Karlsruhe Institute of Technology

Towards Holistic Concept Representations:
Embedding Relational Knowledge, Visual Attributes, and Distributional Word Semantics

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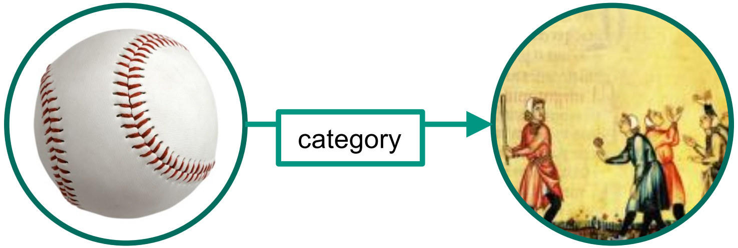
What is captured in entity-embeddings learned from KGs?

KG Embedding Approaches – Overview

[Nic16]

- Latent Feature Models
  - Latent Translation Models
  - Tensor Decomposition
  - Multi Layer Perceptrons
  - Latent Graphical Models

- Approaches
  - **TransE**
  - TransH
  - TransR
  - Rescal
  - HolE,
  - ComplEx,
  - RDF2Vec
  - ….



$$\begin{bmatrix}0.2\\0.8\end{bmatrix} \xrightarrow[\text{category}]{\begin{bmatrix}0.7\\0.1\end{bmatrix}} \begin{bmatrix}0.9\\0.9\end{bmatrix}$$

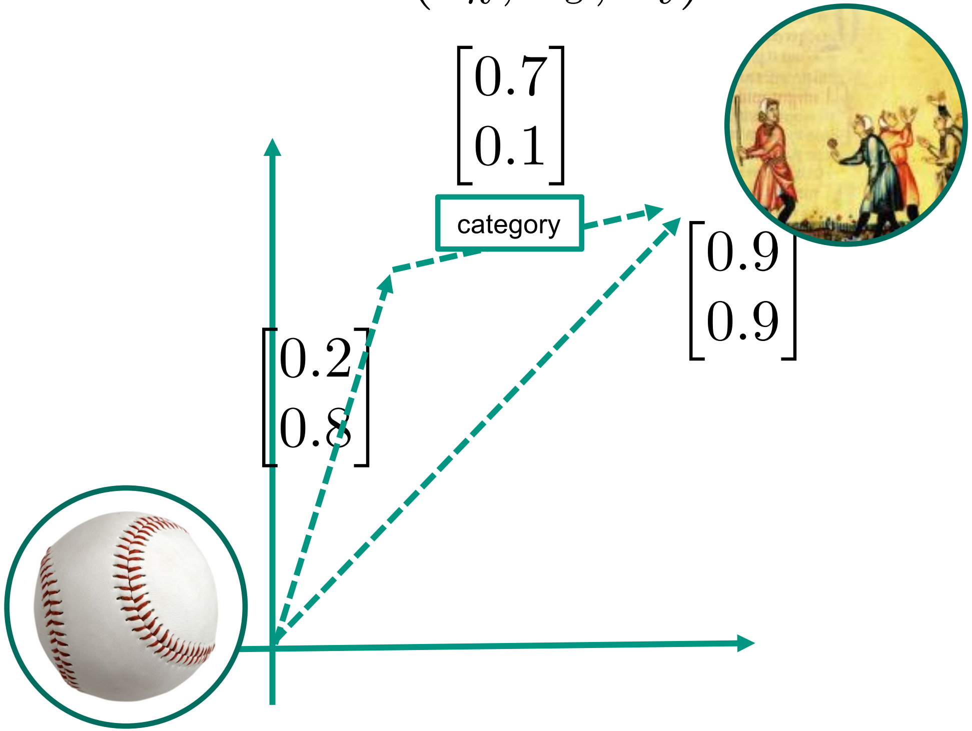
$$score(\mathbf{r}_k, \mathbf{e}_i, \mathbf{e}_j)$$

Latent Distance Models – TransE – Model

[Bor13]

$$score^{TransE}(\mathbf{r}_k, \mathbf{e}_i, \mathbf{e}_j)^{known} > score^{TransE}(\mathbf{r}_k, \mathbf{e}_s, \mathbf{e}_t)^{corrupted}$$

$$\begin{aligned} & score^{TransE}(\mathbf{r}_k, \mathbf{e}_i, \mathbf{e}_j) \\ = & -d(\mathbf{e}_i + \mathbf{r}_k, \mathbf{e}_j) \\ = & -\|\mathbf{e}_i + \mathbf{r}_k - \mathbf{e}_j\|_2 \end{aligned}$$



What is captured in entity-embeddings
learned from a KG?

They capture abstract relational context.

Is there other types of context that could complement entity embeddings?

