PARIS: Probabilistic Alignment of Relations, Instances, and Schema

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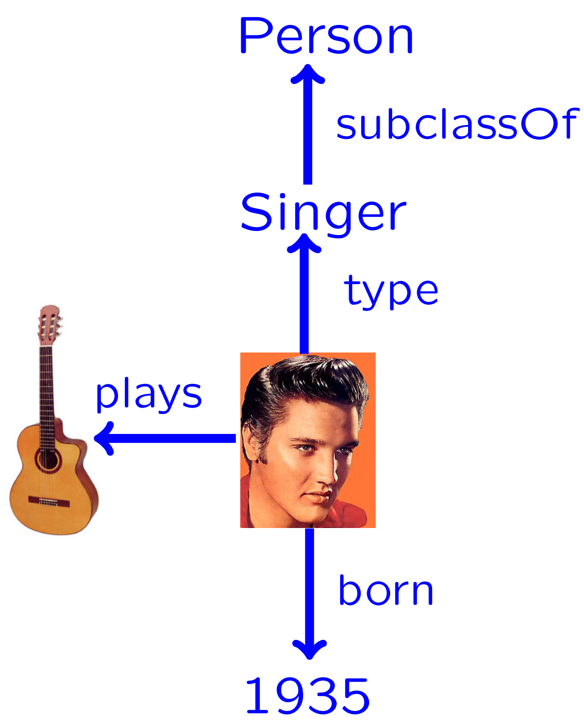
RDF Ontologies

An RDF ontology can be seen as a graph of entities



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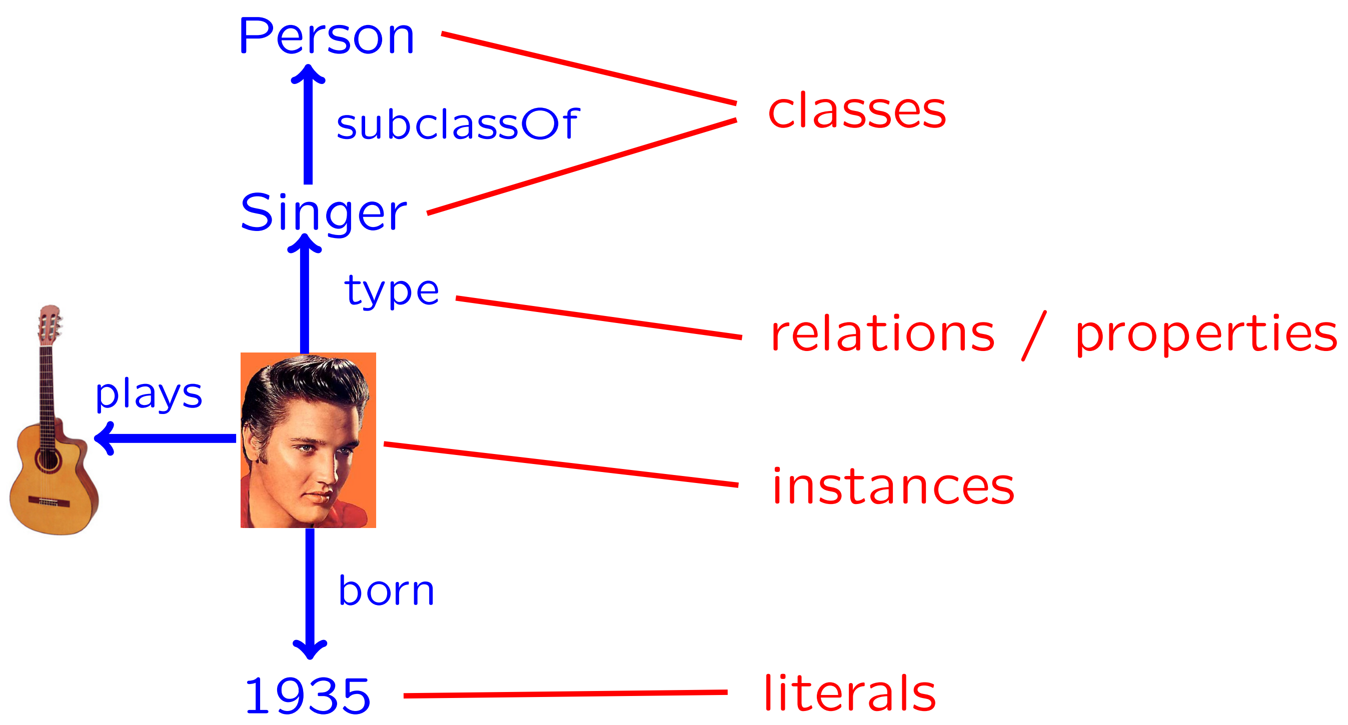

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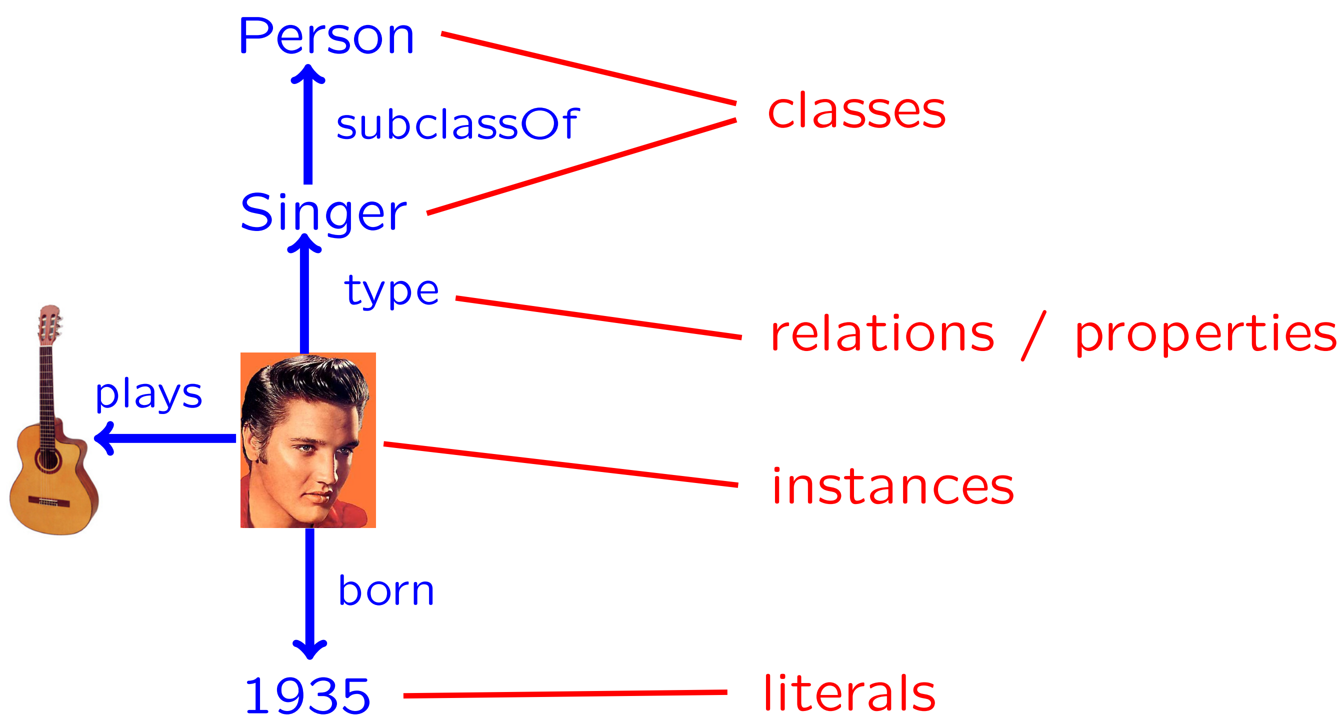
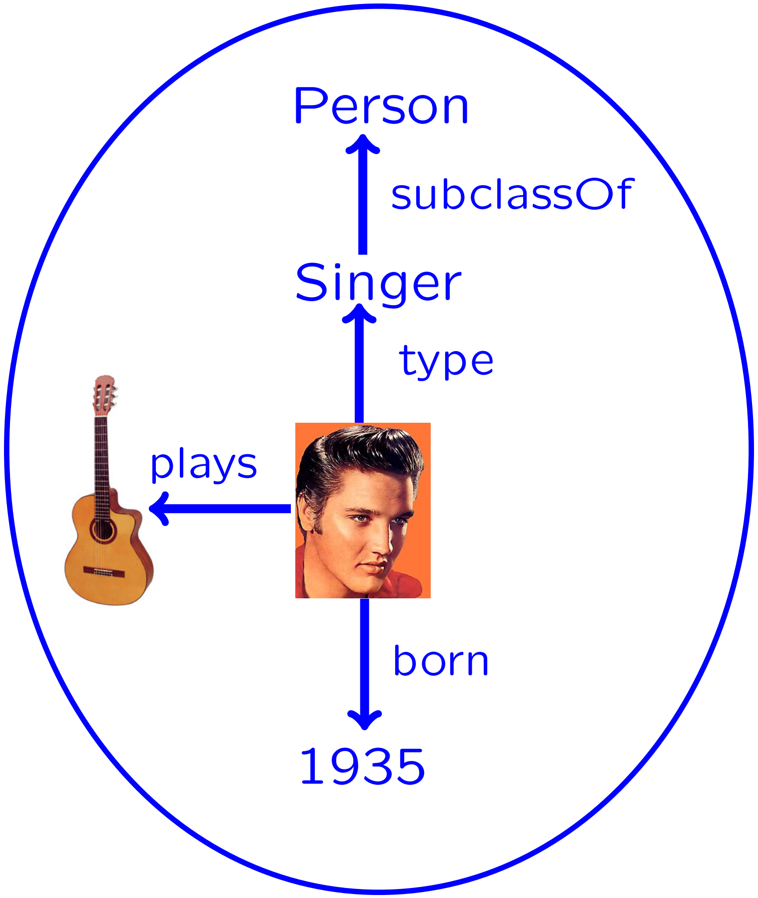


Ontologies serve all kinds of purposes:
intelligent search, QA, machine translation...

