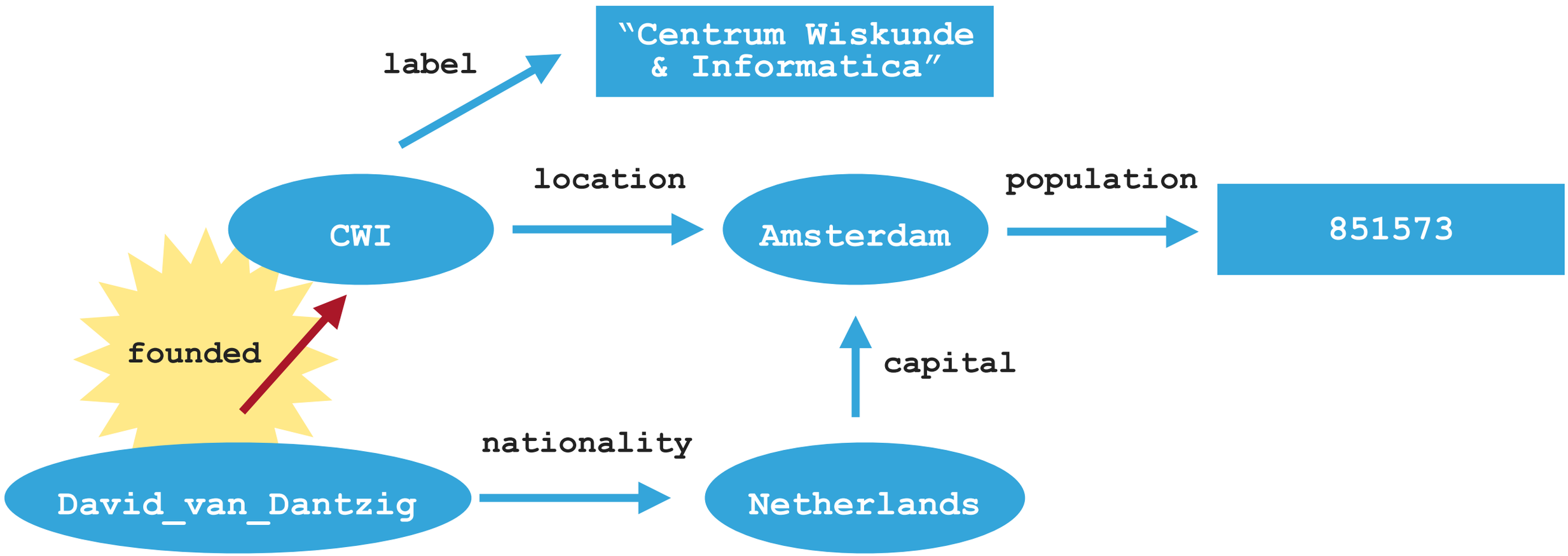
**BENNO KRUIT**, PETER BONCZ, JACOPO URBANI

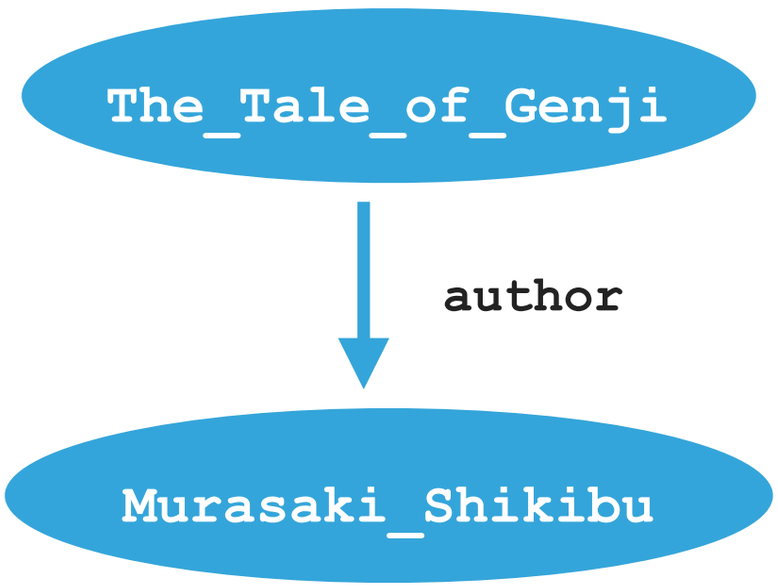
# EXTRACTING NOVEL FACTS FROM TABLES FOR KNOWLEDGE GRAPH COMPLETION

# MOTIVATION: Web Tables For Knowledge Graph Completion

- Knowledge Graphs are very big, but still highly incomplete
- We'd like to **add links** using web tables: slot filling



# PROBLEM: Interpret Web Tables For Fact Extraction




| title of great novel | year | author |
|---|---|---|
| moby-dick | 1851 | herman melville |
| madame bovary | 1857 | gustave flaubert |
| middlemarch | 1871-72 | george eliot |
| the magic mountain | 1924 | thomas mann |
| the tale of genji | 11th century | murasaki shikibu |