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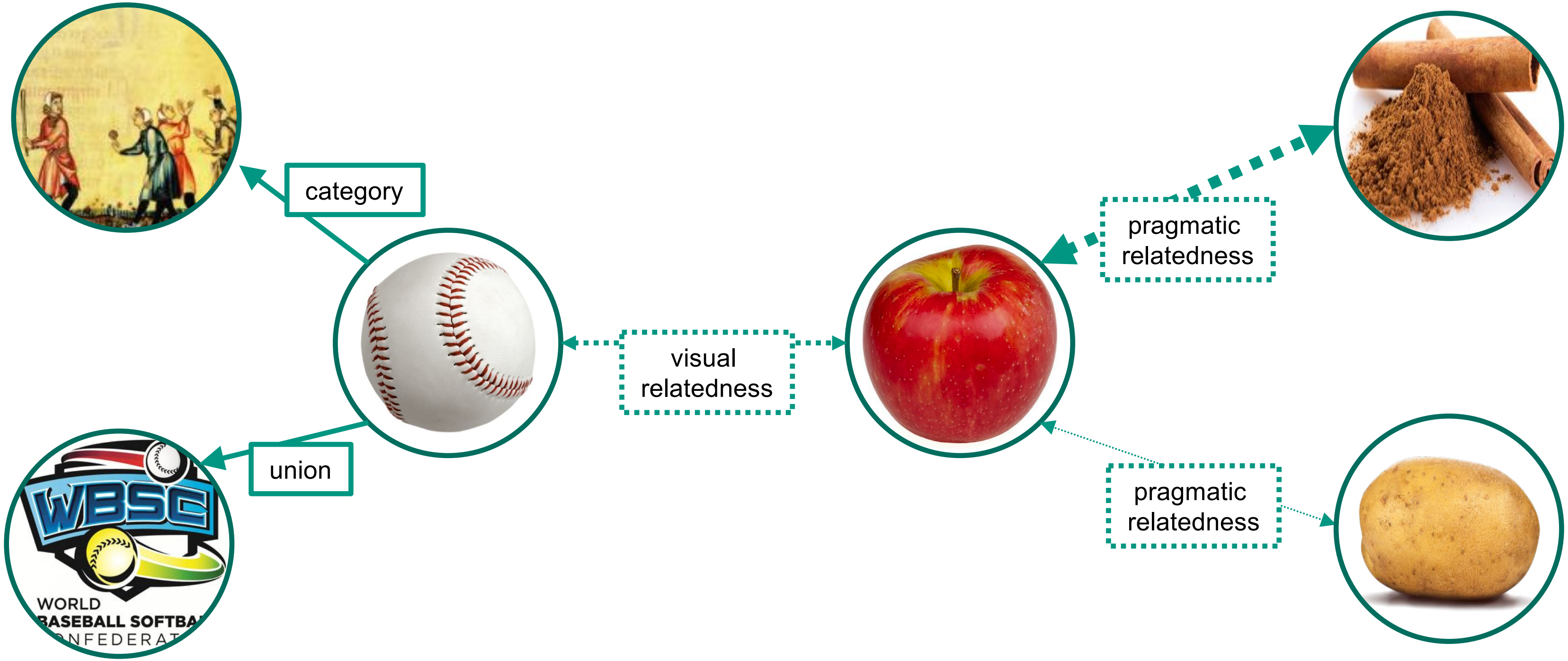

category
union
WBSC
WORLD
visual
relatedness
pragmatic
relatedness
pragmatic
relatedness

Motivation

Other media (images, text documents) contain additional information:

Example Baseball:

- ***Visual*** – Shape, Color, Background

- ***Textual*** – Co-occurrence Correlation

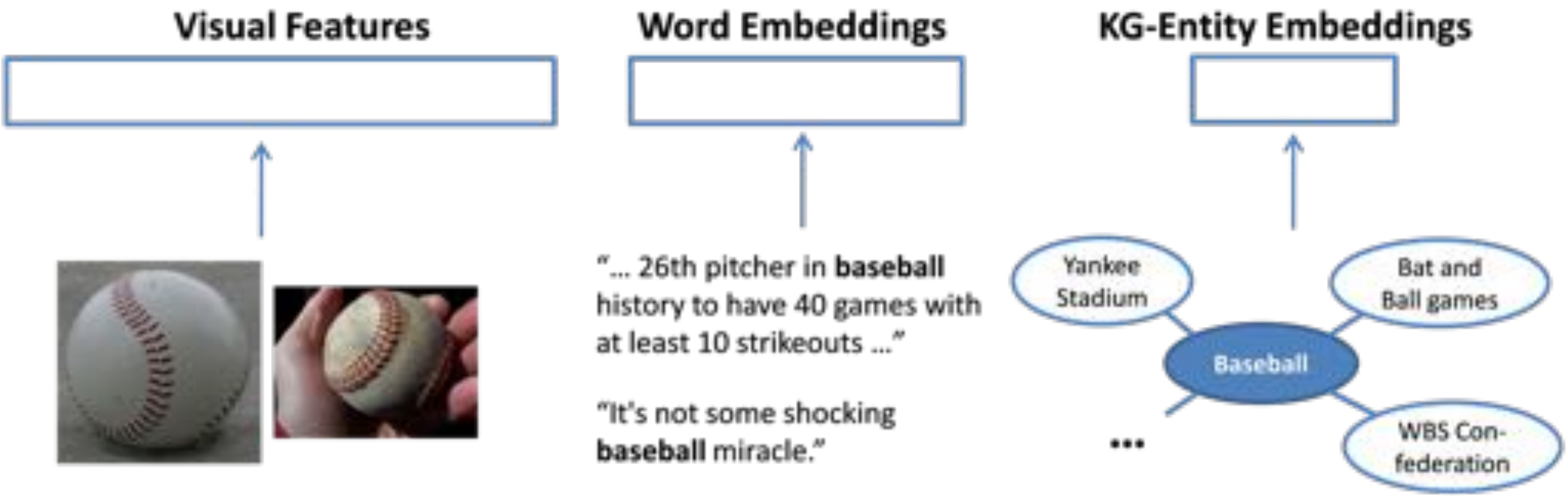
"… 26th pitcher in **baseball** history to have 40 games with at least 10 strikeouts …"

- ***Knowledge Graph*** - Relational Knowledge

Is there other types of context that could complement entity embeddings?

Yes. Context from the visual and lingual modality.

How do we collect such diverse content with a common encoding?



Visual Features
Word Embeddings
KG-Entity Embeddings
"... 26th pitcher in **baseball** history to have 40 games with at least 10 strikeouts ..."
"It's not some shocking **baseball** miracle."
Yankee Stadium
Bat and Ball games
Baseball
WBS Con-federation
...

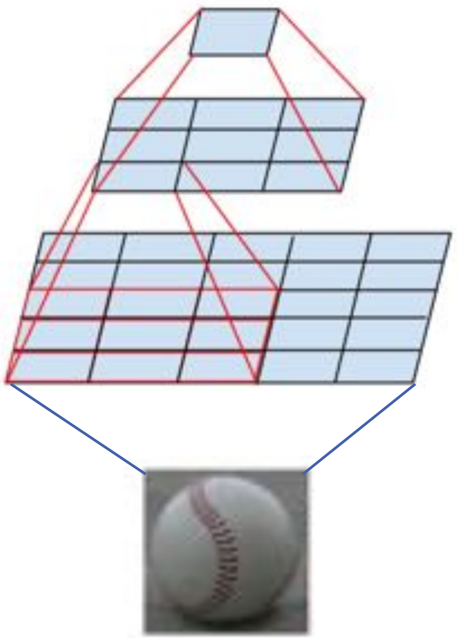
Visual Embedding – Inception V3

[Rus15]