Existing Ontologies

There are literally hundreds of ontologies on the Web



Freebase

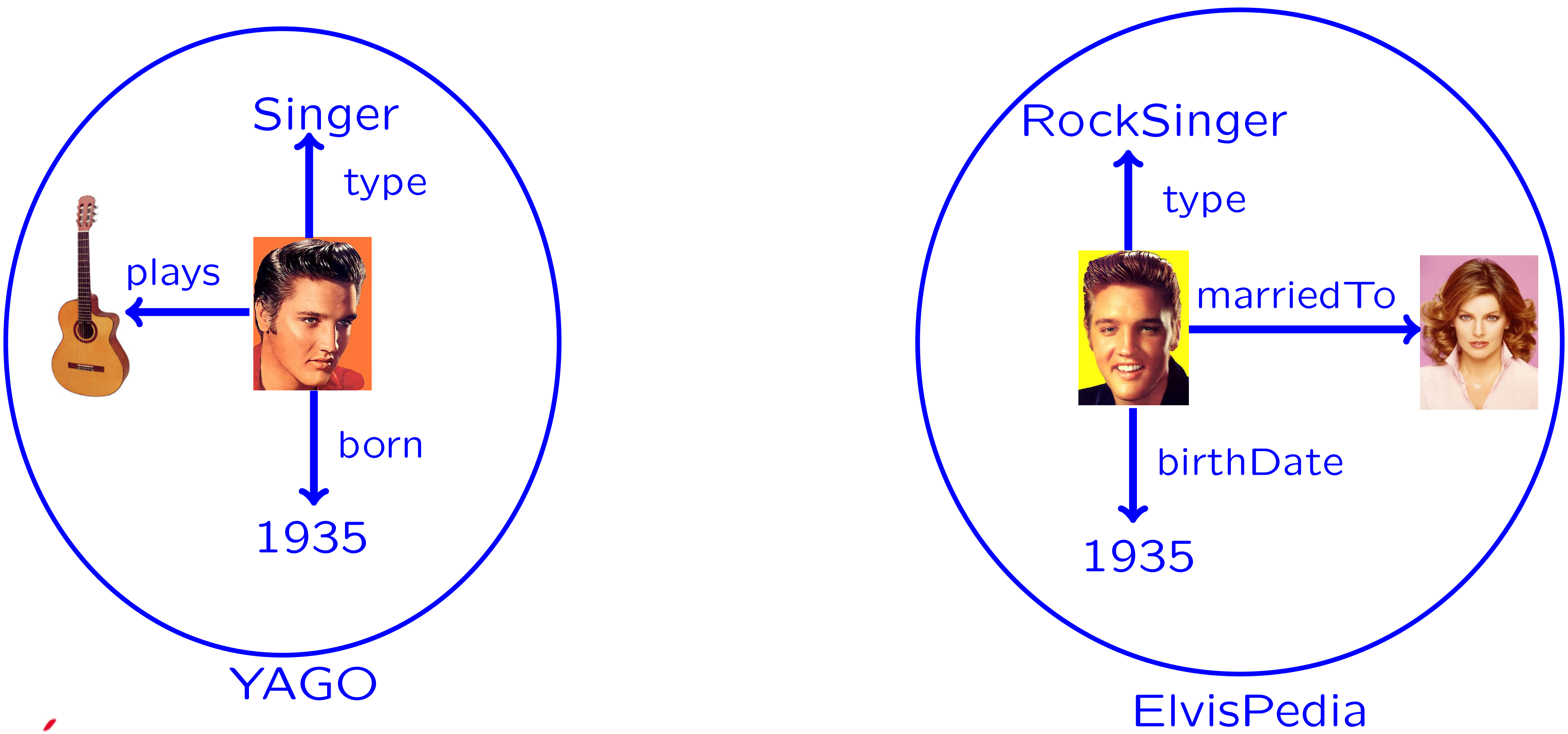
DBpedia

YAGO

UniProt

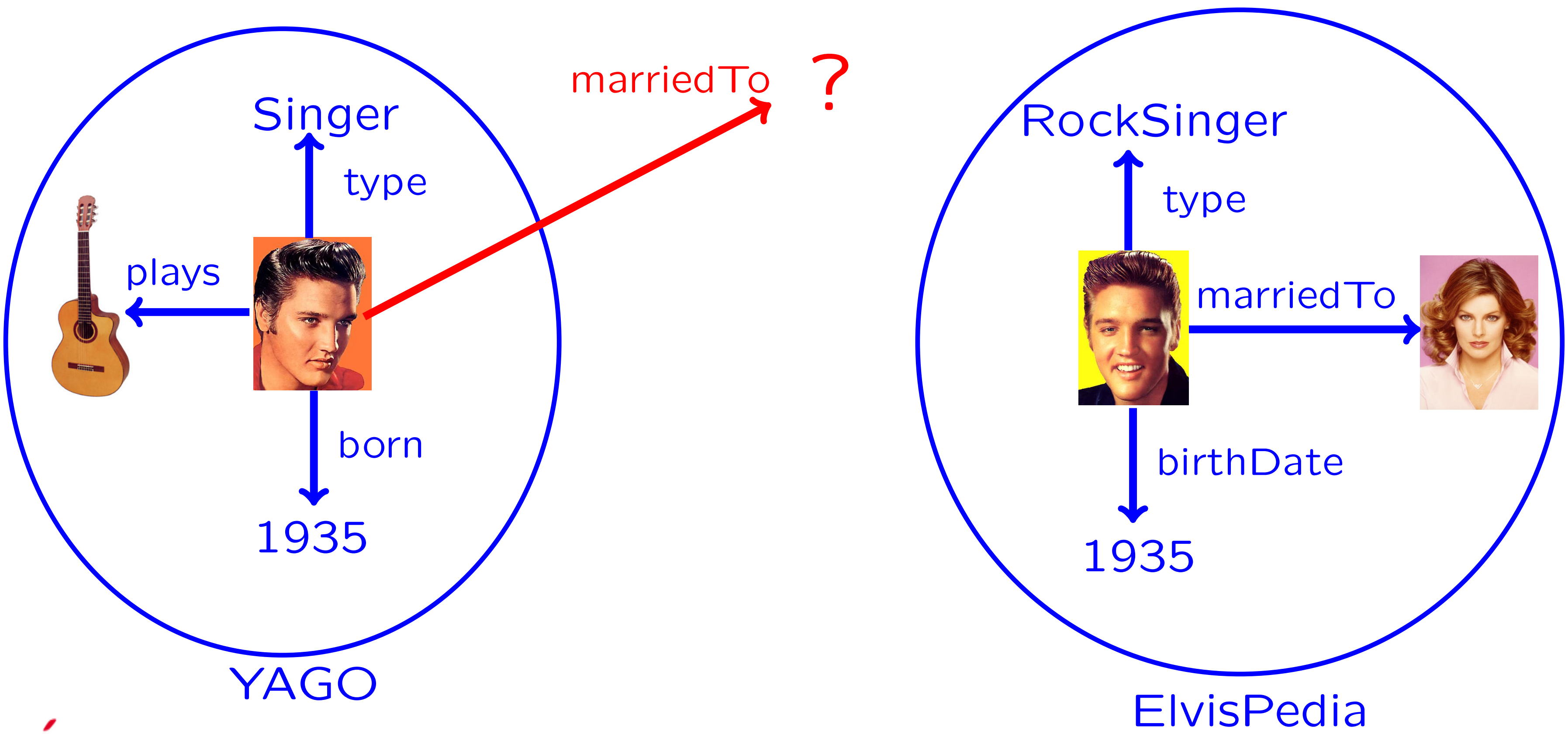
Overlapping Data

Many ontologies contain similar
or overlapping entities and facts



Problem: Elvis is lonely

Who is the spouse
of the guitar player?



