Knowledge Graphs

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Source:

Aidan Hogan et al. ( ) Knowledge Graphs

Contents

Hogan, A. et al. (2022). Knowledge Graphs. *ACM Computing Surveys*, *54*(4), 1–37. https://doi.org/10.1145/3447772

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Definitions

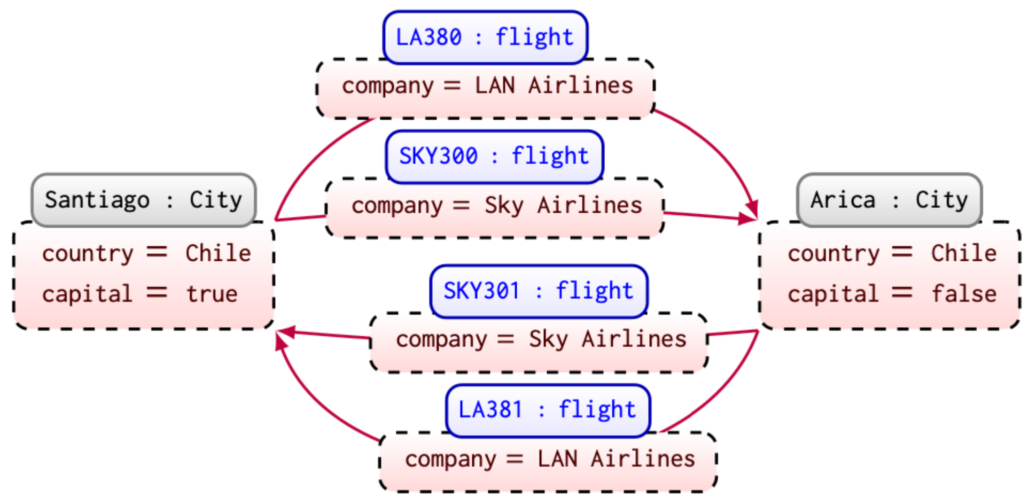
A knowledge graph as a graph of data intended to accumulate and convey knowledge of the real world, whose nodes represent entities of interest and whose edges represent relations between these entities.

- Knowledge may be composed of simple statements,
  - “Santiago is the capital of Chile”,
- or quantified statements
  - “all capitals are cities”.
- Simple statements can be accumulated as edges in the data graph.
- Quantified statements require a more expressive way to represent knowledge – such as ontologies or rules

Data models and query languages

- Directed edge-labelled graphs
  - e.g. RDF
- Graph datasets
  - e..g RDF datasets

- **Property graphs**
  - property-value pairs
    - on nodes
    - on edges
  - typed nodes and edges



- Translation without loss of information DELG ↔ PG

Schema

Semantic schema

- e.g. RDF Schema

Table 1. Definitions for sub-class, sub-property, domain and range features in semantic schemata

Feature	Definition	Condition	Example
SUBCLASS	c —subc. of→ d	x —type→ c implies x —type→ d	City —subc. of→ Place
SUBPROPERTY	p —subp. of→ q	x —p→ y implies x —q→ y	venue —subp. of→ location
DOMAIN	p —domain→ c	x —p→ y implies x —type→ c	venue —domain→ Event
RANGE	p —range→ c	x —p→ y implies y —type→ c	venue —range→ Venue

Schema

Validating schema

- to represent diverse, incomplete data at large-scale → OWA
- in some scenarios → guarantee that (part of) the data graph is "complete".