- Deep Convolutional Neural Networks
  - Optimized on object recognition

- Abstract visual features

  Higher level layers correspond to more abstract features



Schematic Convolutional Net, abstracting visual features

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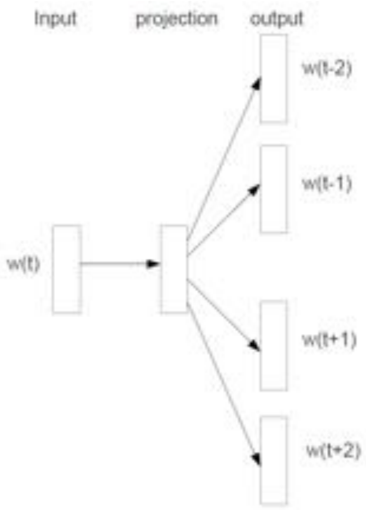
Text Embedding – Word2Vec

[Mik13]

- Words represented as vectors

„King“ →

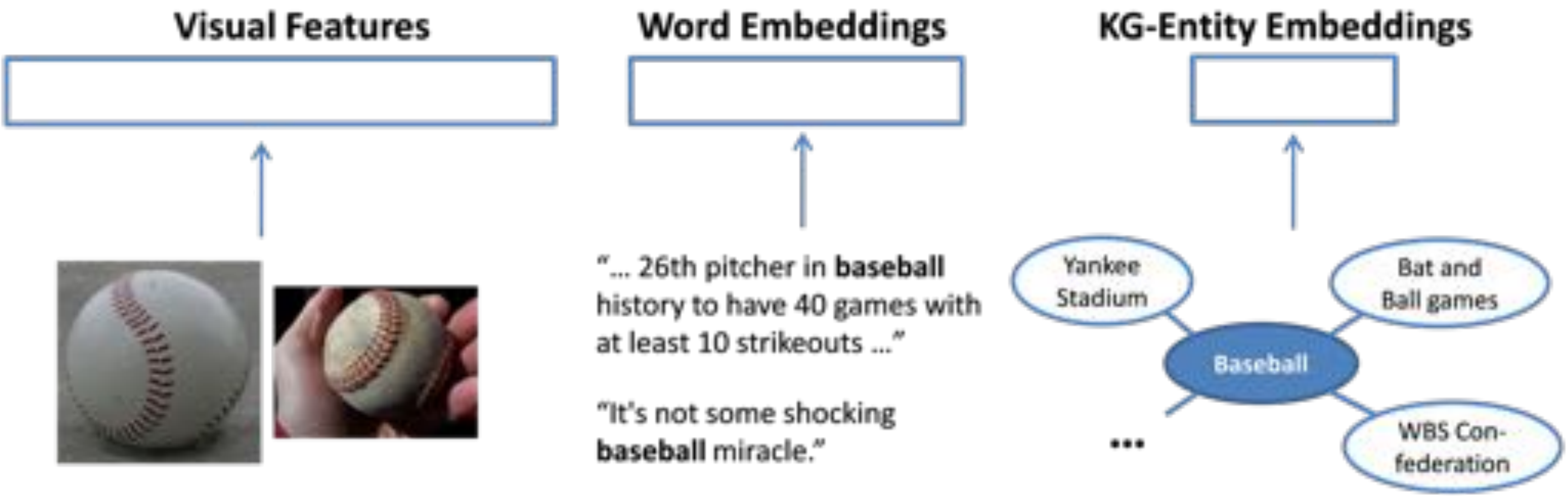
0.2	0.1	1.5	0.3	…					



Skip-gram: Predicting surrounding words

- Arithmetic operations

vector() - vector() + vector() = vector ()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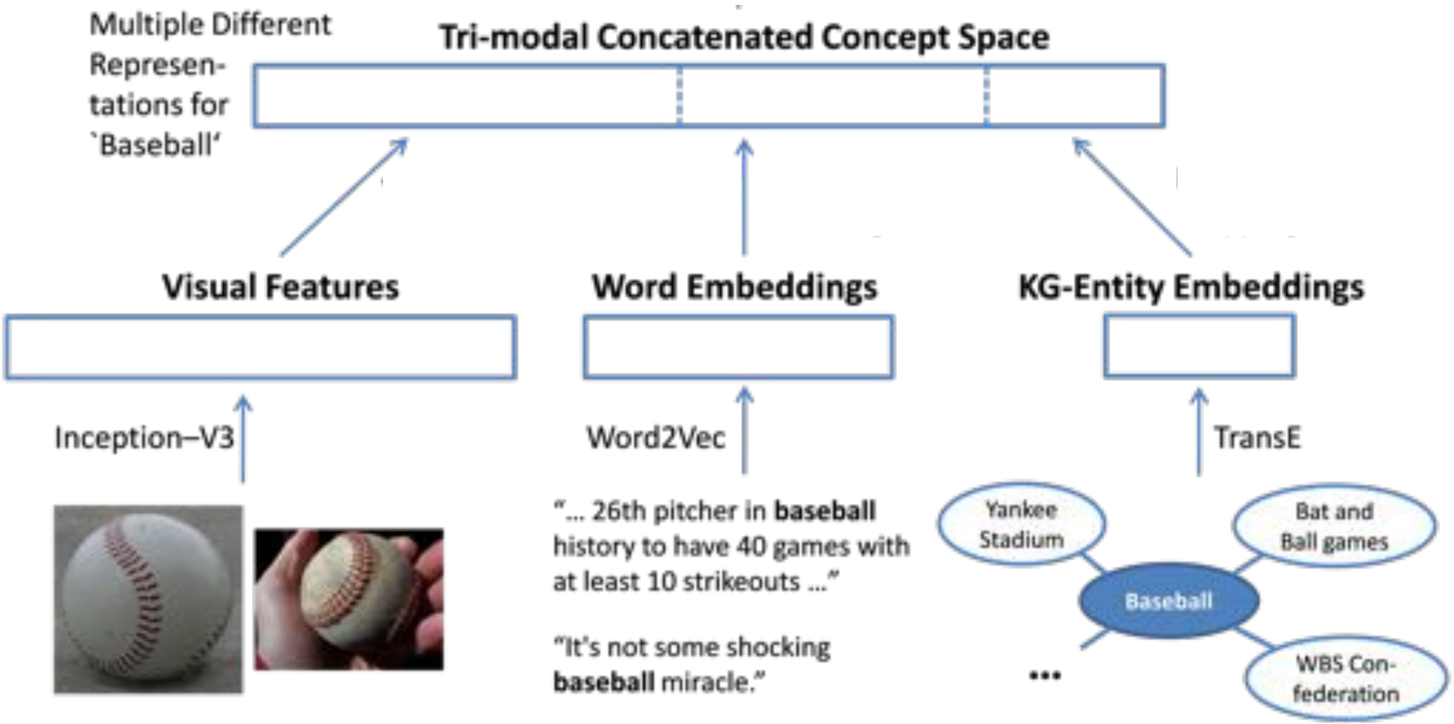
How do we collect such diverse content with a common encoding?