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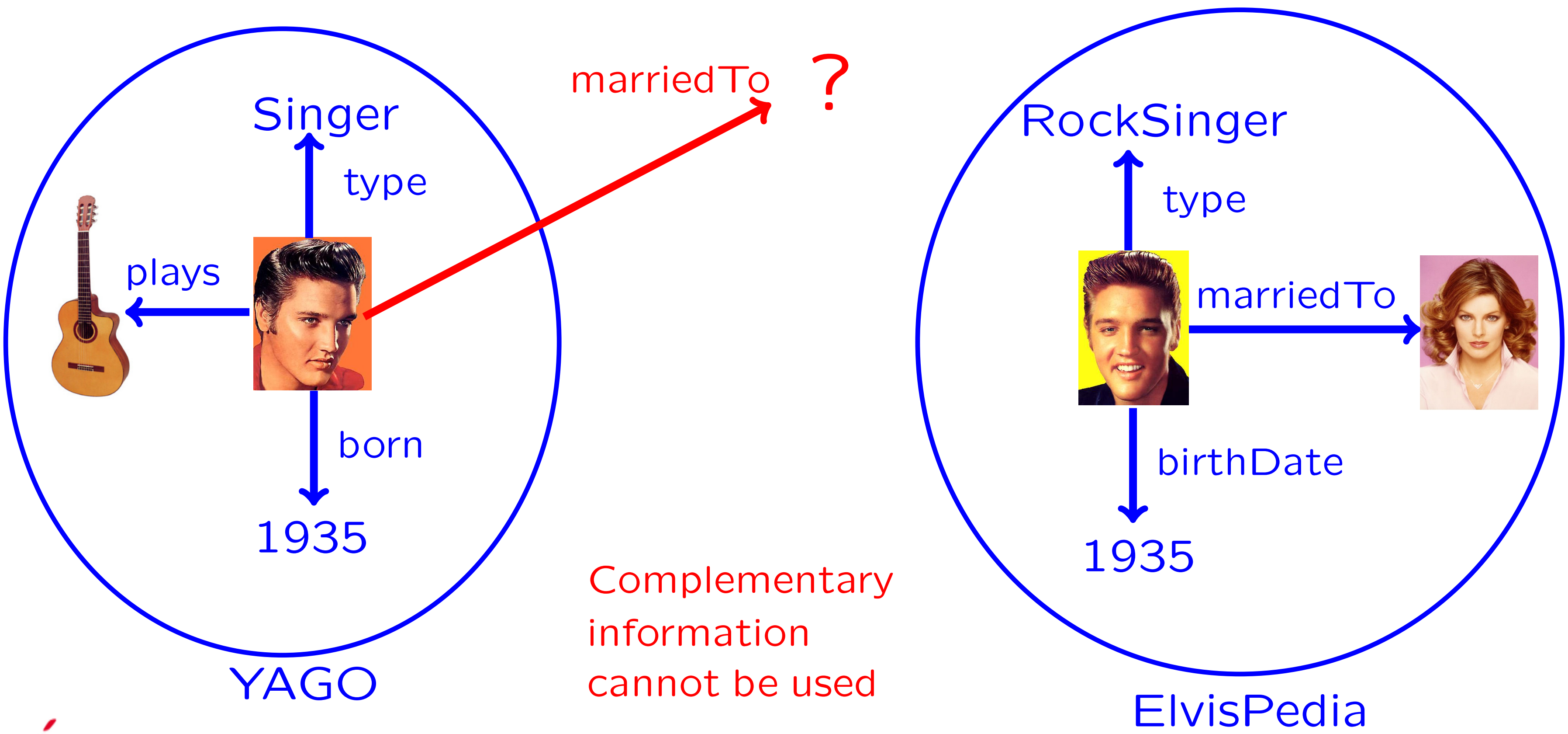
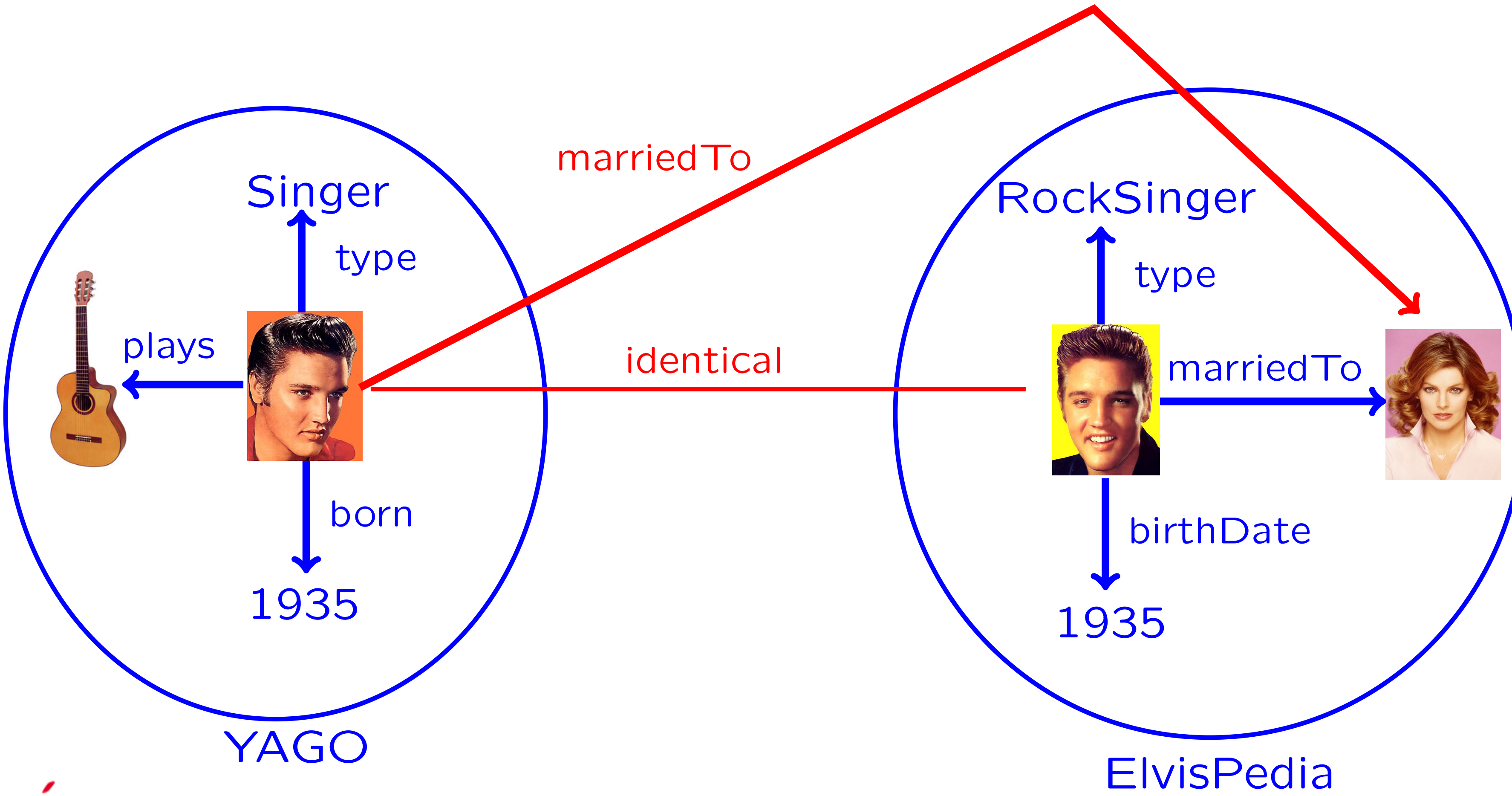
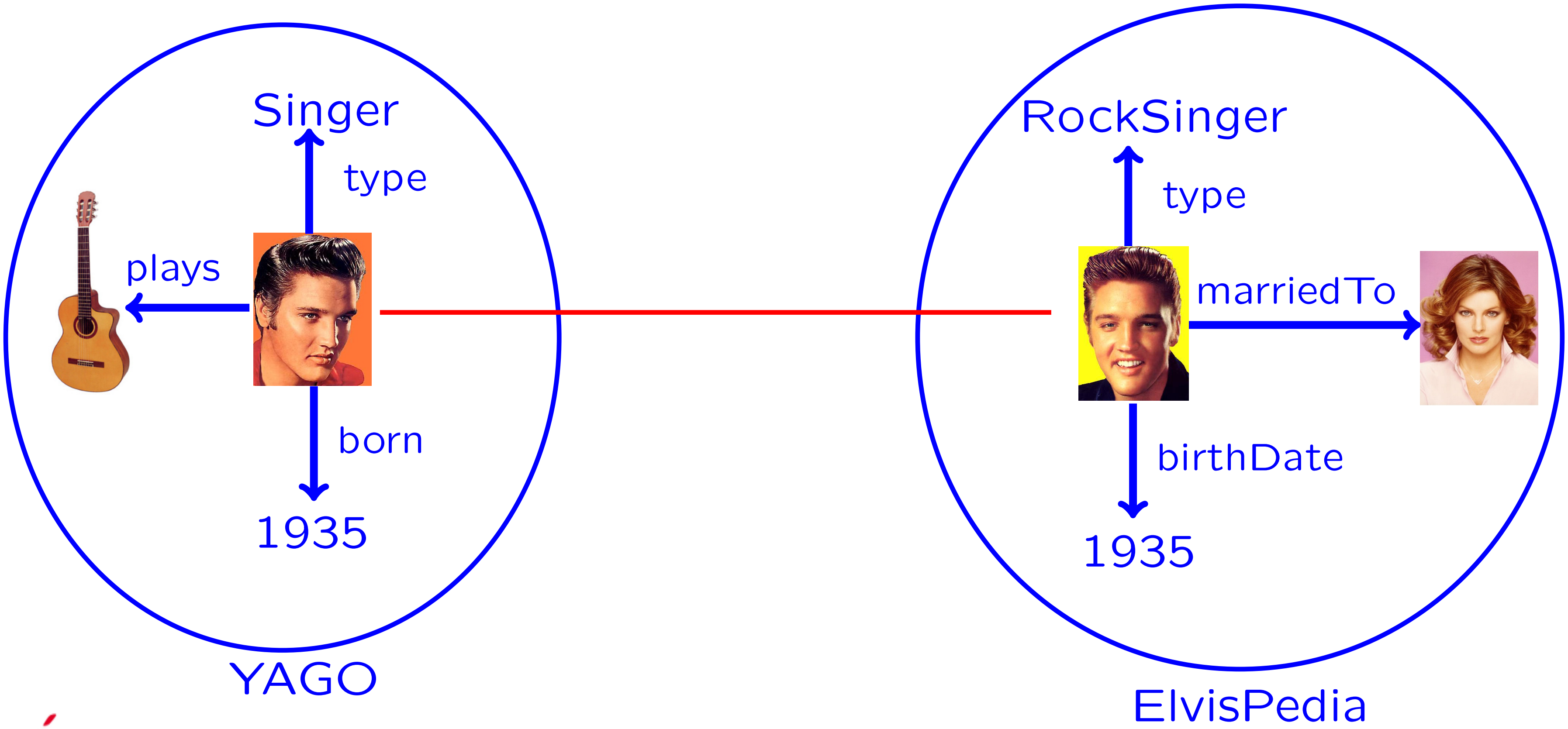