`The_Tale_of_Genji` Entity

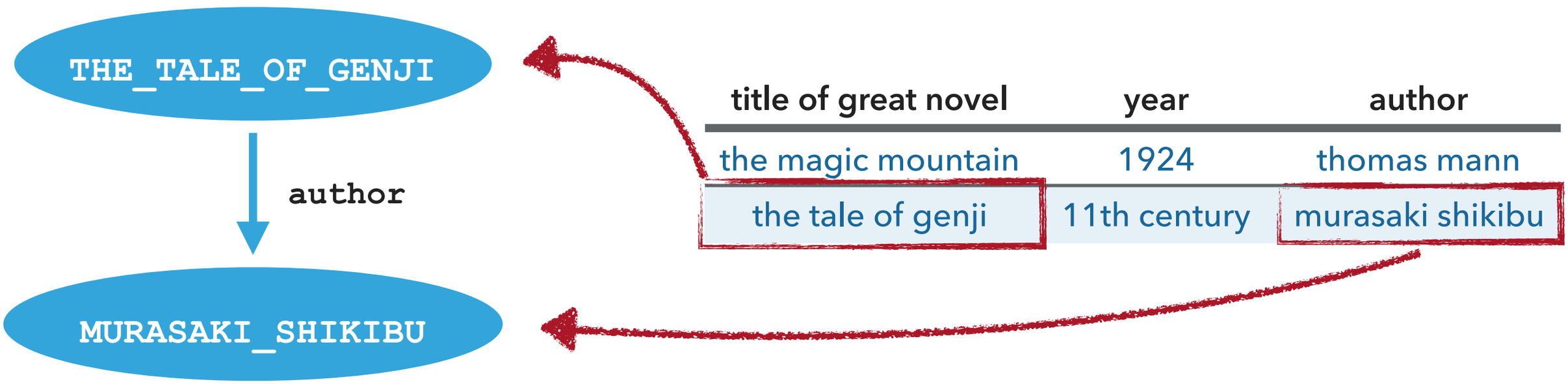
`book` Class

`author` Relation

- Disambiguate cells, classes and relations
- Add KG links using disambiguations

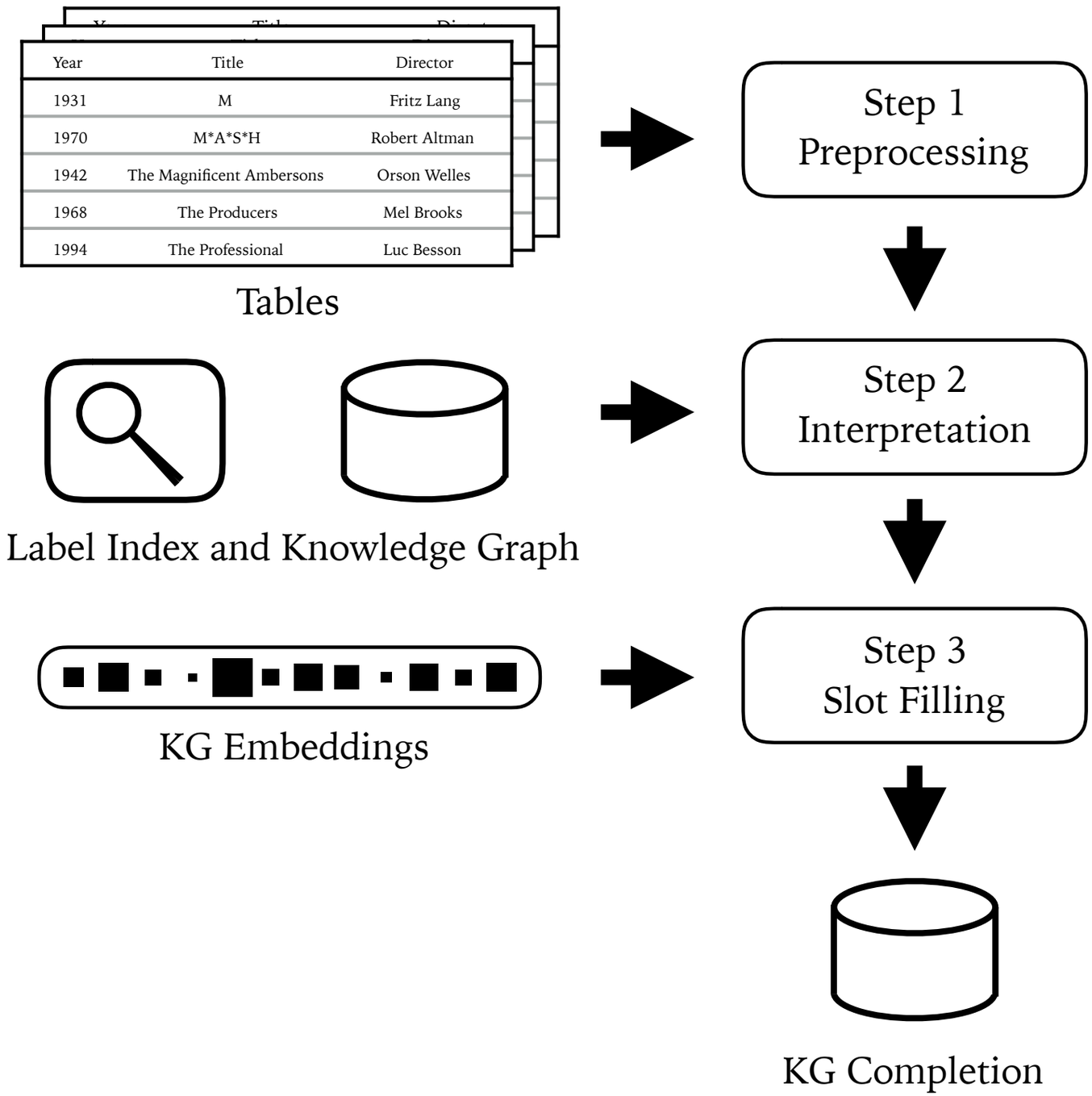
# STATE OF THE ART for Table Interpretation

- **T2K** [Ritze et al. 2015]
- **TableMiner+** [Zhang 2017]
- Both systems interpret tables based on **KG support**
  - More support = more confidence = *less novelty?*
- Both built for specific KGs



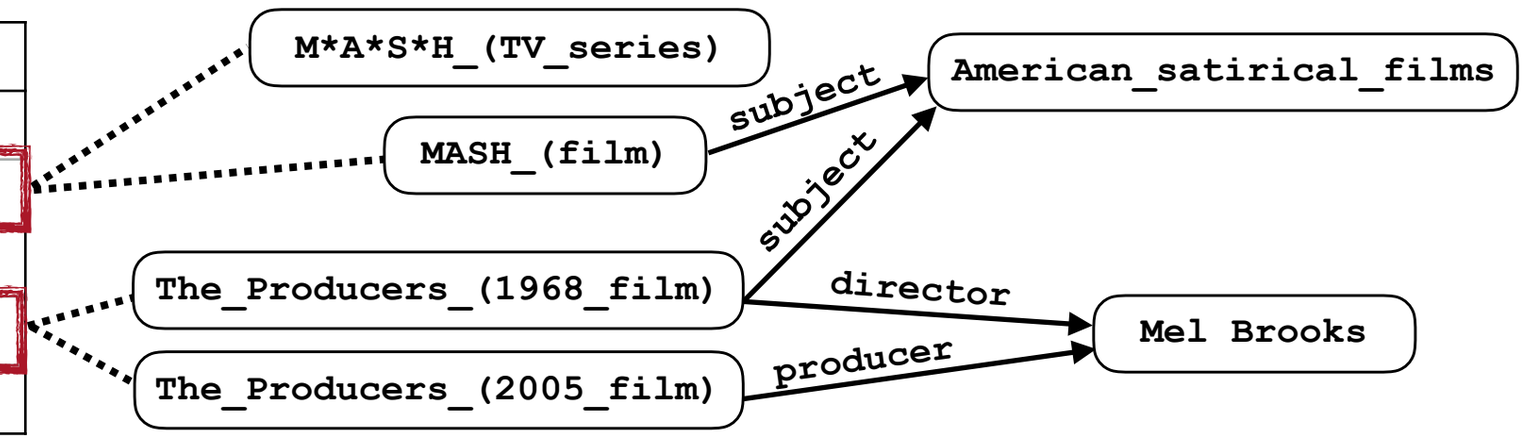
# TAKCO: Table-based Knowledge graph Completion