Multiple Embeddings

How do we align the embeddings across modalities?


Multiple Different Represen-tations for `Baseball'
Tri-modal Concatenated Concept Space
Visual Features
Word Embeddings
KG-Entity Embeddings
Inception–V3
Word2Vec
TransE
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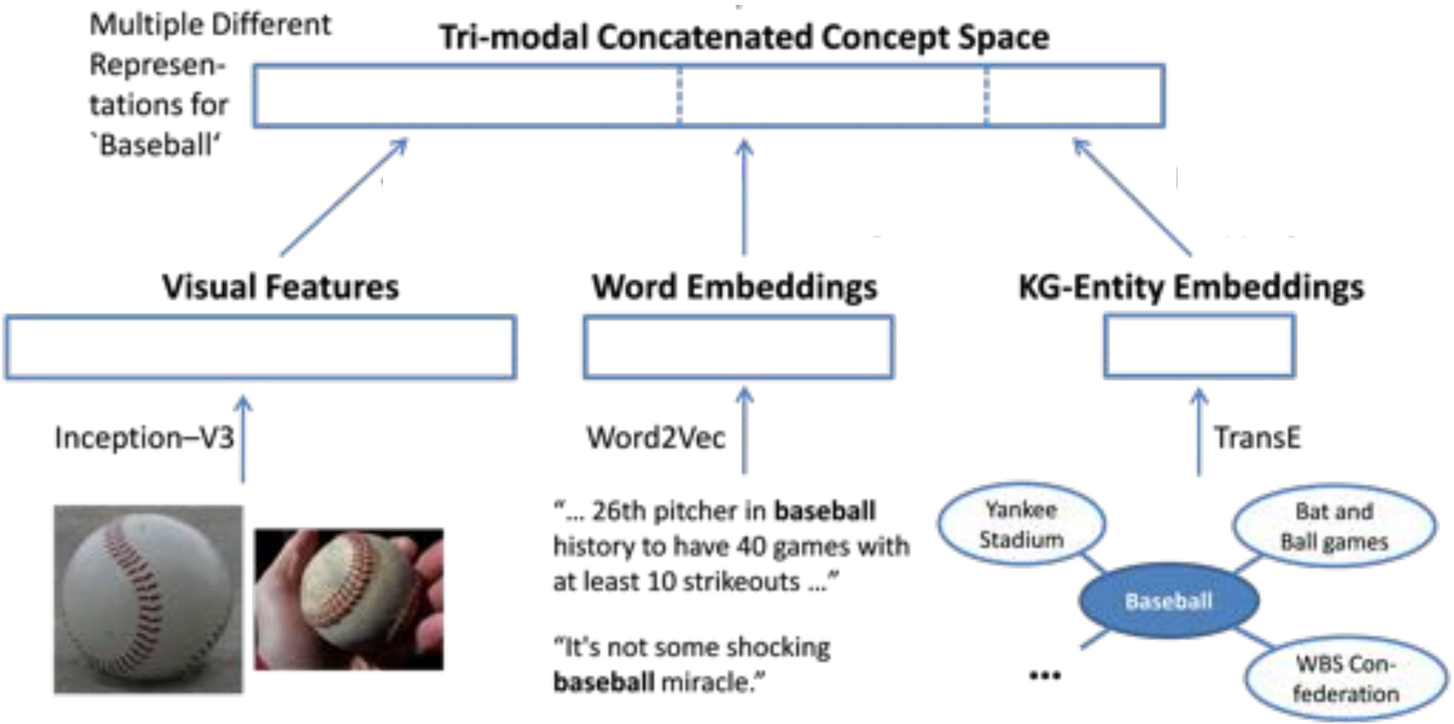
Shared Concept Space

Alignment of concepts from model space to shared space.

- Textual
  - Direct matching to words in model
- KG (DBPedia)
  - Get most probable URI (entity) for a given word
- Visual
  - Use WordNet hierarchy to get from image categories (synsets) to words



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How do we align the embeddings across modalities?

Match them across modalities

How do we identify complementary information?