Solution: Unify Entities



Goal: Merging Ontologies

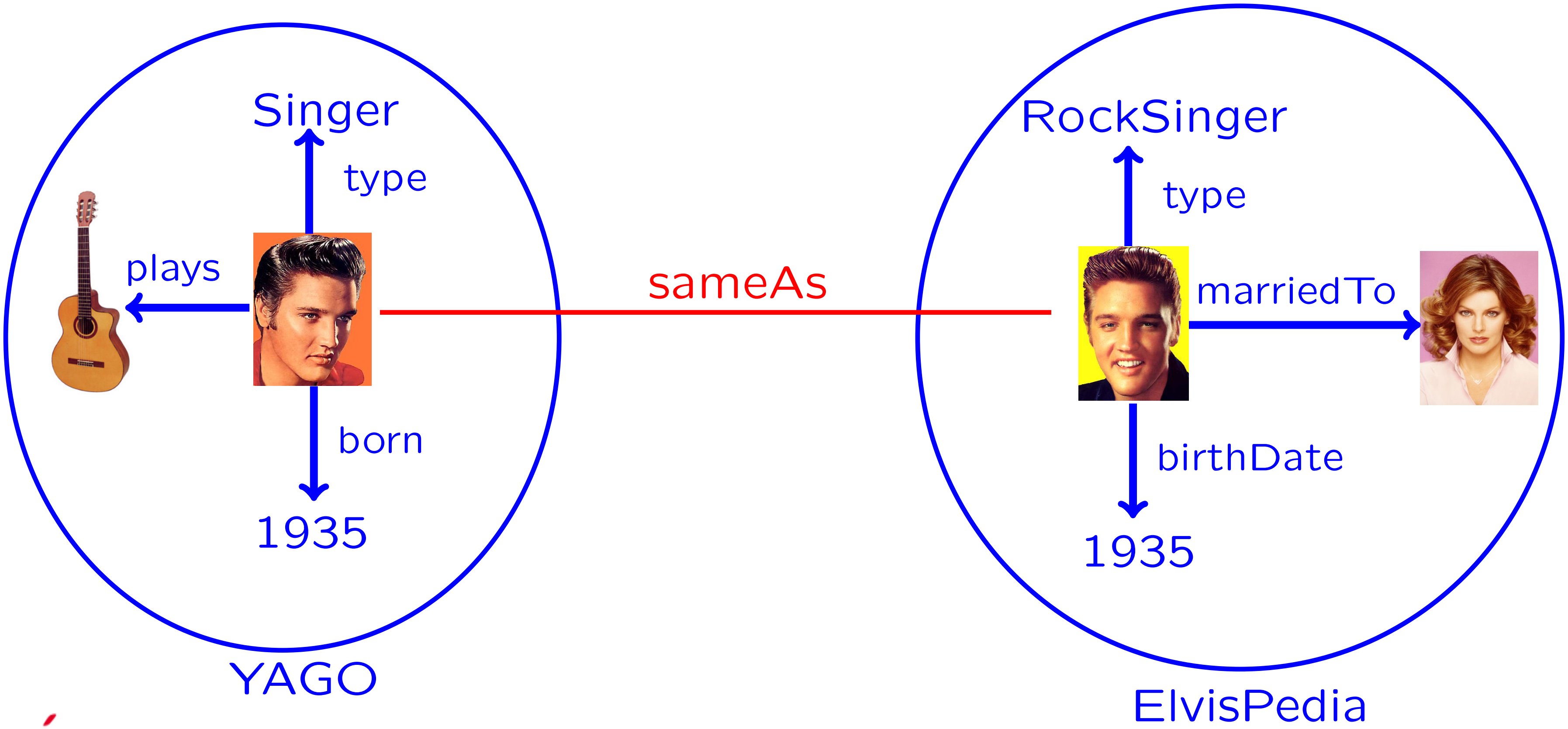
To merge two ontologies, we have to identify



Goal: Merging Ontologies

To merge two ontologies, we have to identify

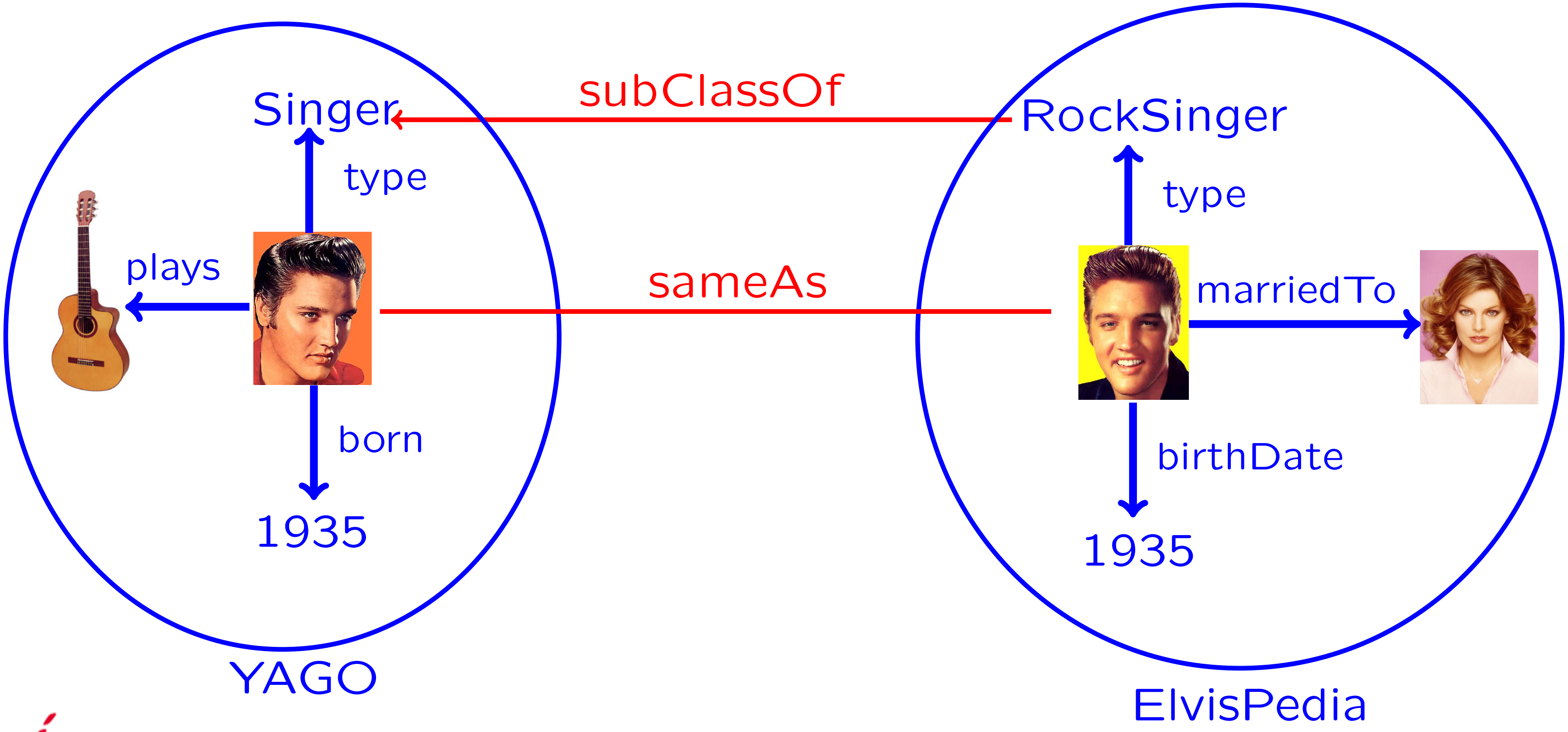
- equivalent instances



Goal: Merging Ontologies

To merge two ontologies, we have to identify

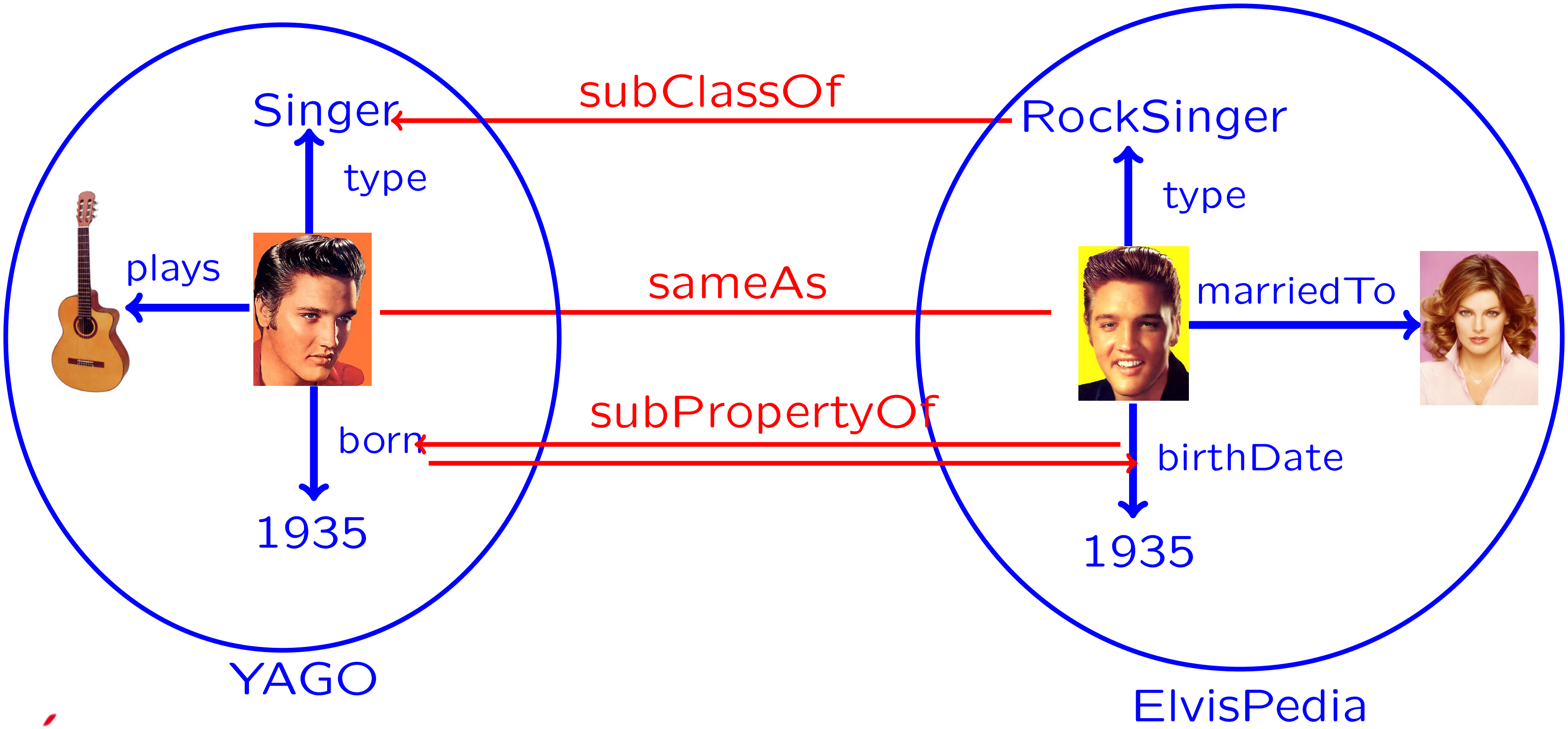
- equivalent instances
- equivalent or subsuming classes