- **Novelty-oriented**
  - Recall first
  - Precision later
- KG-agnostic



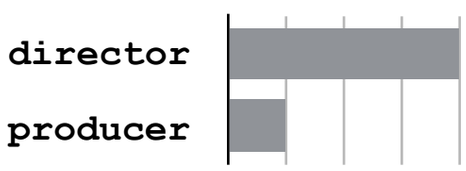
# CELL DISAMBIGUATION

| Director | Title |
|---|---|
| Fritz Lang | M |
| Robert Altman | M*A*S*H |
| Orson Welles | The Magnificent Ambersons |
| Mel Brooks | The Producers |
| Luc Besson | The Professional |

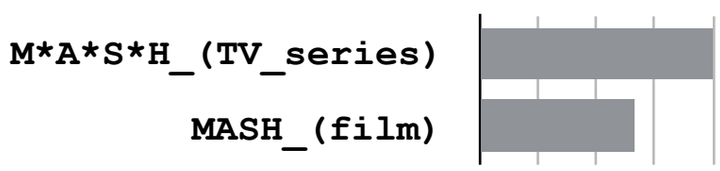



Cell Candidates

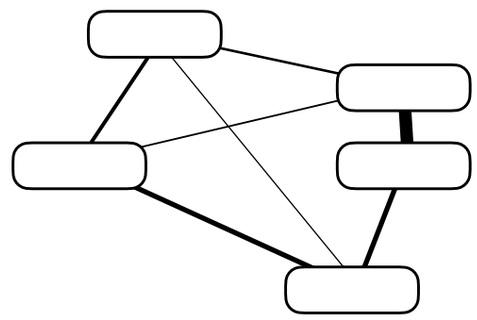
Attributes in the KB




Column-Predicate Scores

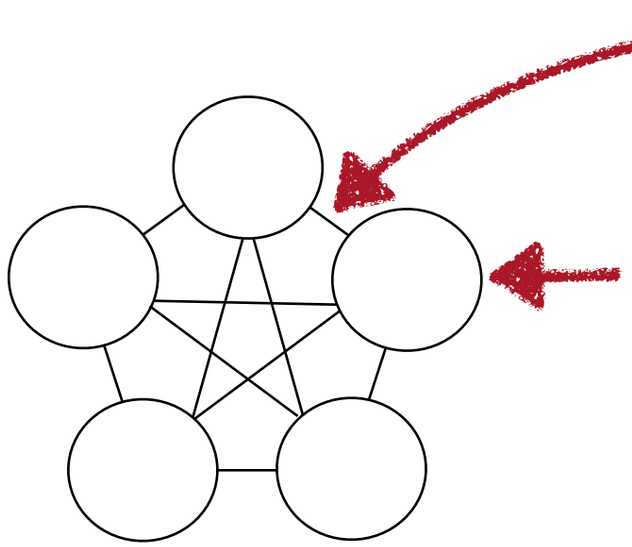



Cell-Candidate Scores

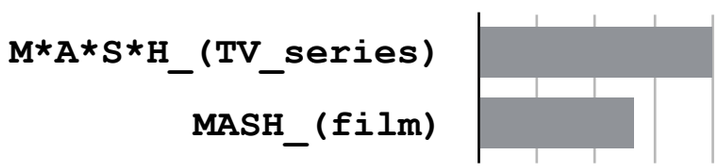


Entity Similarities

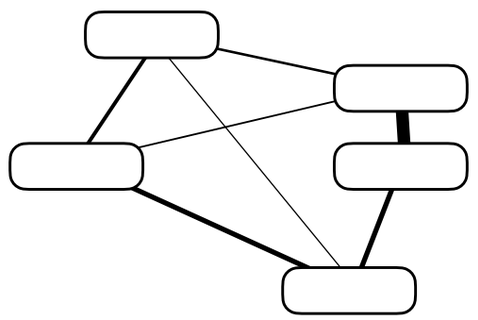
# CELL DISAMBIGUATION



Loopy Belief Propagation




Nodes:
Cell-Candidate Scores $\mathbf{L}$



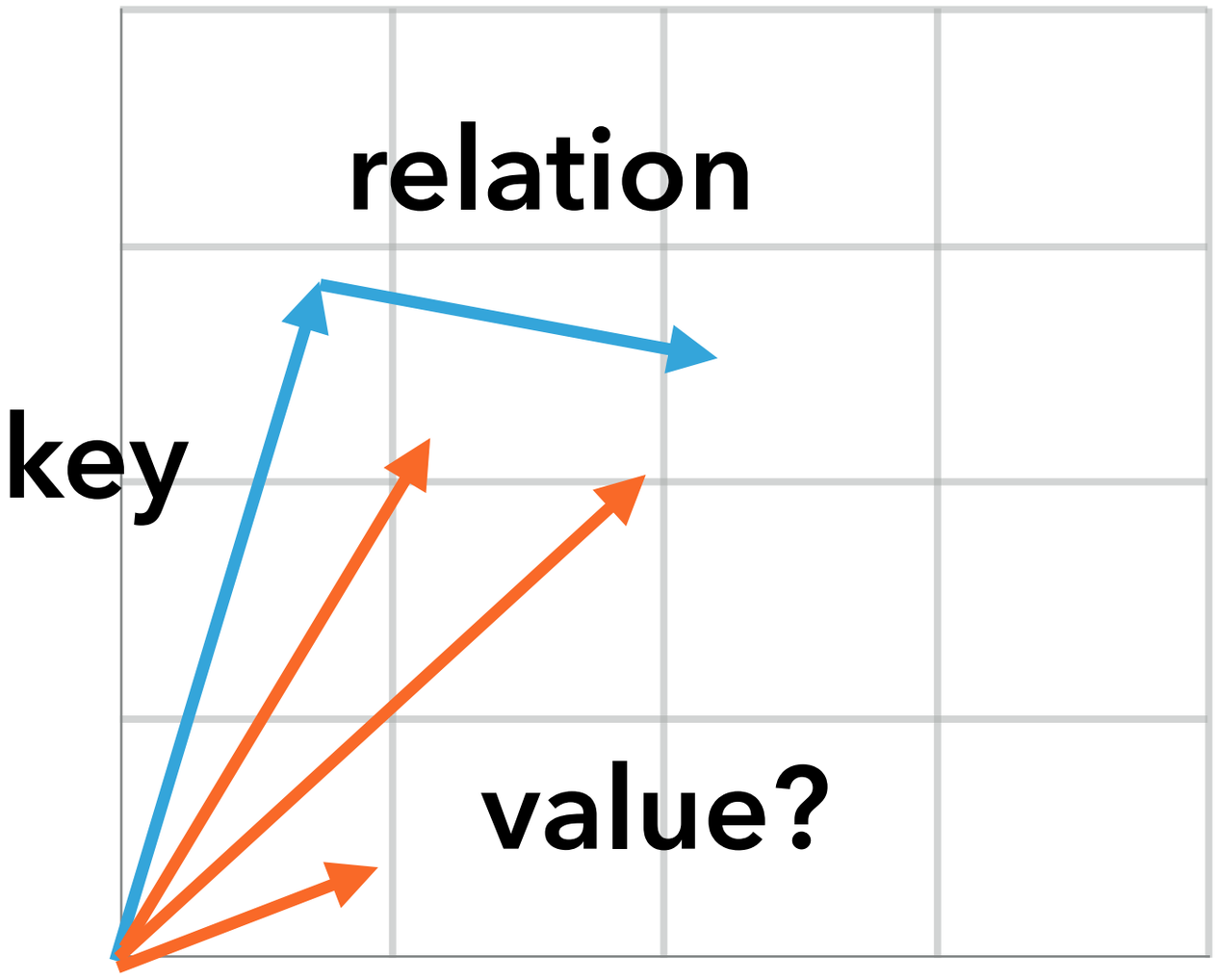
Edges:
Entities Similarities $\mathbf{S}$

