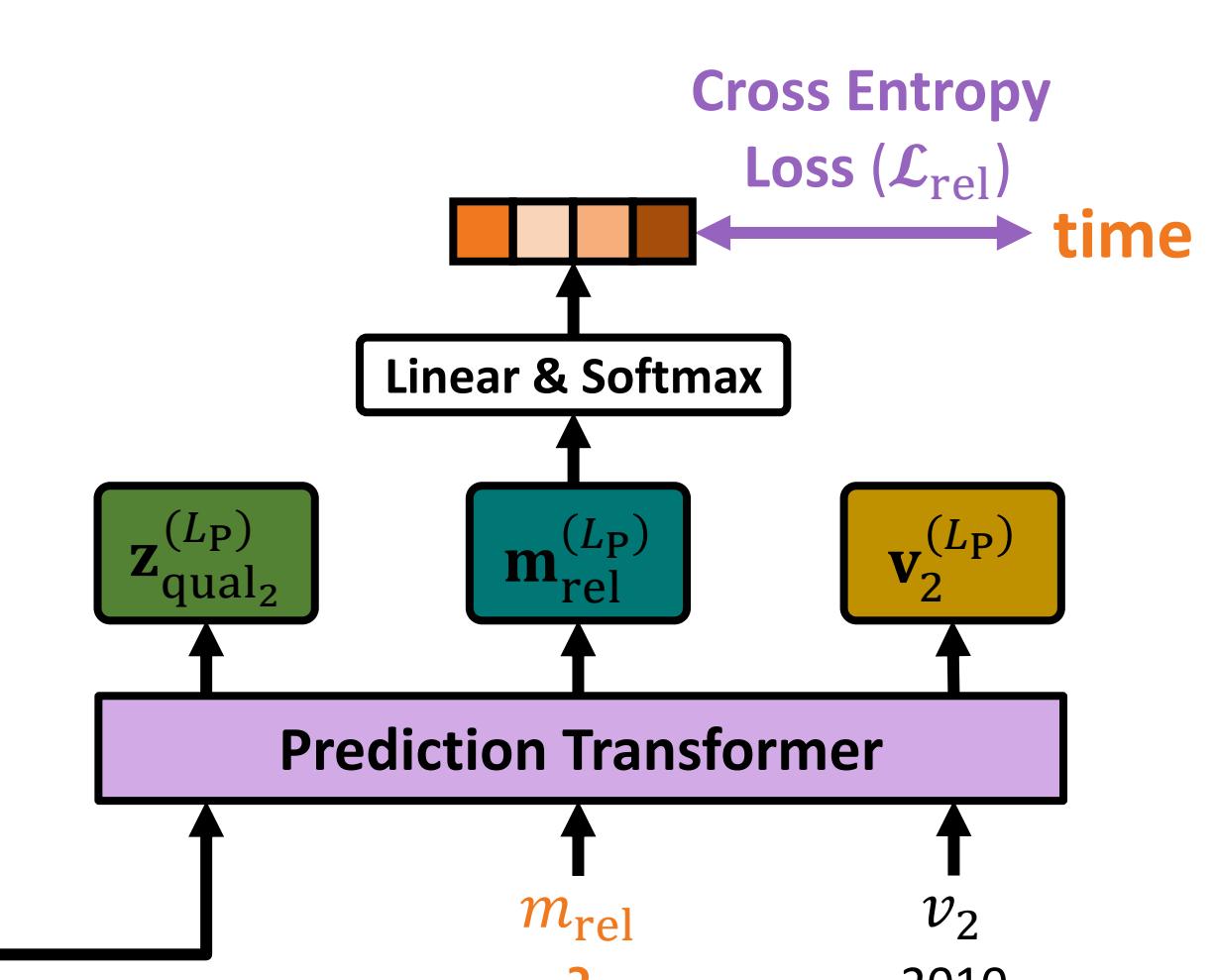