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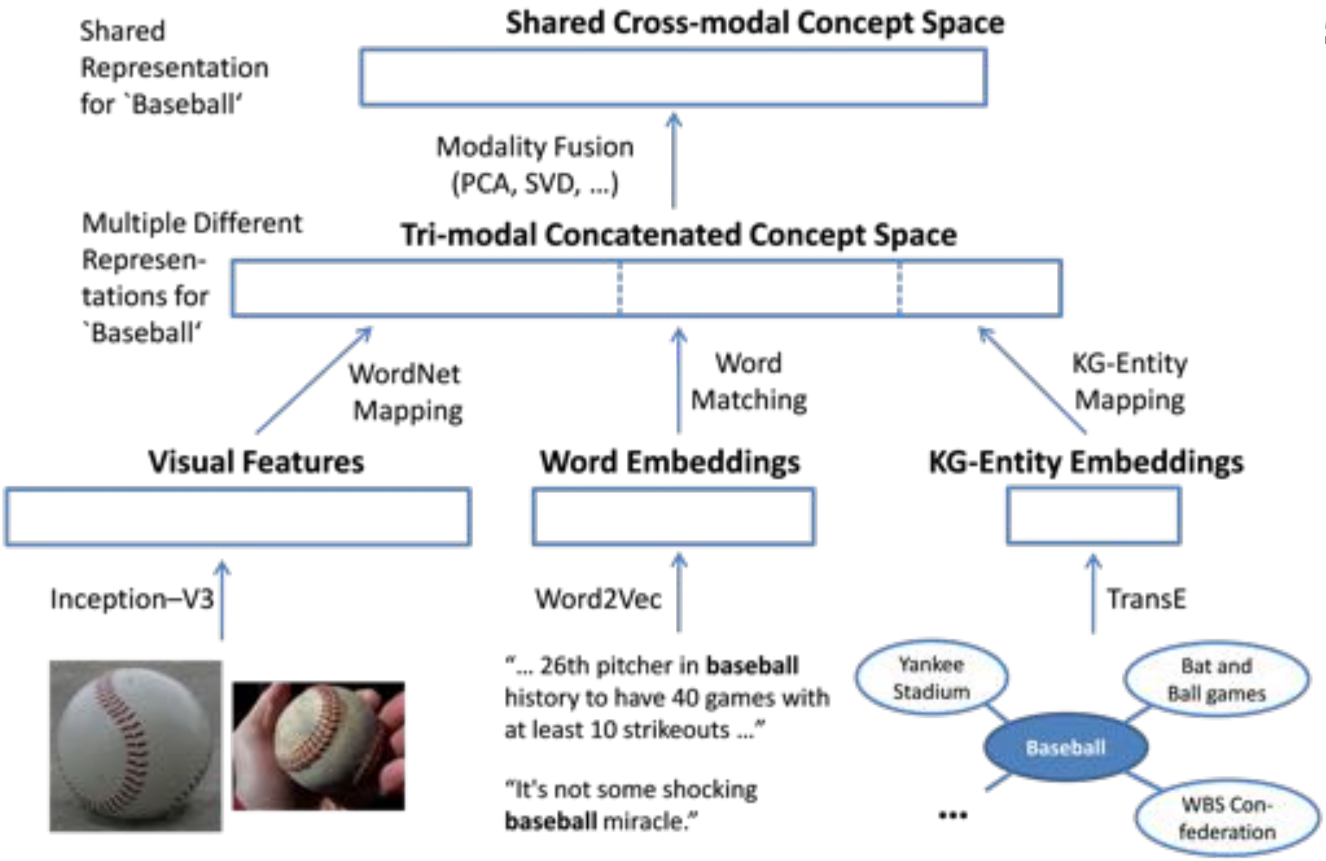
Shared Representation for `Baseball'
Shared Cross-modal Concept Space
Modality Fusion (PCA, SVD, ...)
Multiple Different Represen- tations for `Baseball'
Tri-modal Concatenated Concept Space
WordNet Mapping
Word Matching
KG-Entity Mapping
Visual Features
Word Embeddings
KG-Entity Embeddings
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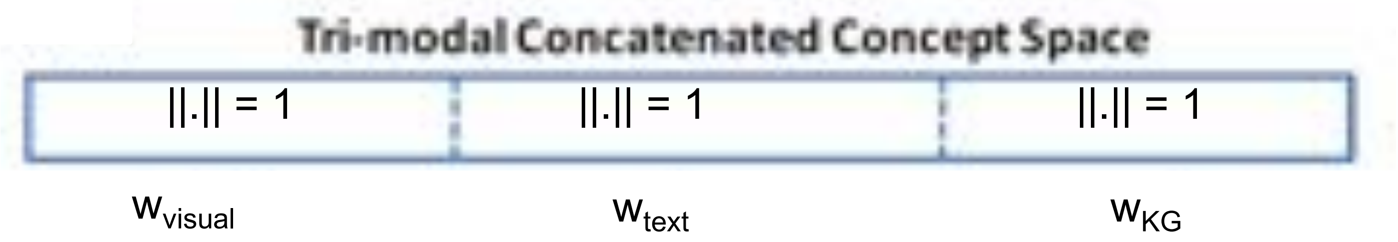
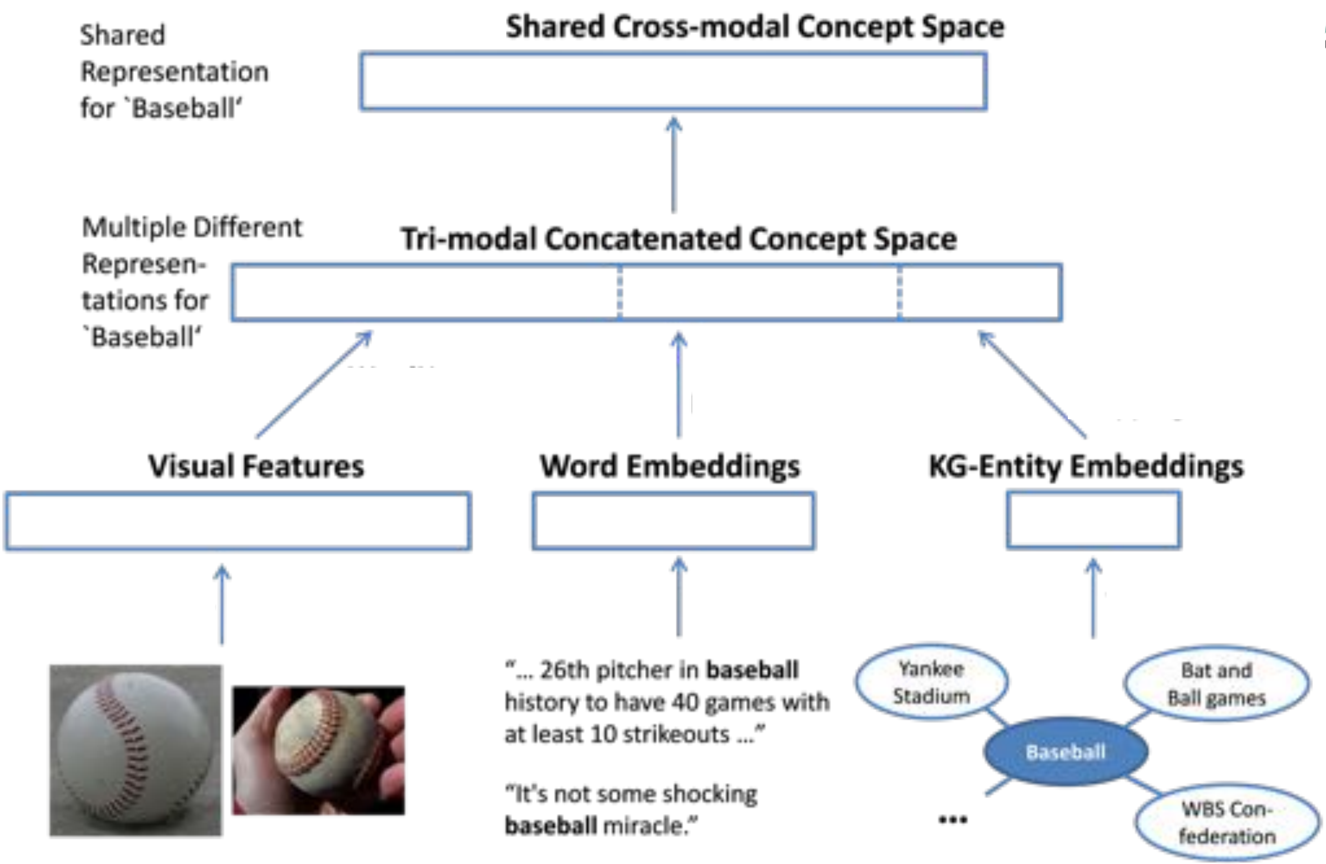
Fusion techniques