$$\mathbf{q} = \Pi_{\text{row}} \left( \underset{\text{Rows}}{\overset{\text{Entities}}{\mathbf{L}}} \times \underset{\text{Entities}}{\overset{\text{Entities}}{\mathbf{S}}} \right)$$

Coherence score: best *cluster* of entities

# SLOT-FILLING

## Rank possible disambiguated values by distance



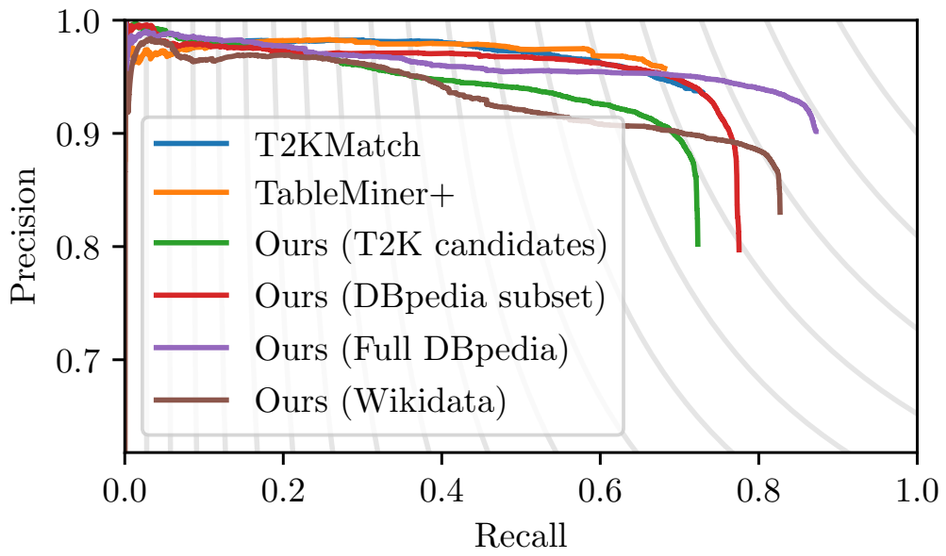

| title of great novel | author |
|---|---|
| don quixote | miguel de cervantes |
| war and peace | leo tolstoy |
| ulysses | james joyce |
| in search of lost time | marcel proust |
| the brothers karamazov | feodor dostoevsky |
| moby-dick | herman melville |
| madame bovary | gustave flaubert |
| middlemarch | george eliot |
| the magic mountain | thomas mann |
| the tale of genji | murasaki shikibu |

`author`

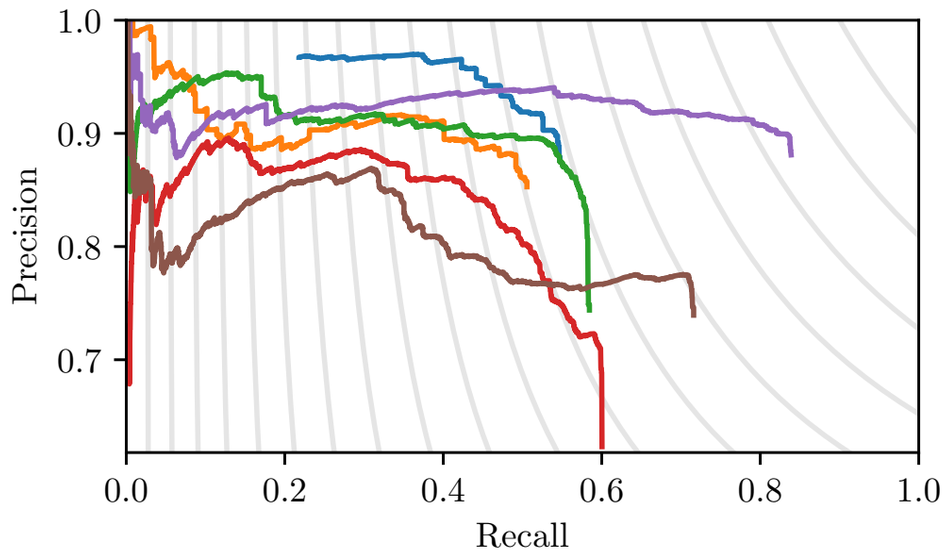
`The_Tale_of_Genji`

`?`

# RESULTS: CELL DISAMBIGUATION




Performance tradeoff, T2D-v2




Performance tradeoff, Webaroo

| System | Pr. | Re. | $F_1$ |
|---|---|---|---|
| T2KMatch | .94 | .73 | .82 |
| TableMiner+ | **.96** | .68 | .80 |
| Ours (T2K candidates) | .88 | .72 | .79 |
| Ours (DBpedia subset) | .90 | .76 | .83 |
| Ours (Full DBpedia) | .92 | **.86** | **.89** |
| Ours (Wikidata) | .87 | .82 | .84 |