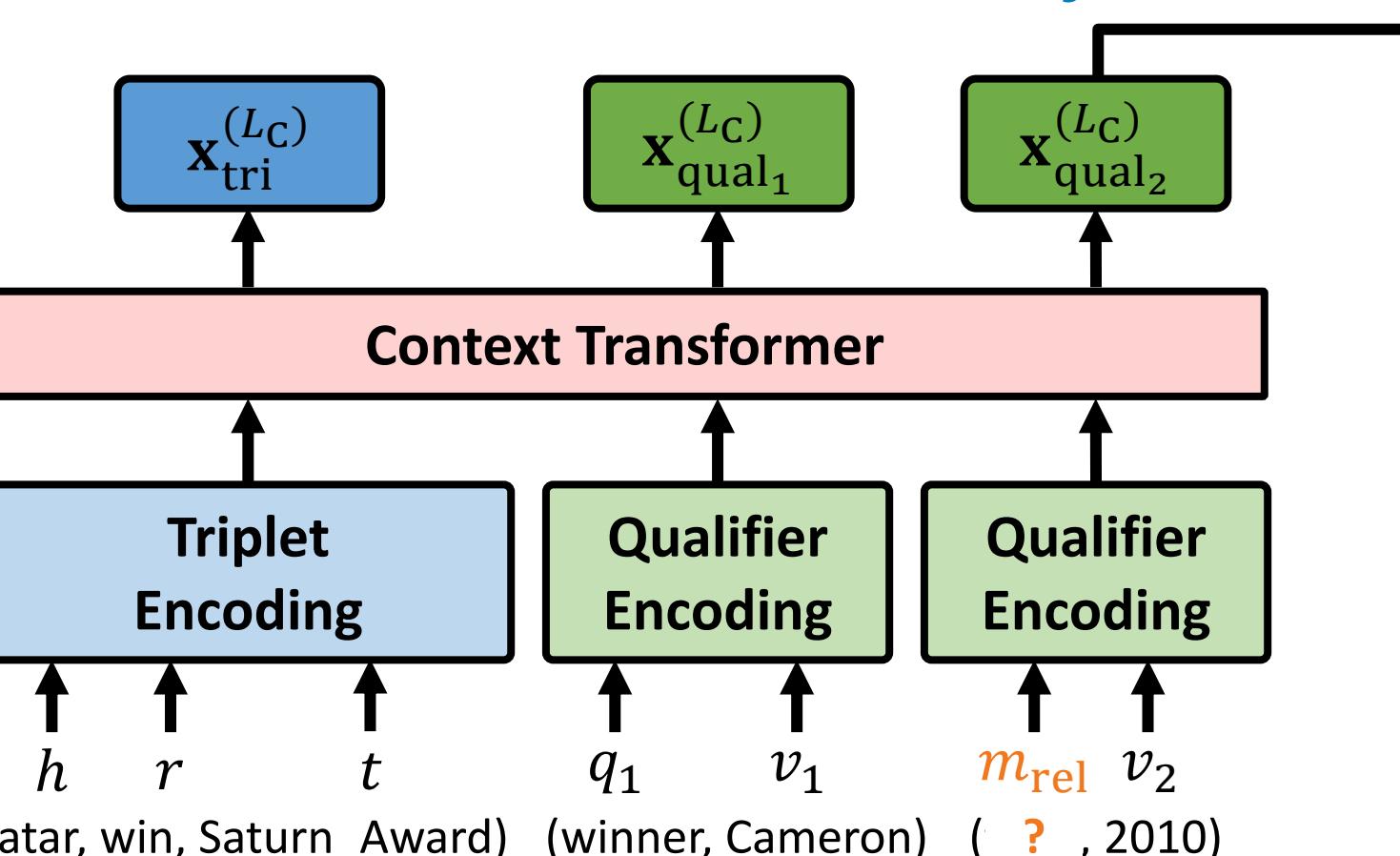
Link Prediction Loss of HyNT