- UML class diagram
- SHACL shapes

Schema

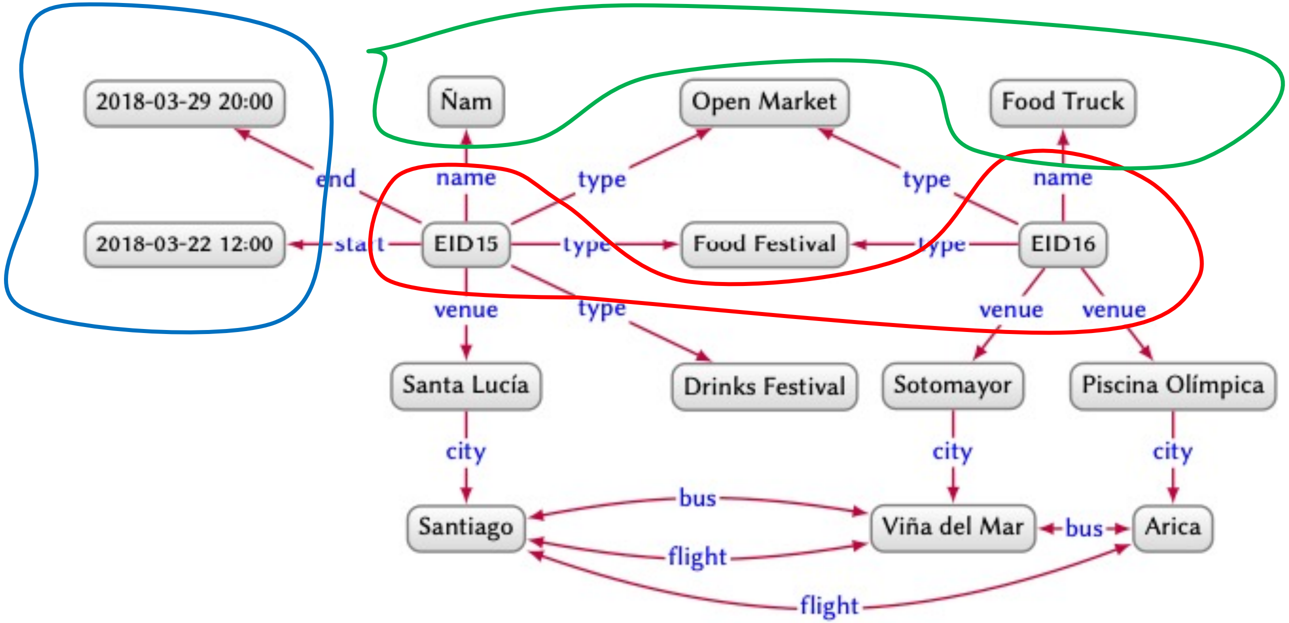
Emergent schema

Quotient graph

- partition node set into equivalence classes
  - based on their context

- replace node x by its class $[x]$, keep the edges

  - simulation $(s\ p\ o) \Rightarrow [s]\ p\ [o]$
  - bisimulation $(s\ p\ o) \Rightarrow [s]\ p\ [o]$ iff $\forall x \in [s] \exists z \in [o]: (x\ p\ z)$


2018-03-29 20:00
Ñam
Open Market
Food Truck
end
name
type
type
name
2018-03-22 12:00
start
EID15
type
Food Festival
type
EID16
venue
type
venue
venue
Santa Lucía
Drinks Festival
Sotomayor
Piscina Olímpica
city
city
city
Santiago
bus
Viña del Mar
bus
Arica
flight
flight

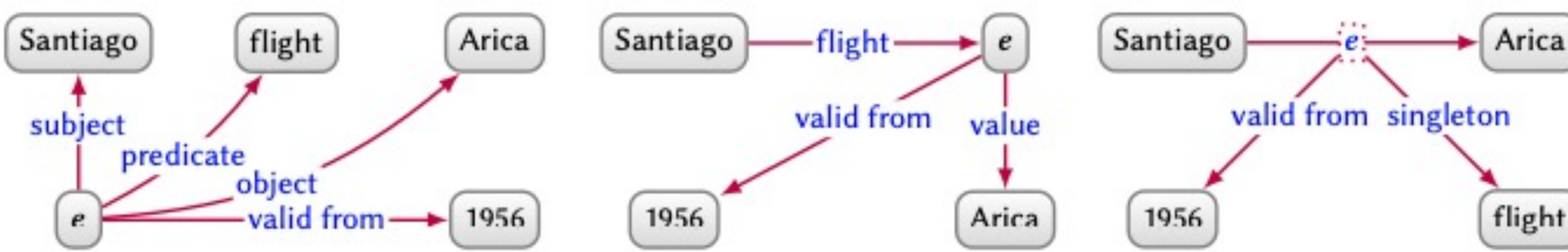
Context

- Facts considered true with respect to a context (scope of truth)
  - temporal
  - geographic
  - provenance

  Often left implicit, e.g. temporal context = now

- Representation
  - direct (with TIME, PROV, ... ontologies)
  - reification
  - higher arity
  - annotation

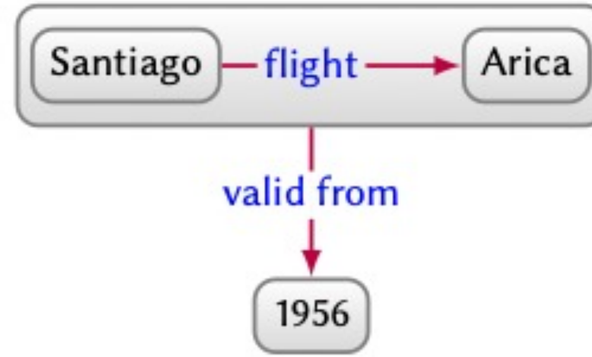
Reification techniques



(a) RDF Reification (b) *n*-ary Relations (c) Singleton properties

Higher-arity: RDF*

<<:Santiago :flight :Arica>> :valid_from 1956



Remark

<<:Taylor :spouse :Burton>> :from 1968 ; to 1978 .