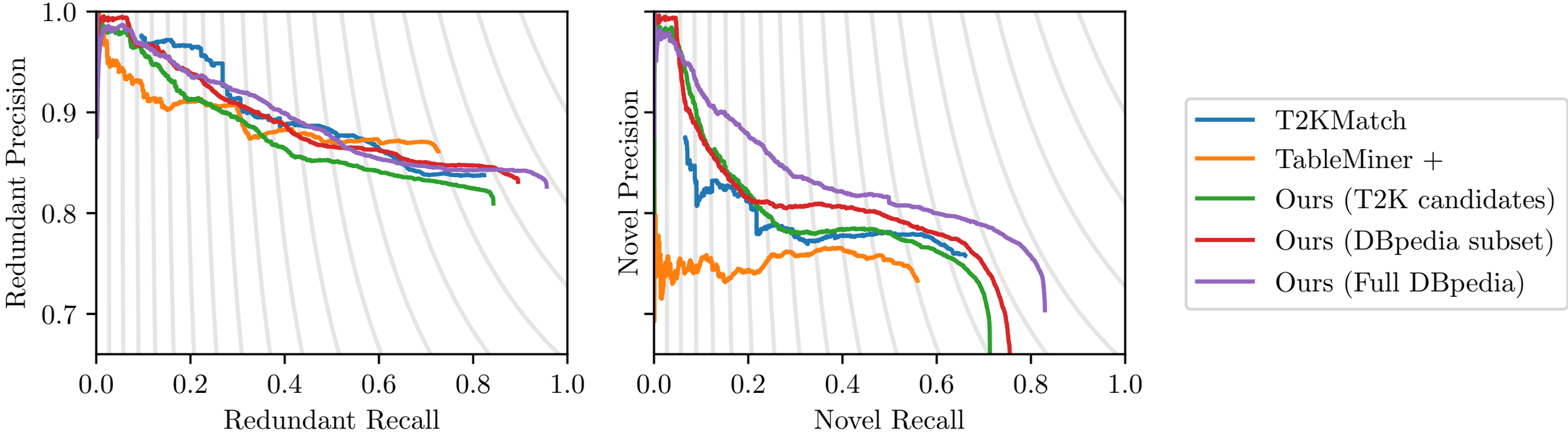
Row-entity evaluation, T2D-v2

| System | Pr. | Re. | $F_1$ |
|---|---|---|---|
| T2KMatch | .88 | .55 | .67 |
| TableMiner+ | .85 | .51 | .63 |
| Ours (T2K candidates) | .74 | .58 | .65 |
| Ours (DBpedia subset) | .72 | .59 | .65 |
| Ours (Full DBpedia) | **.88** | **.84** | **.86** |
| Ours (Wikidata) | .77 | .71 | .74 |

Row-entity evaluation, Webaroo

# RESULTS: NOVEL FACT EXTRACTION

| System | Redundant | | | Novel | | |
|---|---|---|---|---|---|---|
| | Pr. | Re. | $F_1$ | Pr. | Re. | $F_1$ |
| T2KMatch | .84 | .82 | .83 | **.76** | .66 | .71 |
| TableMiner + | **.86** | .73 | .79 | .73 | .56 | .63 |
| Ours (T2K candidates) | .81 | .84 | .83 | .61 | .71 | .66 |
| Ours (DBpedia subset) | .83 | .90 | .86 | .59 | .76 | .66 |
| Ours (Full DBpedia) | .83 | **.96** | **.89** | .70 | **.83** | **.76** |



# RESULTS: SLOT-FILLING ATTRIBUTE DISAMBIGUATION

| Ranking | Dataset | Prec@1 | Prec@3 |
|---|---|---|---|
| Only Label Index (TF-IDF score) | Wikitable | 0.37 | 0.42 |
| | T2D-v2 | 0.24 | 0.31 |
| Labels + Embeddings (TransE) | Wikitable | **0.61** | **0.72** |
| | T2D-v2 | **0.62** | **0.74** |

Precision of slot-filling with/out KG embeddings.

Wikitable: 1.6M tables → 786K entity tables → 498K linked

2.8M statements (1.8M slots, 823K known); 307K redundant

# CONCLUSION

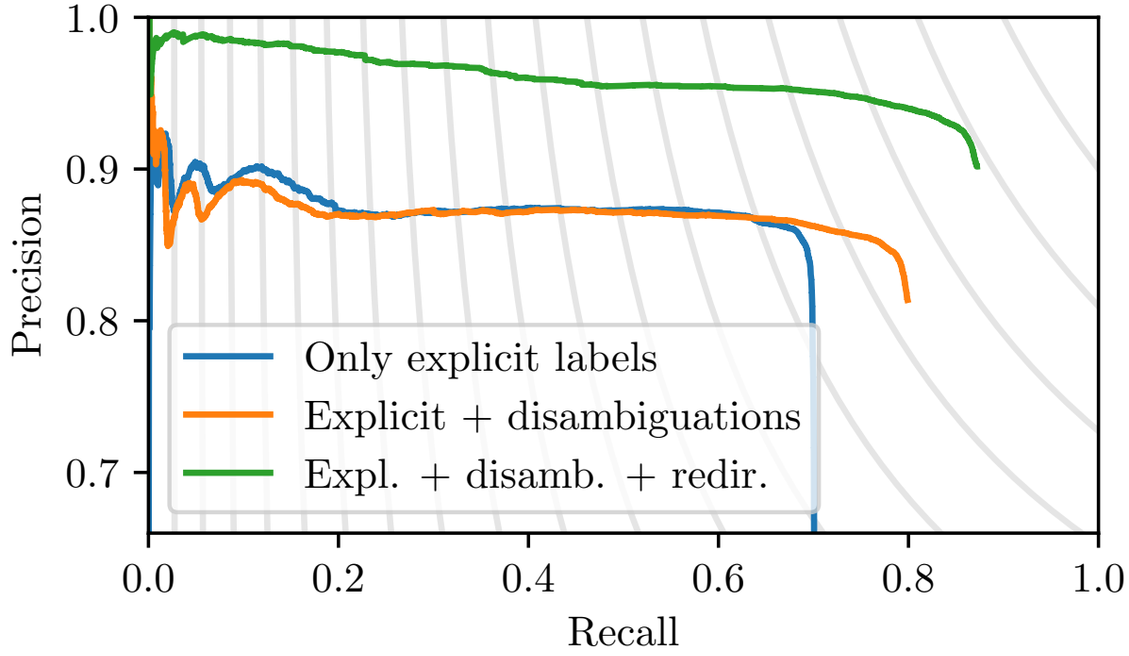
- **TAKCO**: Novelty-oriented table interpretation
  - Better disambiguation of **incomplete** entities
  - `github.com/karmaresearch/takco`
- Evaluation of **novel triples** provides new perspective
- Future work:
  - Use **statistics** from large corpus for generalisation
  - Extract **n-ary** relations