Goal: Merging Ontologies

To merge two ontologies, we have to identify

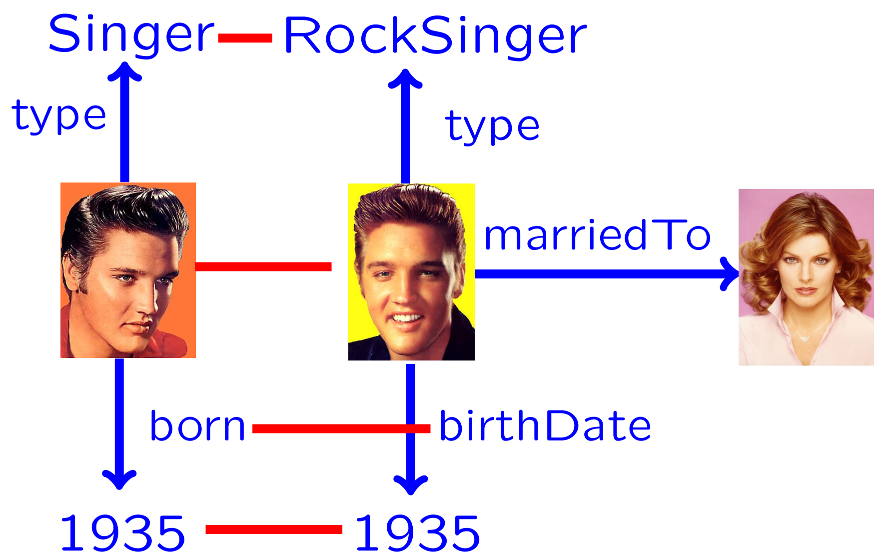
- equivalent instances
- equivalent or subsuming classes
- equivalent or subsuming relations



Previous work

Previous work

- uses hard logical constraints, which may be inadequate
- requires parameter tuning
- has not been tried on large ontologies

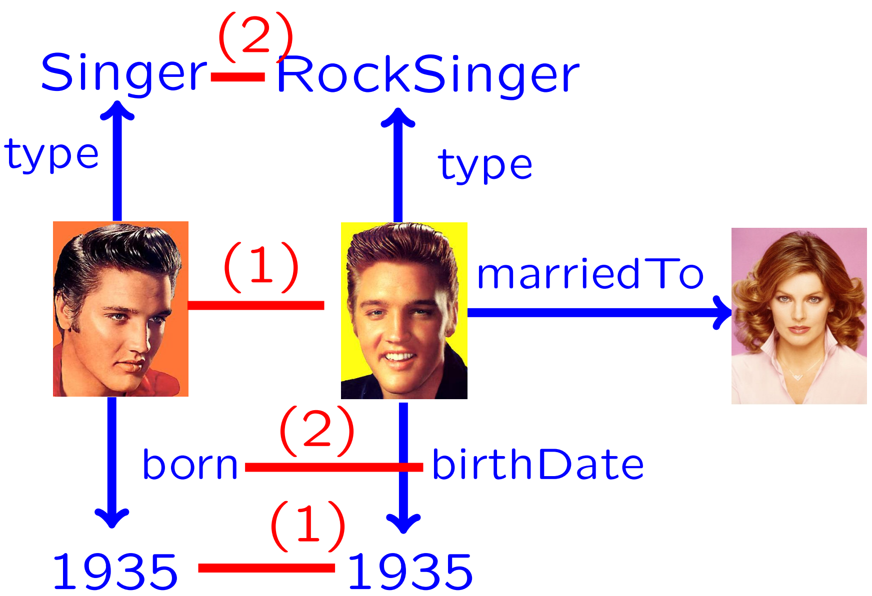


[Gracia 2009, Jean-Mary 2009, Isaac 2007, Aumueller 2005, Wang 2008, Noessner 2010, Sais 2007/2009, Arasu 2009, Volz 2009, Bhattacharya 2007, Hogan 2007/2010, Hu 2011, Li 2009, Udrea 2007, and more]

Previous work

Previous work
- uses hard logical constraints, which may be inadequate
- requires parameter tuning
- has not been tried on large ontologies

- has mostly focused on
  (1) instance matching or
  (2) schema alignment,
  ... but not both



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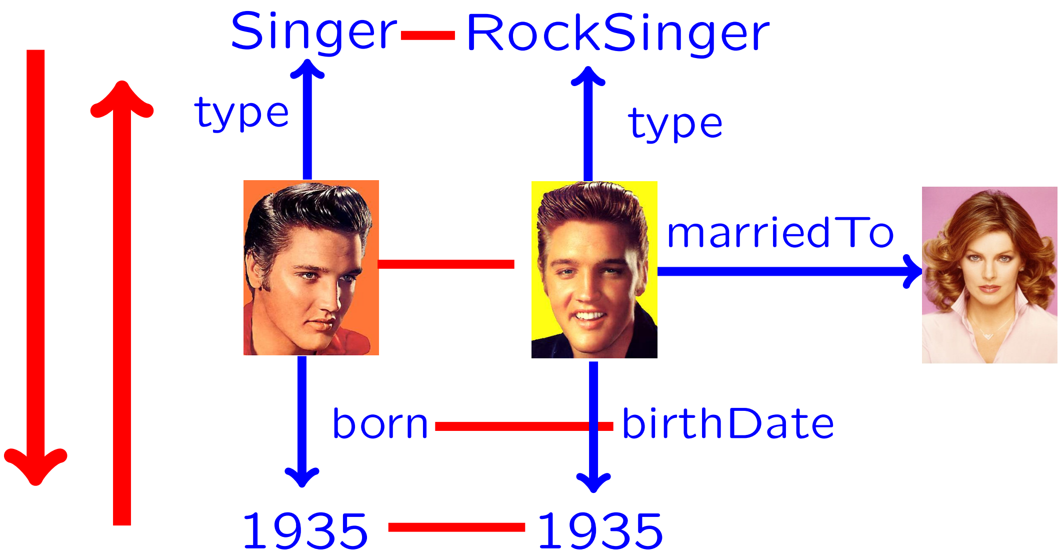
PARIS: Aligning Everything At Once

There is a synergy between equality of instances, properties and classes!

=> Compute all together!
PARIS



Probabilistic Model

We chose a probabilistic model

$Pr(c_1 \subseteq c_2) =$

the probability that c_1
is a sub-class of c_2

$Pr(x \equiv y) =$

the probability that x=y

$Pr(p_1 \subseteq p_2) =$

the probability that p_1
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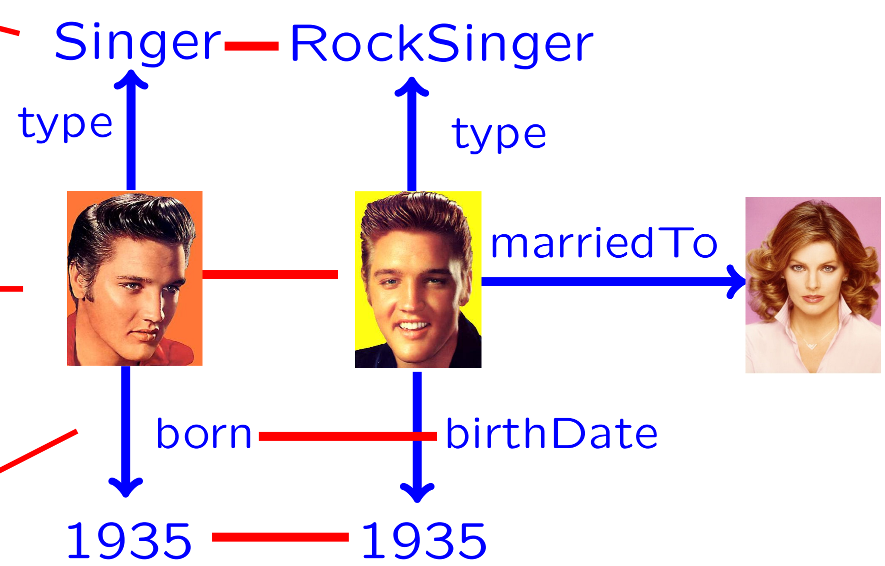
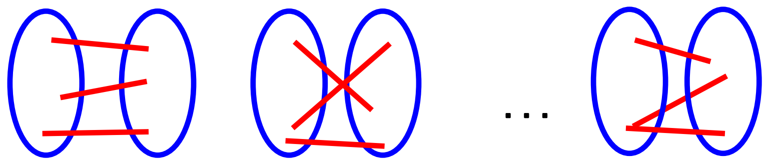


Probabilistic Model

Worlds:

w_1 w_2 ... w_n



All possible alignments between the ontologies

Probabilistic Model

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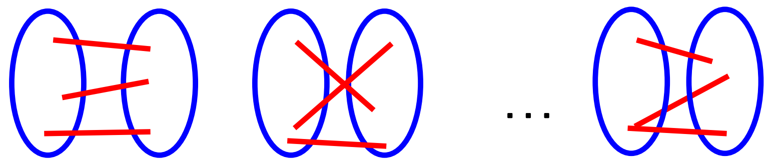


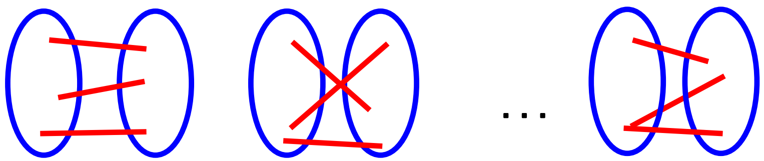
All possible alignments between the ontologies

Probabilities: $Pr(w_1)$ $Pr(w_2)$ ... $Pr(w_n)$

$\sum_i Pr(w_i) = 1$

Probabilistic Model

Worlds: w_1 w_2 $\ldots$ w_n



All possible alignments between the ontologies

Probabilities: $Pr(w_1)$ $Pr(w_2)$ $\ldots$ $Pr(w_n)$

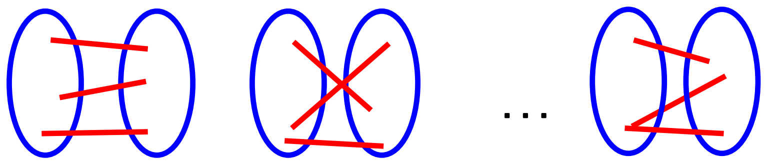
$\sum_i Pr(w_i) = 1$

Events: $e^1_{42} \equiv e^2_{42}$

We care here mainly about equality and subsumption events.
Each event can be true or false in a particular world.