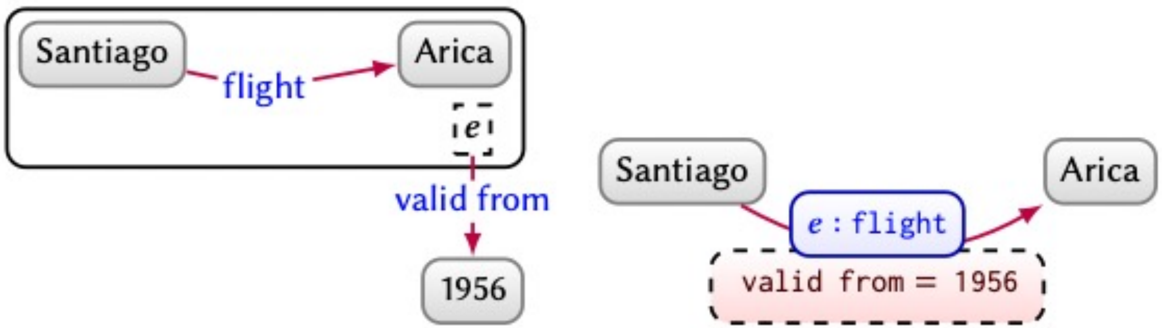
<<:Taylor :spouse :Burton>> :from 1981 ; to 1983 .

$\rightarrow$

<<:Taylor :spouse :Burton>> :from 1968 ; from 1981 ; to 1978 ; to 1983 .

.

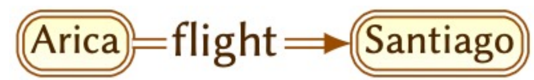
Higher-arity



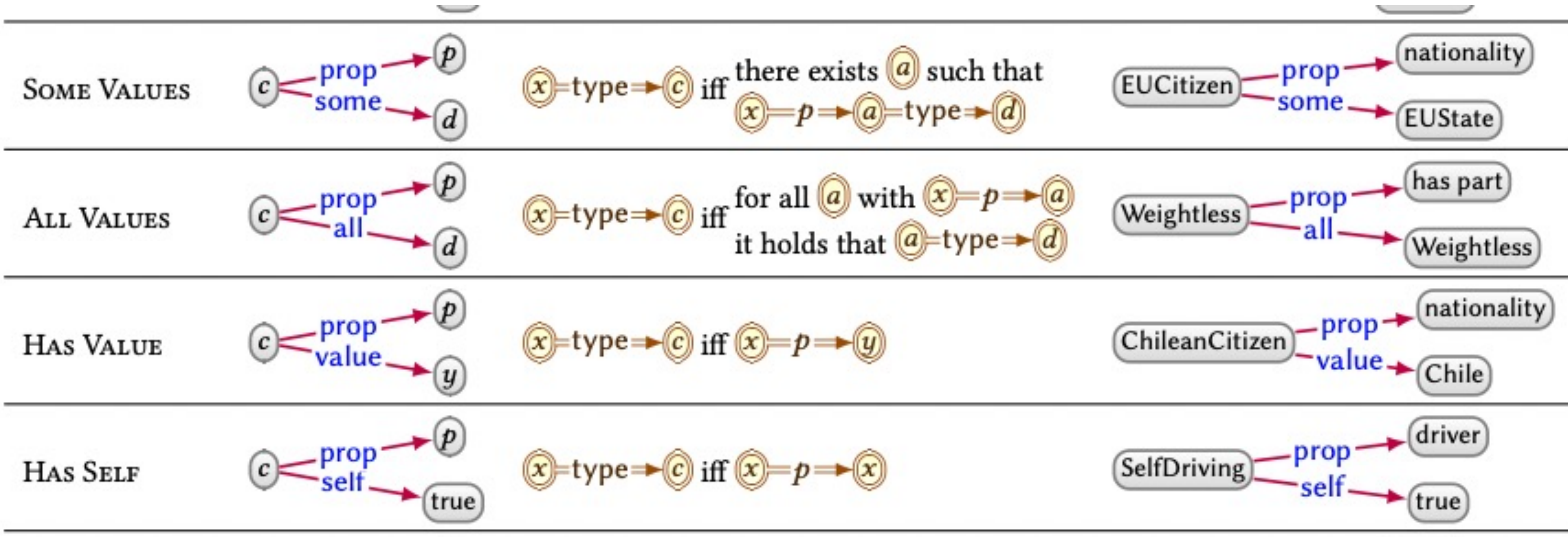
(a) Named graph (b) Property graph

DEDUCTIVE KNOWLEDGE

- Ontologies
  - Interpretation
    - Data graph (nodes, edges) $\rightarrow$ Domain graph (entities, relations)