# THANK YOU!

# LIMITATIONS

| party | 05-02-08 | min | max |
|---|---|---|---|
| unity list | 34 | 17 | 22 |
| socialist party | 60 | 108 | 134 |
| social democrats | 258 | 245 | 255 |
| social liberal party | 92 | 57 | 70 |
| christian democrats | 17 | 6 | 12 |
| new alliance | | 38 | 72 |
| liberal party | 290 | 245 | 257 |
| conservative party | 103 | 84 | 101 |
| danish people's party | 133 | 122 | 134 |

# RESULTS: ENTITY LINKING – DIFFERENT LABEL INDEX

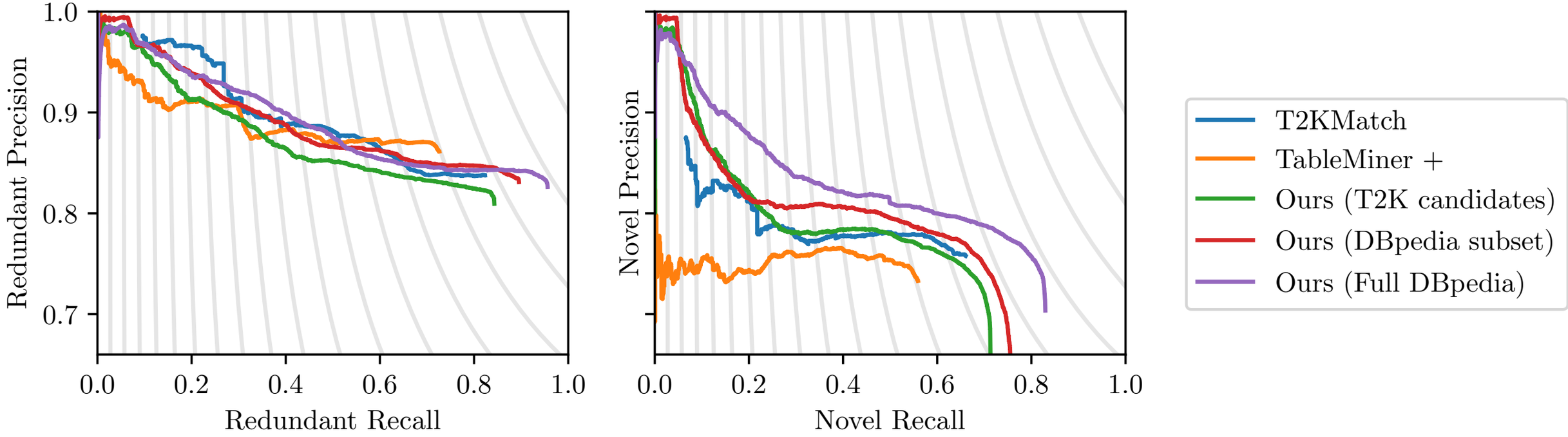



| System | Pr. | Re. | $F_1$ |
|---|---|---|---|
| Only explicit labels | .85 | .69 | .76 |
| Explicit + disambiguations | .84 | .79 | .81 |
| Expl. + disamb. + redir. | **.92** | **.86** | **.89** |

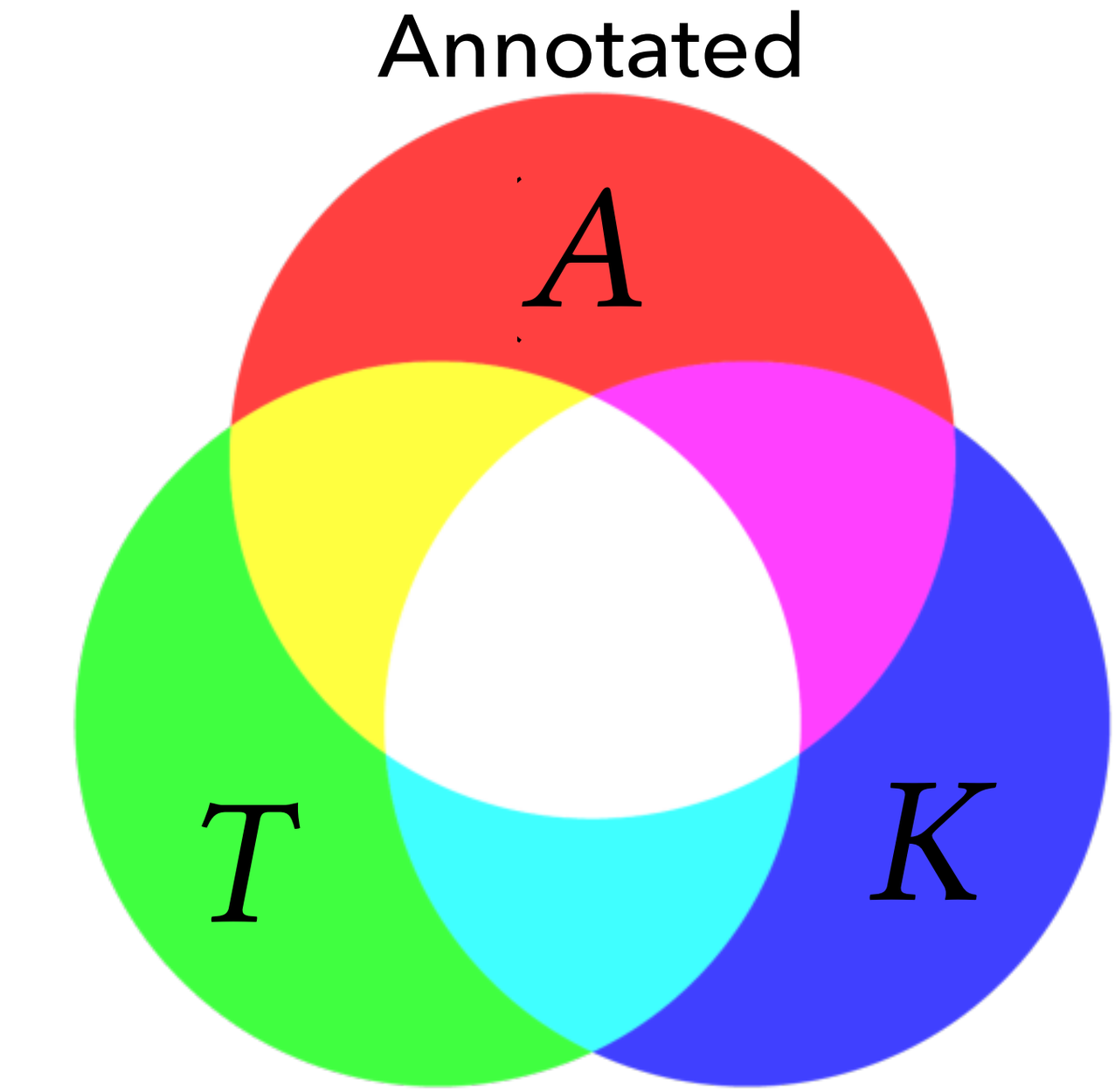
Label set is very important!