- Crucial: **normalization** and **weighting** before combination



- Shared Cross-modal Concept Space
  - PCA, SVD, Autoencoder



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How do we identify complementary information?

Dimensionality reduction techniques

How do we measure if those embeddings are more holistic in terms of covered context?

Empirical Analysis – Word Similarity

Examples for word similarity:

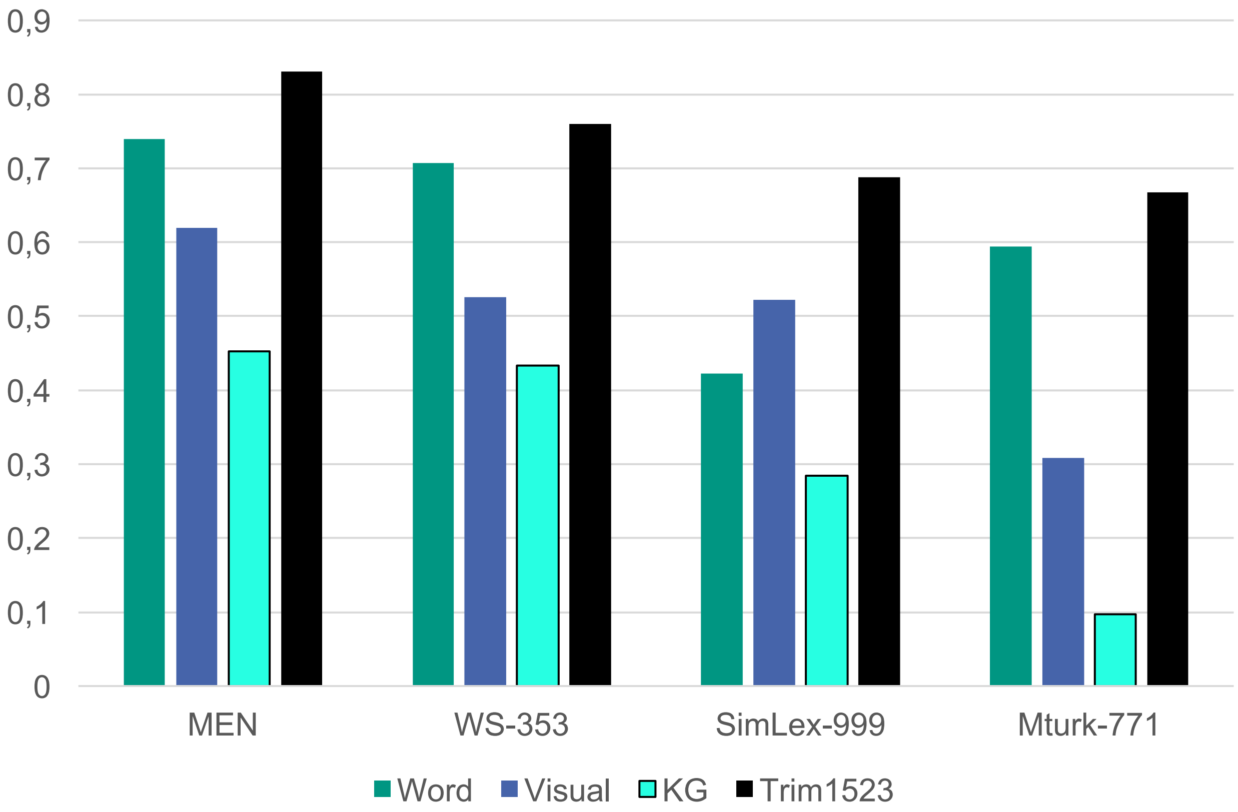
(sun, sunlight) → 50.0 (high similiartity)

(happy, kiss) → 26.0 (medium similarity)

(bakery, zebra) → 0.0 (low similiartity)