Feature	Axiom	Condition	Example
Assertion	$x \xrightarrow{y} z$	$x \xrightarrow{y} z$	Chile $\xrightarrow{\text{capital}}$ Santiago
Negation	$n \xrightarrow{\text{type}}$ Neg $n \xrightarrow{\text{sub}} x$ $n \xrightarrow{\text{pre}} y$ $n \xrightarrow{\text{obj}} z$	not $x \xrightarrow{y} z$	$n \xrightarrow{\text{type}}$ Neg $n \xrightarrow{\text{sub}}$ Chile $n \xrightarrow{\text{pre}}$ capital $n \xrightarrow{\text{obj}}$ Arica
Same As	$x_1 \xrightarrow{\text{same as}} x_2$	$x_1 = x_2$	Región V $\xrightarrow{\text{same as}}$ Región de Valparaíso
Different From	$x_1 \xrightarrow{\text{diff. from}} x_2$	$x_1 \neq x_2$	Valparaíso $\xrightarrow{\text{diff. from}}$ Región de Valparaíso


Some Values
c prop p
some d
x type c iff there exists a such that
x p a type d
EUCitizen prop nationality
some EUState
All Values
c prop p
all d
x type c iff for all a with x p a
it holds that a type d
Weightless prop has part
all Weightless
Has Value
c prop p
value y
x type c iff x p y
ChileanCitizen prop nationality
value Chile
Has Self
c prop p
self true
x type c iff x p x
SelfDriving prop driver
self true

INDUCTIVE KNOWLEDGE

- Graph Analytics
- Knowledge Graph Embeddings
- Graph Neural Networks
- Symbolic Learning

Graph Analytics

- Discovering interesting patterns

- Techniques
  - Centrality computation
    - PageRank, ...
  - Community detection
  - Connectivity
  - Node similarity

Knowledge Graph Emdeddings

- Predicting new edges
- Identifying erroneous edges

- Machine learning techniques $\rightarrow$ Numeric input as vectors

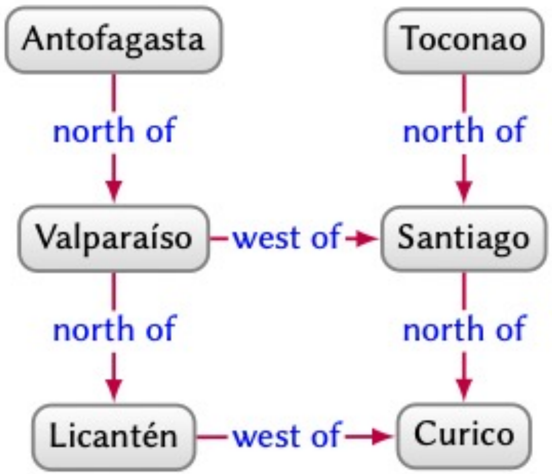
  - How to encode graphs as numeric vectors?

- Graph embedding
  - entity embedding: node $\rightarrow$ d-dimensional vector
  - relation embedding: edge $\rightarrow$ d-dimensional vector

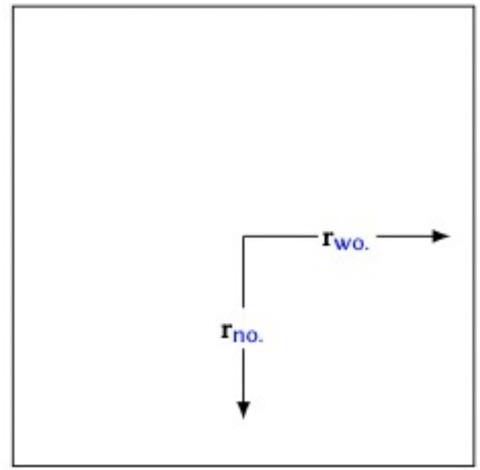
- (s p o) $\rightarrow$ (es rp eo)
  - define a plausibility function for the edge
  - goal: find embeddings that
    - maximize the plausibility of positive edges (in the graph)
    - minimize the plausibility of negative edges (not in the graph)
- Tasks
  - assign a confidence level to edges
  - complete edges with missing lables
  - a basis for similarity measures
    - duplicate detection
    - recommendation