# RESULTS: NOVEL FACT EXTRACTION

| System | Redundant | | | Novel | | | $R^+$ | $R^-$ |
|---|---|---|---|---|---|---|---|---|
| | Pr. | Re. | $F_1$ | Pr. | Re. | $F_1$ | | |
| T2KMatch | .84 | .82 | .83 | **.76** | .66 | .71 | 0.55 | **0.44** |
| TableMiner + | **.86** | .73 | .79 | .73 | .56 | .63 | **0.57** | 0.39 |
| Ours (T2K candidates) | .81 | .84 | .83 | .61 | .71 | .66 | 0.55 | 0.44 |
| Ours (DBpedia subset) | .83 | .90 | .86 | .59 | .76 | .66 | 0.55 | 0.31 |
| Ours (Full DBpedia) | .83 | **.96** | **.89** | .70 | **.83** | **.76** | 0.55 | 0.25 |



# REDUNDANCY OF EXTRACTED FACTS




## Positive Redundancy

$$R_p(T, A) = \frac{|(A \cap T) \cap K|}{|A \cap T|}$$

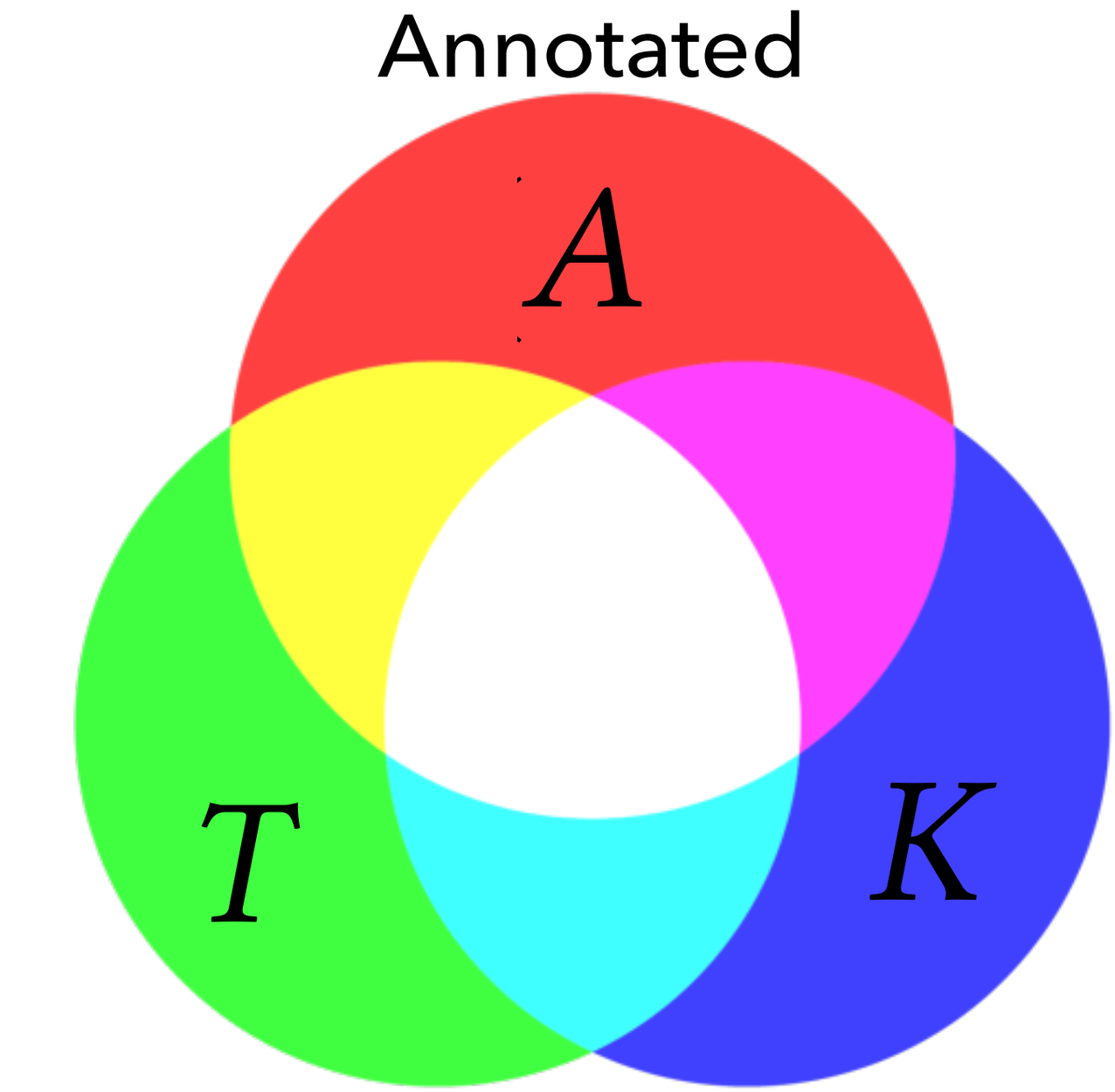
## Negative Redundancy

$$R_n(T, A) = \frac{|(A \setminus T) \cap K|}{|A \setminus T|}$$

## Hypothesis:

$$R_p(T, A) > R_n(T, A)$$

# RECALL OF EXTRACTED FACTS




## Novel Recall

$$Q_n(T, A) = \frac{|T \cap (A \setminus K)|}{|A \setminus K|}$$

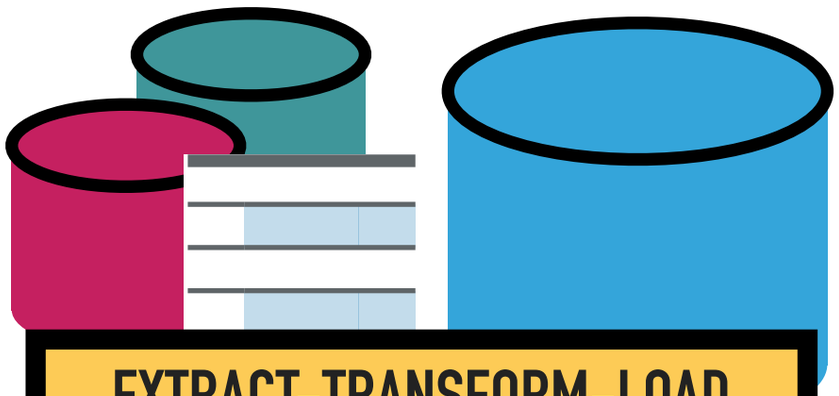