Datasets : MEN, WSS-353, SIMLEX-999, Mturk-771

Empricial Analysis – Word Similarity – Rank Correlation

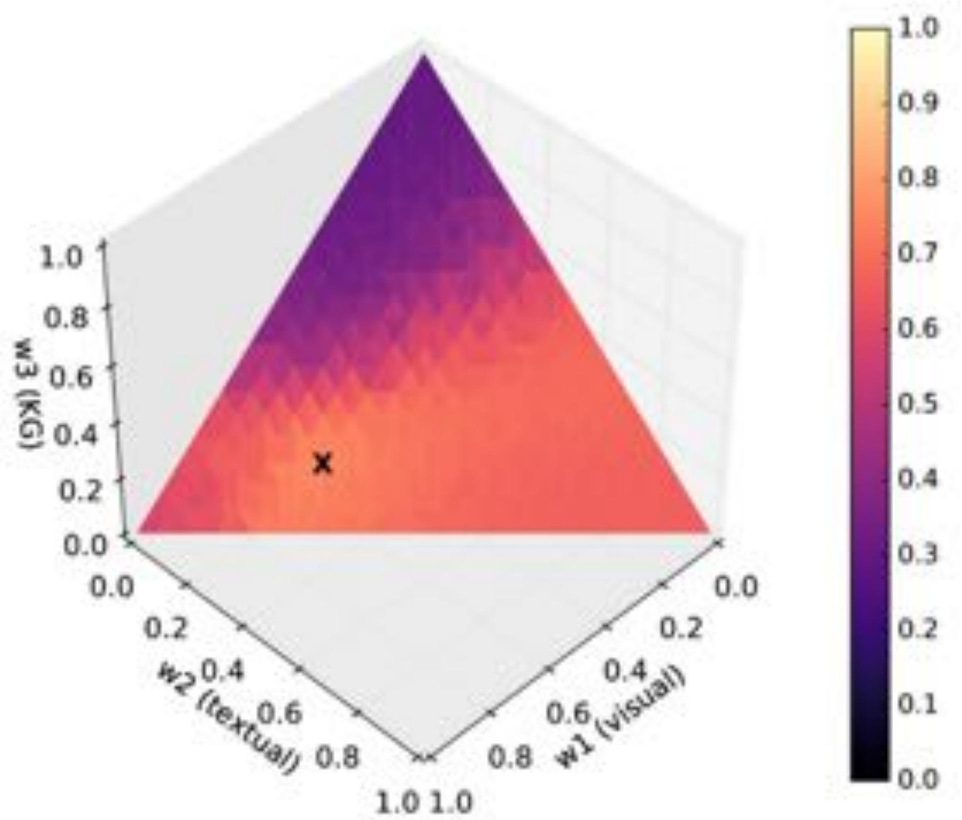


How do we measure if those embeddings are more holistic in terms of covered context?

Word similarity assessed by humans

Is every modality contributing information?

Empirical Analysis – Word Similarity – Influence of Modalities



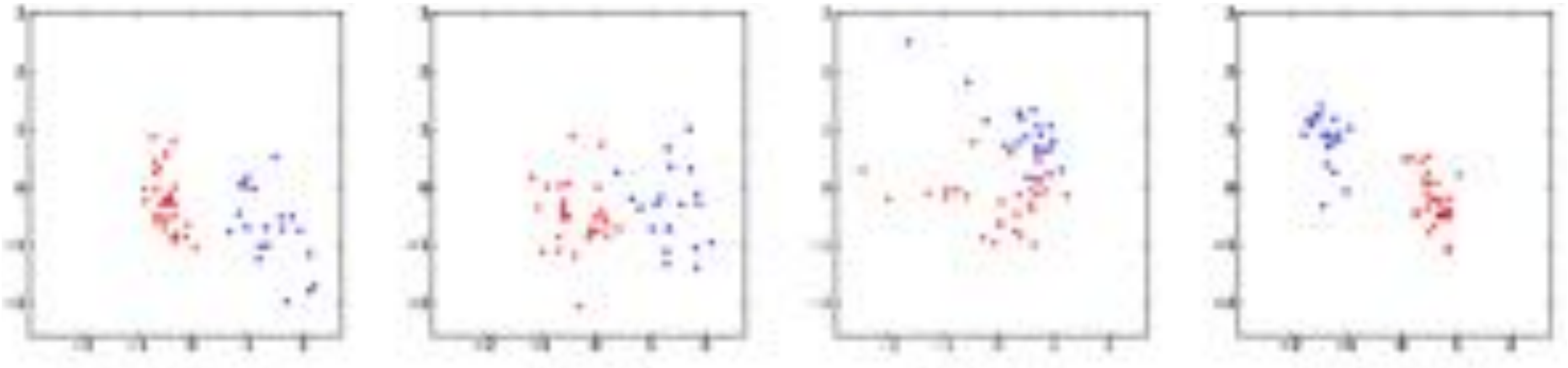
Is every modality contributing information?

Yes.

How do the embedding spaces differ?

Empirical Analysis – Entity Segmentation

First two PCA components for various birds (blue) and land vehicles (red)



(a) Textual (b) KG (c) Visual (d) CONC

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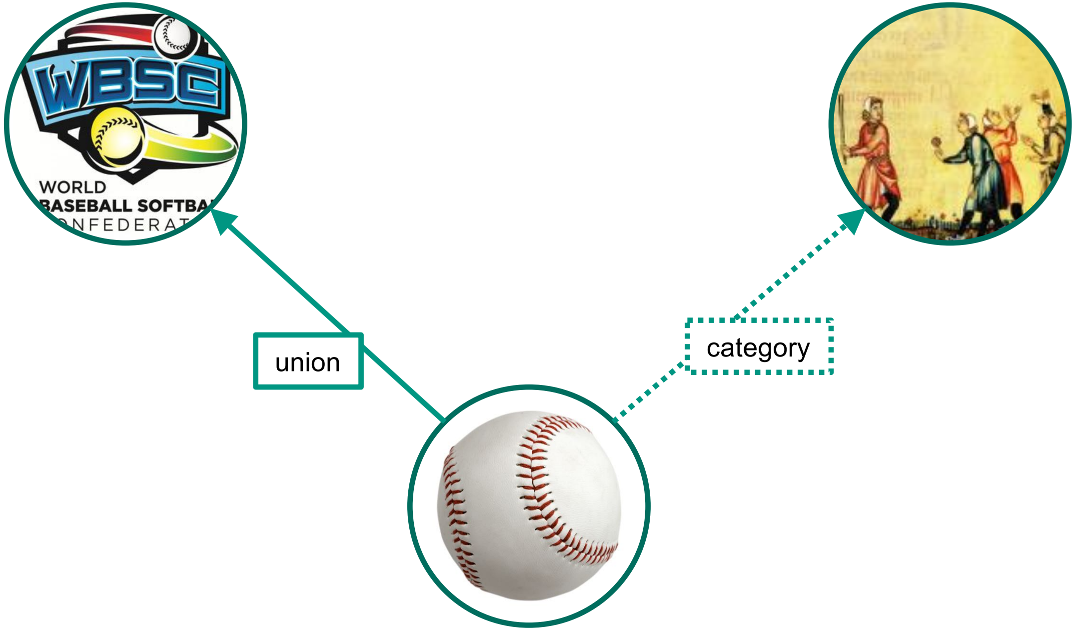
How do the embedding spaces differ?

Do knowledge graph tasks benefit?