Translational model

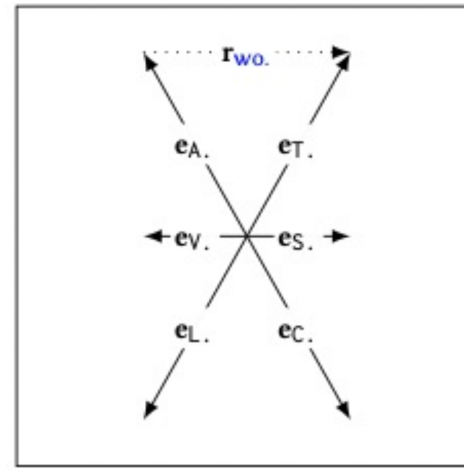
- TransE (edges as transformers)
  - from (s p o) learn es, rp, eo
  - goal:
    - on positive examples: es + rp close to eo
    - on negative example: es + rp far from eo



(a) Original graph



(b) Relation embeddings



(c) Entity embeddings

- Limitations
  - transforms everything
  - (s p o1) (s p o2) $\rightarrow$ tend to define eo1 = eo2
  - cyclical relations $\rightarrow$ 0

- Improvements
  - separate hyperplanes for different relations, ...

Language models for embeddings

- Leverage proven approaches for language embeddings

$$\text{word} \rightarrow \text{vector}$$

- RDF2Vec
  - build "sentences" by performing random walks in the graph
  - input to word2vec

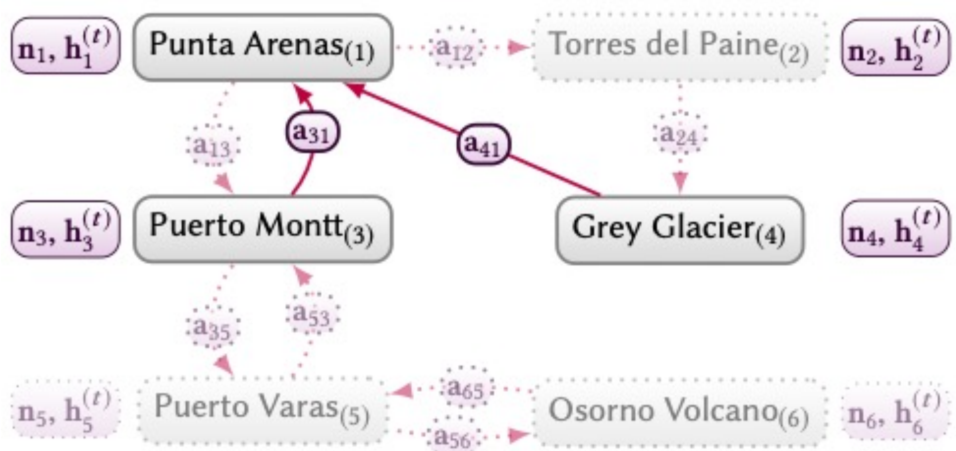
Graph Neural Networks

- Classical NN: homogeneous topology (layers)
- GNN: topology of the data graph

- node $\rightarrow$ feature vector (fixed)
- node $\rightarrow$ state vector
  - parametric transition function, input = neighbour nodes information
  - output function
- execution until a fixpoint is reached

- the function are implemented using neural networks
  - learn the parameters to best approximate the results for the supervised nodes

example



$$\mathbf{h}_x^{(t)} := \textstyle\sum_{y \in \mathrm{N}(x)} f_{\mathbf{w}}(\mathbf{n}_x, \mathbf{n}_y, \mathbf{a}_{yx}, \mathbf{h}_y^{(t-1)})$$
$$\mathbf{o}_x^{(t)} := g_{\mathbf{w}'}(\mathbf{h}_x^{(t)}, \mathbf{n}_x)$$

$$\mathbf{h}_1^{(t)} := f_{\mathbf{w}}(\mathbf{n}_1, \mathbf{n}_3, \mathbf{a}_{31}, \mathbf{h}_3^{(t-1)}) + f_{\mathbf{w}}(\mathbf{n}_1, \mathbf{n}_4, \mathbf{a}_{41}, \mathbf{h}_4^{(t-1)})$$
$$\mathbf{o}_1^{(t)} := g_{\mathbf{w}'}(\mathbf{h}_1^{(t)}, \mathbf{n}_1)$$

...

Symbolic Learning

- Learn rules or axioms
- Based on standard data mining techniques
  - support
  - confidence

OTHER TOPICS

1. Creation and enrichment of knowledge graphs from external sources.
2. Quality dimensions by which a knowledge graph can be assessed.
3. Techniques for knowledge graph refinement.
4. Principles and protocols for publishing knowledge graphs.