Numeric Value Prediction Loss of HyNT



Relation Prediction Loss of HyNT



$$\text{Loss of HyNT}: \mathcal{L} := \mathcal{L}_{\text{ent}} + \lambda_1 \cdot \mathcal{L}_{\text{rel}} + \lambda_2 \cdot \mathcal{L}_{\text{num}}$$

Experimental Results

- Baseline methods**: TransEA, MT-KGNN, KBLN, LiteralE, NaLP, tNaLP, RAM, HINGE, NeuInfer, StarE, Hy-Transformer, GRAN

Link Prediction Results (MRR, ↑)

	HN-WK	HN-YG	HN-FB	HN-FB-S
Primary	0.2627	0.1951	0.2602	0.5077
HyNT	0.3037	0.2035	0.4544	0.5079

Numeric Value Prediction Results (RMSE, ↓)

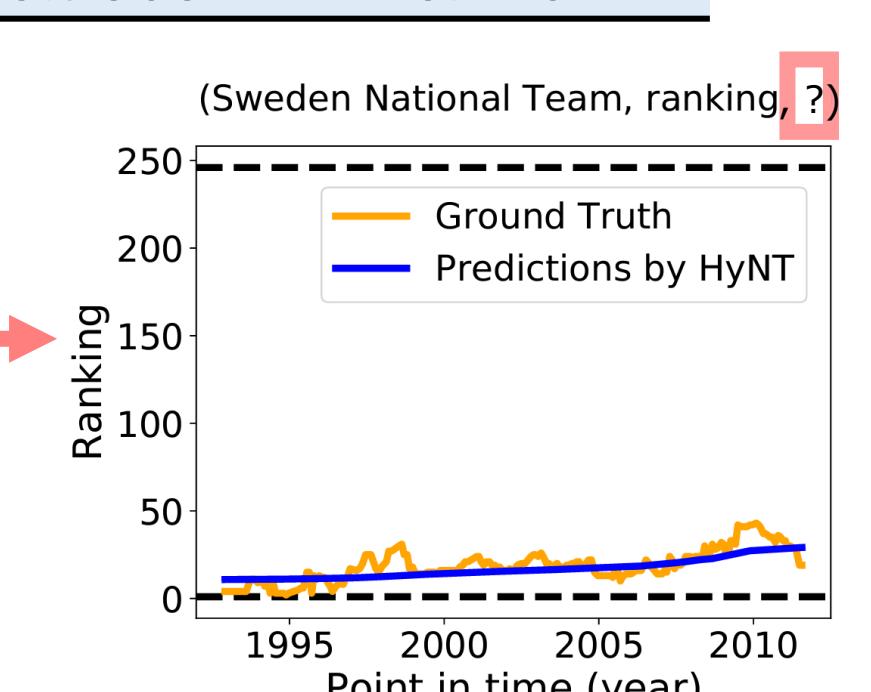
	HN-WK	HN-YG	HN-FB	HN-FB-S
Primary	0.0761	0.0778	0.0637	0.0656
HyNT	0.0548	0.0706	0.0517	0.0532

Relation Prediction Results (MRR, ↑)

	HN-WK	HN-YG	HN-FB	HN-FB-S
Primary	0.9285	0.8347	-	0.9845
HyNT	0.9474	0.8797	0.9809	0.9815

Visualization of Numeric Value Predictions

- Numeric value prediction problems in a particular form
 - ((Sweden National Team, ranking, ?), {(point in time, 1992)})
 - ((Sweden National Team, ranking, ?), {(point in time, 1993)})
 - ((Sweden National Team, ranking, ?), {(point in time, 1994)})



Conclusion & Future Work

- Introduce the concept and real-world datasets for **Hyper-relational and Numeric Knowledge Graphs (HN-KGs)**
- Propose **HyNT** to solve **link prediction**, **numeric value prediction**, and **relation prediction** on HN-KGs
- HyNT significantly outperforms 12 different state-of-the-art methods
- Plan to extend HyNT to **inductive learning scenarios** where new entities and relations appear at test time