Entity segmentation

Empirical Analysis – Entity-Type Prediction



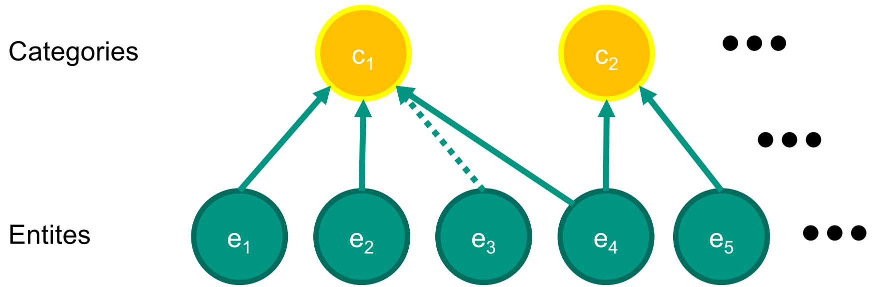
Empirical Analysis – Entity-Type Prediction

Hierarchic Construction (HC)

Constructing categorial embeddings from the multi-modal embeddings:

$$c_j = \frac{1}{N}\sum e_i \,, \forall c_j \text{ iff } (e_i, cj) \text{ exists}$$

In each evaluation run: leave out the edges (e_i, cj) which have to be predicted e.g. e_3 is left out for building c_1 as this connection exists and has to be predicted.



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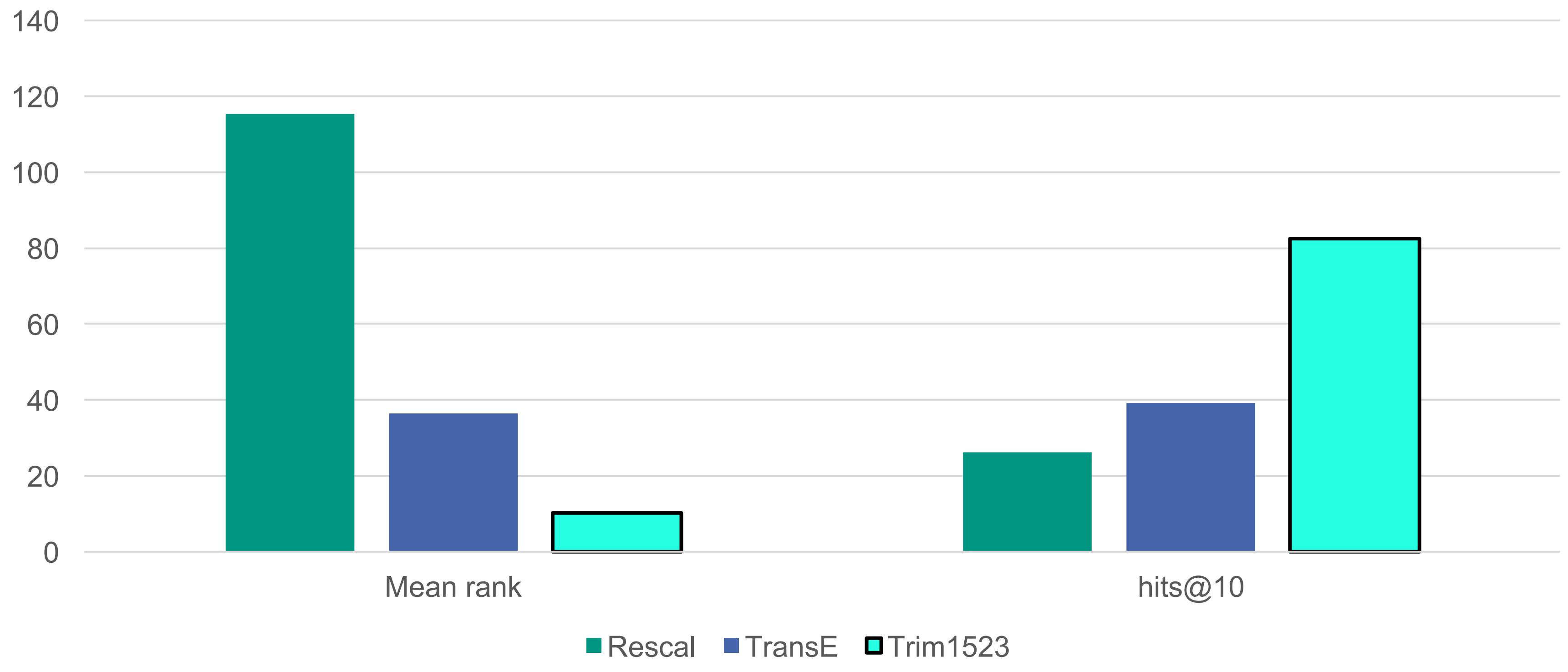

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What are the lessons learned?

Visual common-sense knowledge and distributional text semantics complements entity embeddings.

Cross-modal concept representations show a significantly better performance on various benchmarks.

So, shouldn't everyone try cross-modal concept embeddings?

?

Future Challenges

1. How to scale to the size of KGs?

2. How to learn the most general-purpose entity representations? How to represent them?

3. Which modalities and data sources should/can be exploited?

4. Can you transfer knowledge back to single-modal embeddings? [Bot17]

5. Early-fusion techniques better?

References (related work)

[Rus15] Russakovsky, Deng, Su, Krause, Satheesh, Ma, Huang, Karpathy, Khosla, Bernstein, Berg, Fei-Fei: ImageNet Large Scale Visual Recognition Challenge. International Journal of Computer Vision (IJCV) 115(3), 211–252 (2015)

[Bor13] Antoine Bordes, Nicolas Usunier, Alberto García-Durán, Jason Weston, Oksana Yakhnenko: *Translating Embeddings for Modeling Multi-relational Data.* NIPS 2013: 2787-2795

[Nic16] Maximilian Nickel, Kevin Murphy, Volker Tresp, Evgeniy Gabrilovich: *A Review of Relational Machine Learning for Knowledge Graphs*. Proceedings of the IEEE 104(1): 11-33 (2016)

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[Bot17] Fabian Both, Steffen Thoma, Achim RettingerCross-modal Knowledge Transfer: Improving the Word Embedding of Apple by Looking at OrangesK-CAP2017, The 9th International Conference on Knowledge Capture, ACM, Dezember, 2017

Questions?
Comments?
Ideas?
Request?

Contact me:
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