## Redundant Recall

$$Q_r(T, A) = \frac{|T \cap (A \cap K)|}{|A \cap K|}$$

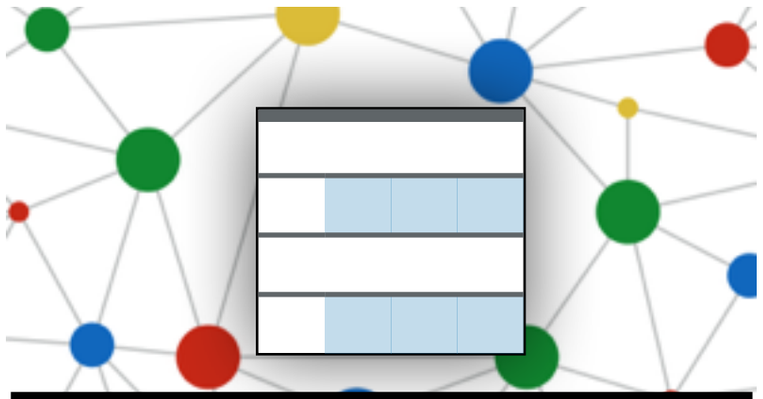
## Hypothesis:

$$Q_n(T, A) < Q_r(T, A)$$

# DATA INTEGRATION



EXTRACT-TRANSFORM-LOAD



WEB TABLE EXTRACTION

OPEN INFORMATION EXTRACTION

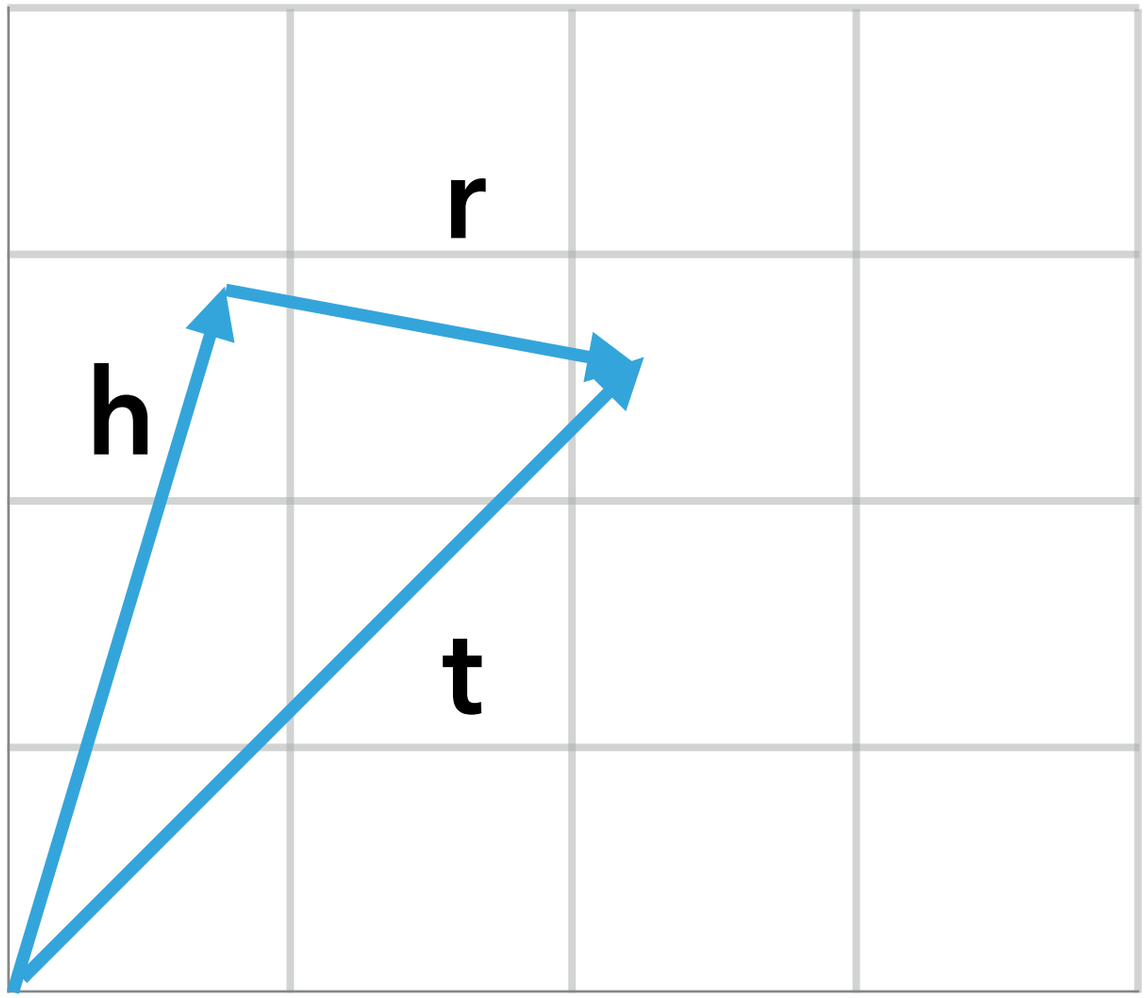
- Structured sources
- Closed domain
- Writing queries
- Enterprise solutions

- Semi-structured sources
- Large domain ontology
- KG matching
- Slot filling candidates

- Unstructured sources
- Open domain
- Machine Learning
- Approximate predictions

# METHOD: SLOT-FILLING

Entity Embeddings: TransE



# FEATURES FOR MAKING PREDICTIONS

- Labels
- Explicit facts
- Ontology
  - hierarchy of types
  - range and domain of relations
- Statistics
  - “soft” ontology: empirical observations
- External data

Model Knowns

Model Unknowns

# EVALUATION

- Manually annotated tables
  - … but different data sources,
  - … and different knowledge bases
  - … and different features
- Measure precision & recall of predictions
  - … but is this most useful for slot filling?