Probabilistic Model

Worlds: w_1 w_2 $\ldots$ w_n



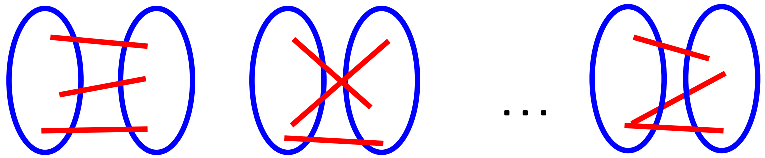
Probabilities: $Pr(w_1)$ $Pr(w_2)$ $\ldots$ $Pr(w_n)$

Marginals: $Pr(e^1_{42} \equiv e^2_{42}\ ) = Pr(w_1) + Pr(w_9)$

The marginal probability of an event
is given by the sum of the probabilities
of the worlds where the event holds.

Probabilistic Model

Worlds: w_1 w_2 $\ldots$ w_n



We do not care about these values.

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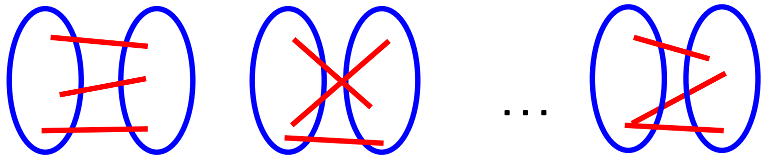

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We only care about these marginals!

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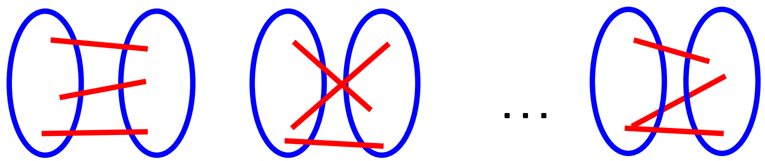

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Marginals: $Pr(e^1_{42} \equiv e^2_{42}\ \ ) = Pr(w_1) + Pr(w_9)$

We only care about these marginals!

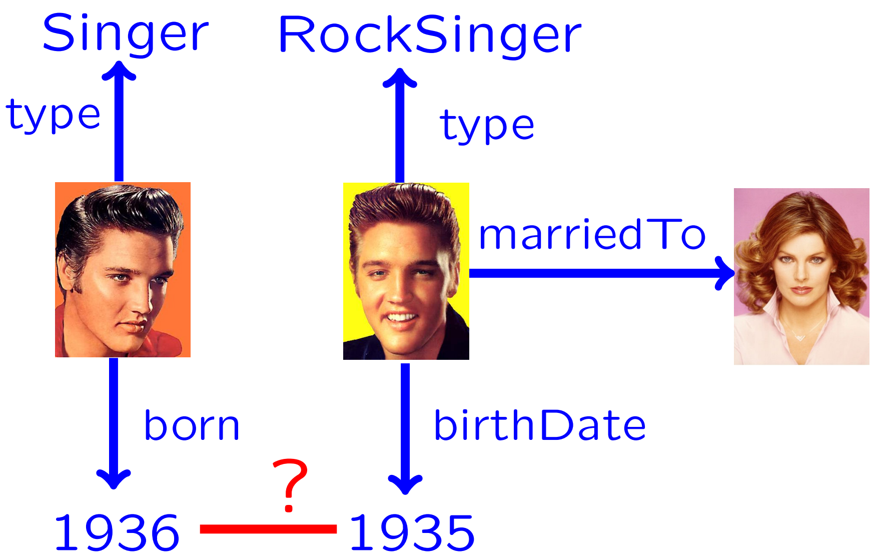
We are interested in marginals that fulfill certain properties.

For any set of marginals, there exists a probability distribution.

(it is the product measure)

Literals

The probability that two literals are equal shall reflect the likelihood that the two literals are intended to refer to the same thing.



Literals

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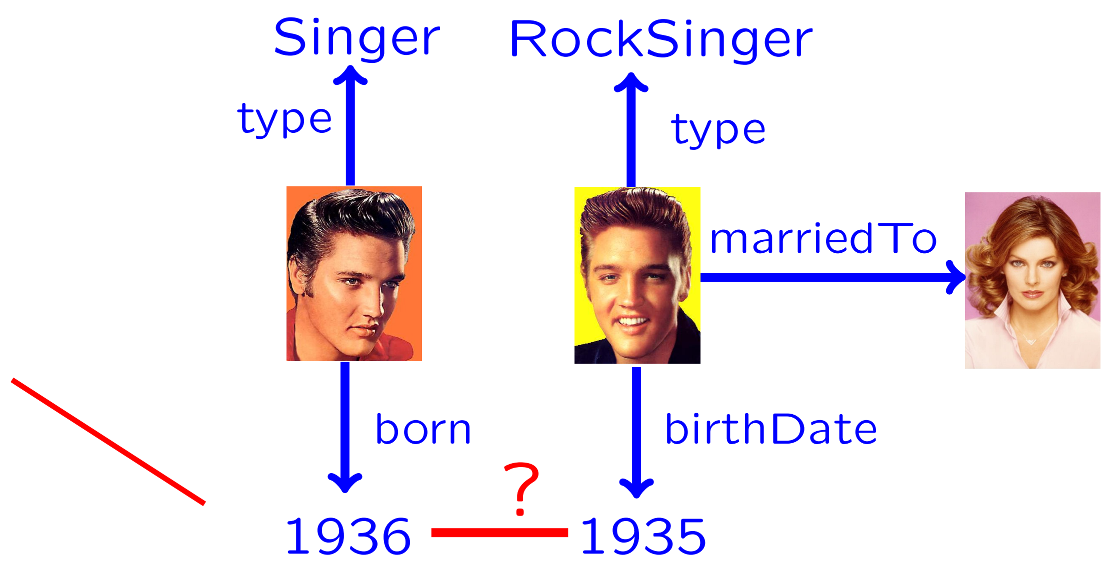
$$Pr(x \equiv y) =$$

- for strings:
  string distance
- for numbers:
  numeric distance
- for other literals:
  domain-specific



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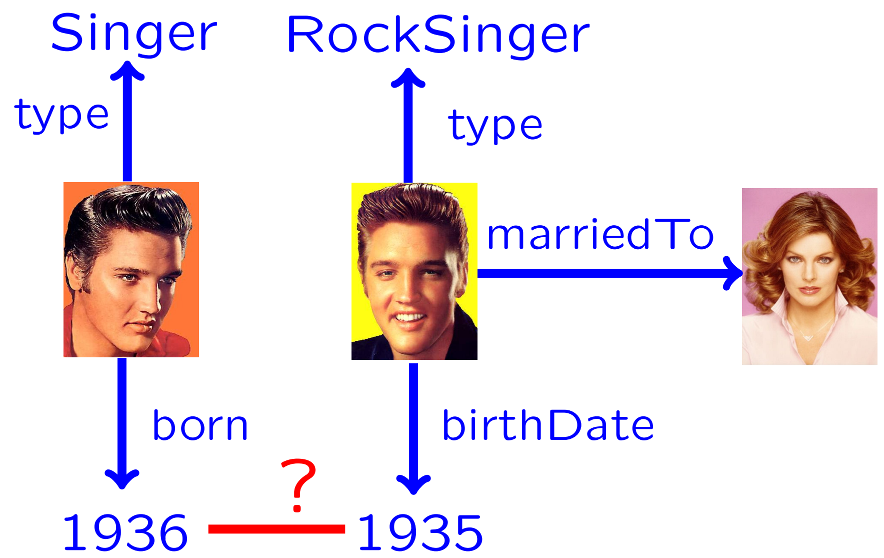
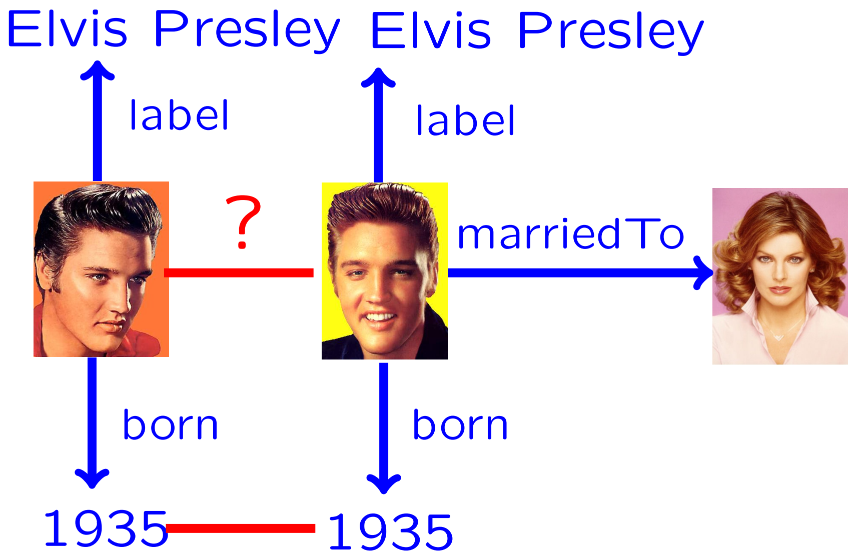


We chose a particularly simple equality:

$$Pr(x \equiv y) := (x = y)?1 : 0$$

Equality of Instances

For instances, relations give a hint:



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Not many people are
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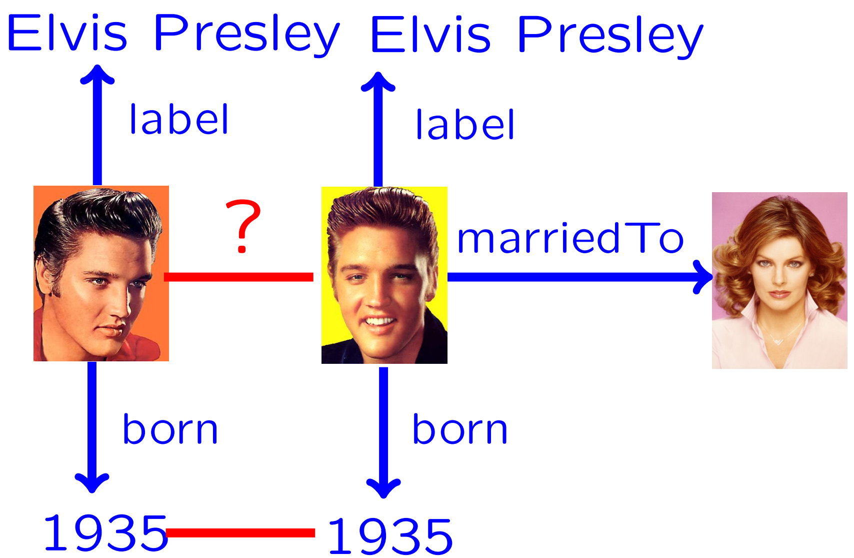

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Many people are born
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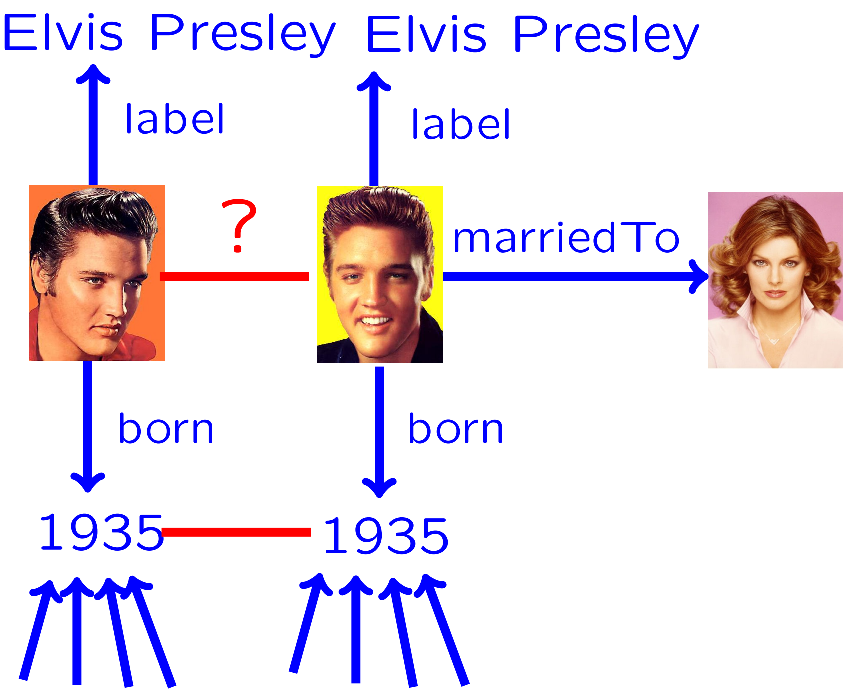

Local Inverse Functionality

The local inverse functionality of a relation with an argument is one over the number of incoming links:

$$ifun(r, y) := \frac{1}{|\{x : r(x,y)\}|}$$

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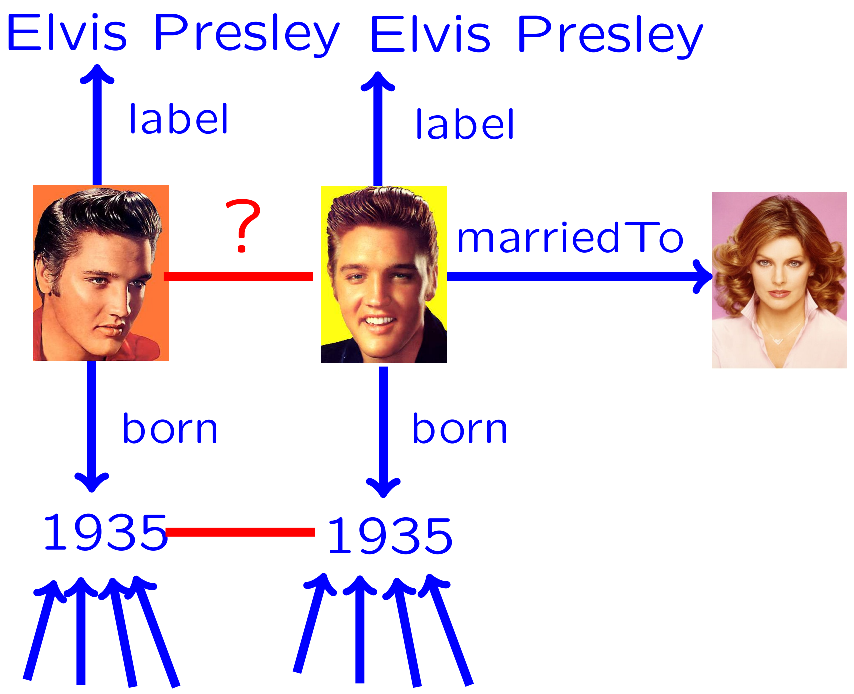

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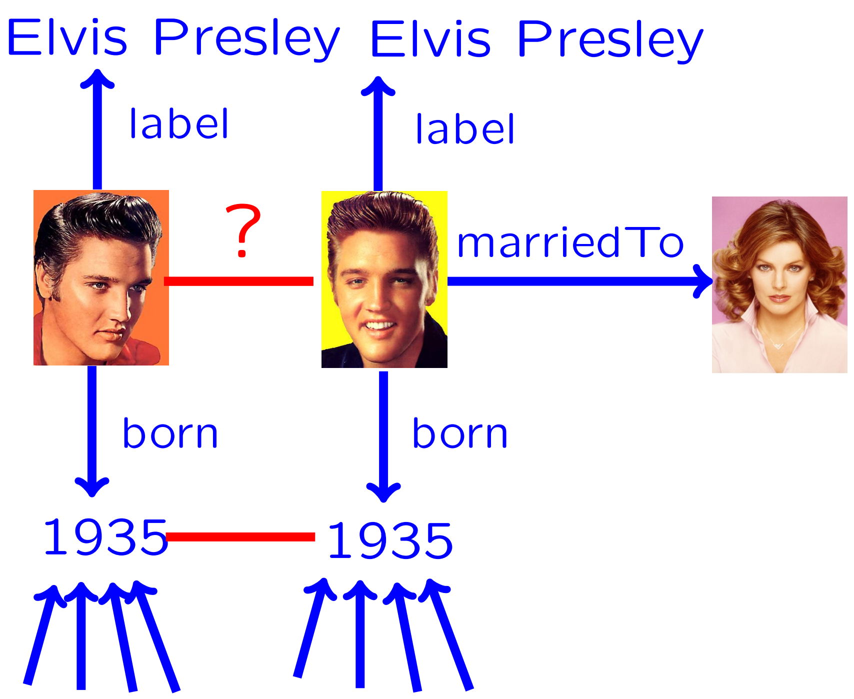
$$ifun(label, Elvis) = 1$$



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Only one person
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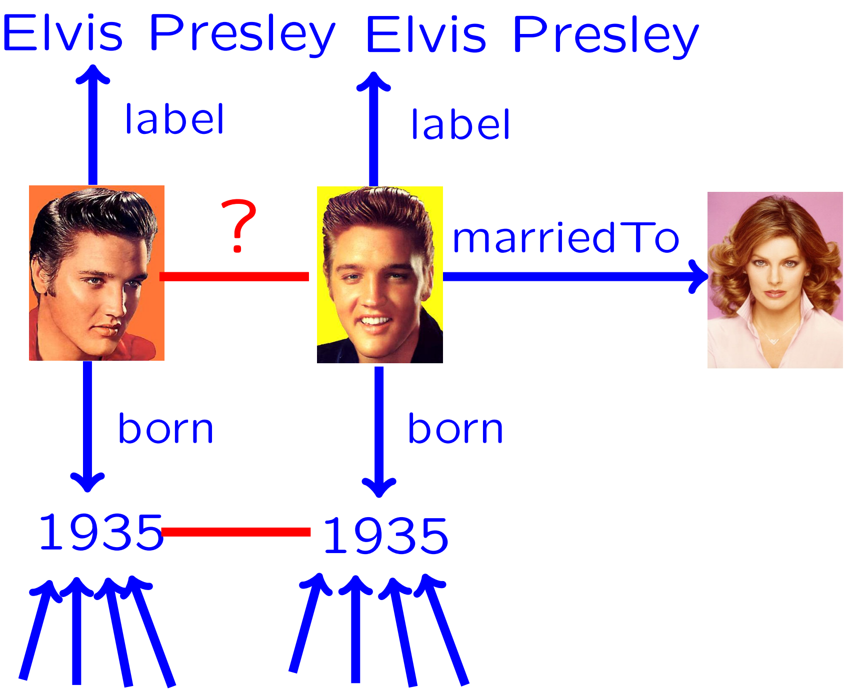
$$ifun(label, Elvis) = 1$$

10 people are born
in 1935

$$ifun(born, 1935) = 0.1$$



Probability of Inverse Functionalit

We define the probability of a relation being inverse functional as the harmonic mean of the local inverse functionalities:

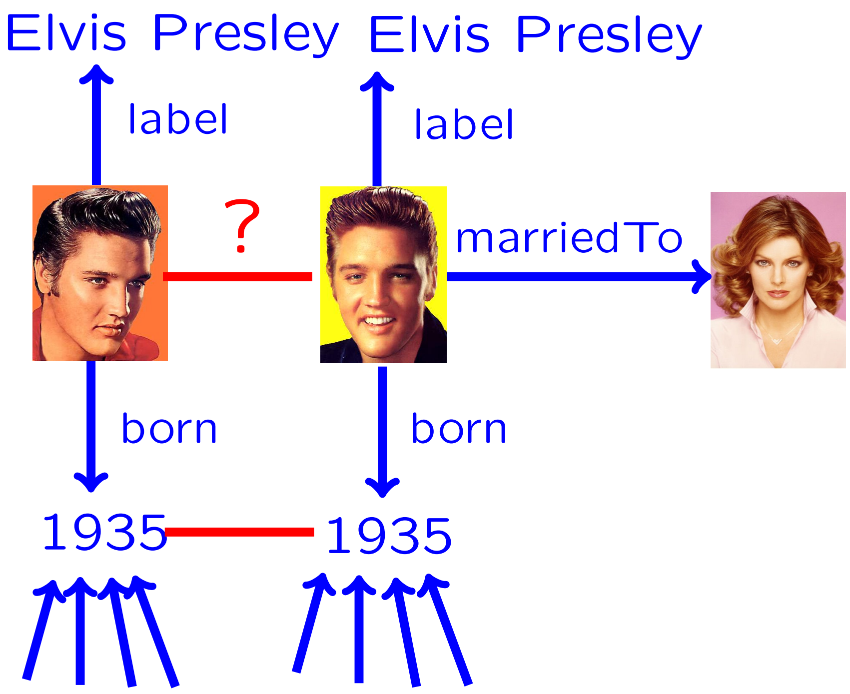
$$Pr(ifun(r)) := HM_y ifun(r, y)$$

Few people share the same name

$$Pr(ifun(label)) = 0.8$$

Many people share their year of birth

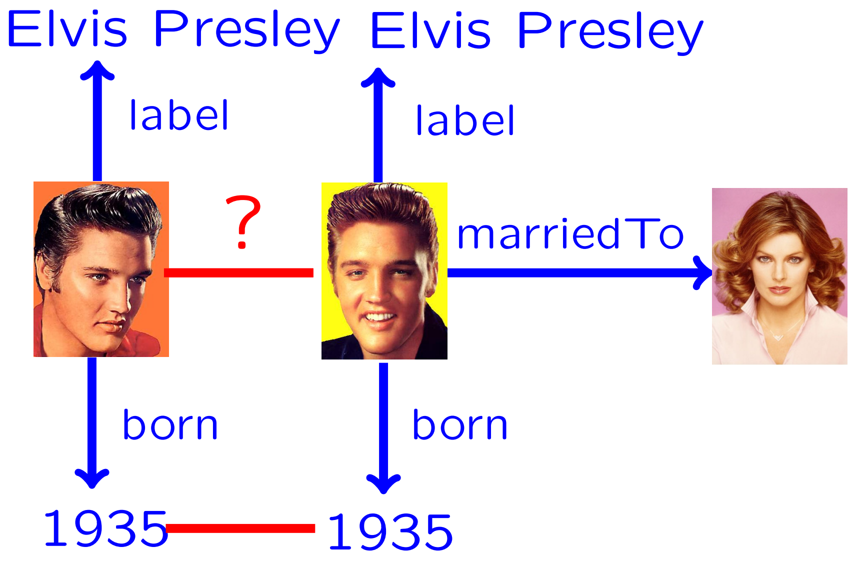
$$Pr(ifun(born)) = 0.01$$



Equality of Instances

x and x' shall be matched if

$$\exists r, y, y' with r(x,y), r(x',y') : y \equiv y' \wedge ifun(r)$$



Equality of Instances

$Pr(x \equiv x')$

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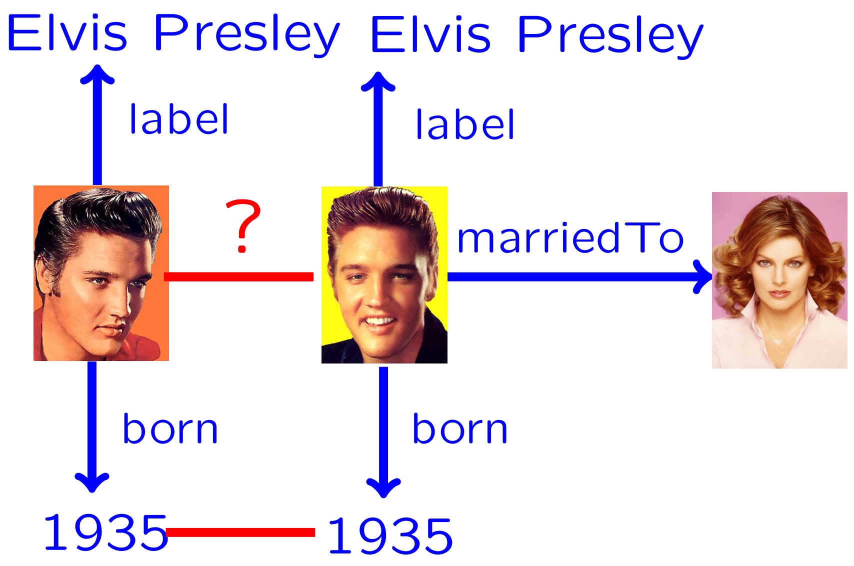

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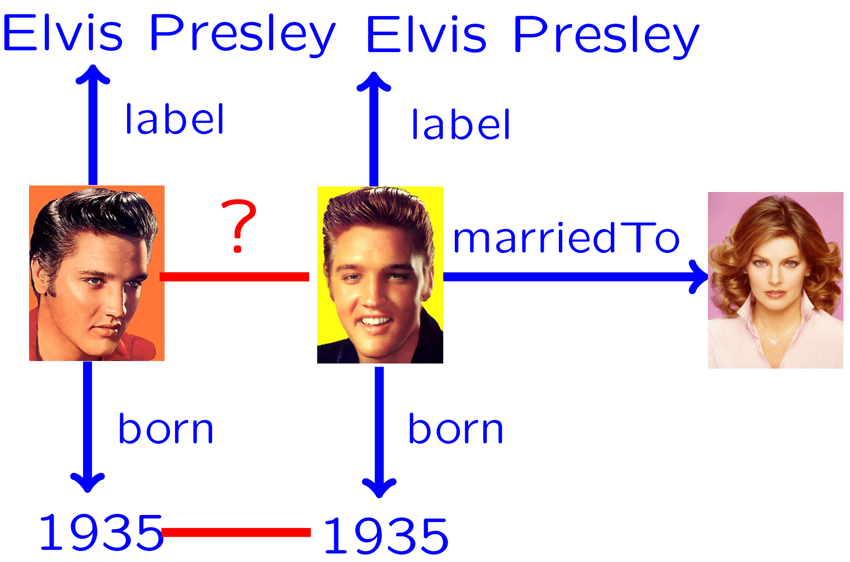

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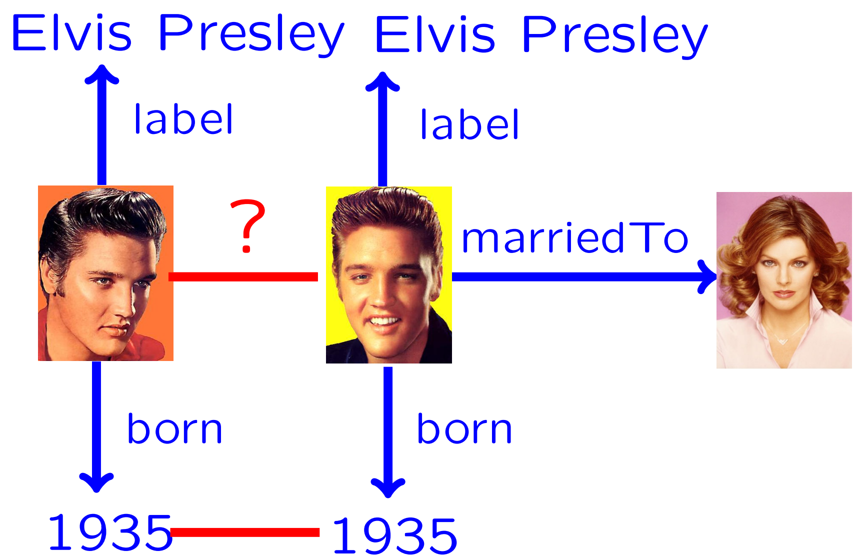
This evaluates to 1 iff

- There is at least one highly inverse functional r
- There is one shared argument y=y'



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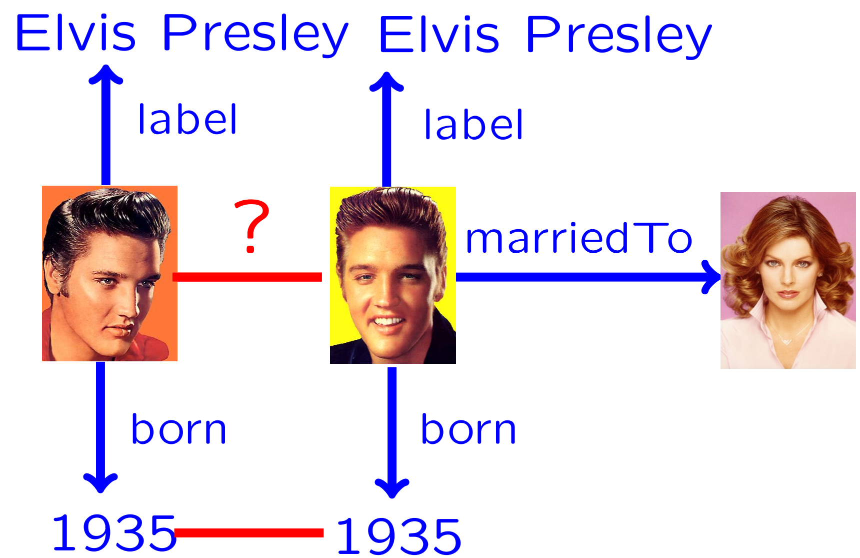
$= 1 - \prod_{r(x,y),r(x',y')}(1 - \underline{Pr(y \equiv y')}Pr(ifun(r)))$

- Literals: precomputed
- Others: recursive



Equality of Classes

If all instances of one class are instances of the other then the former subsumes the latter

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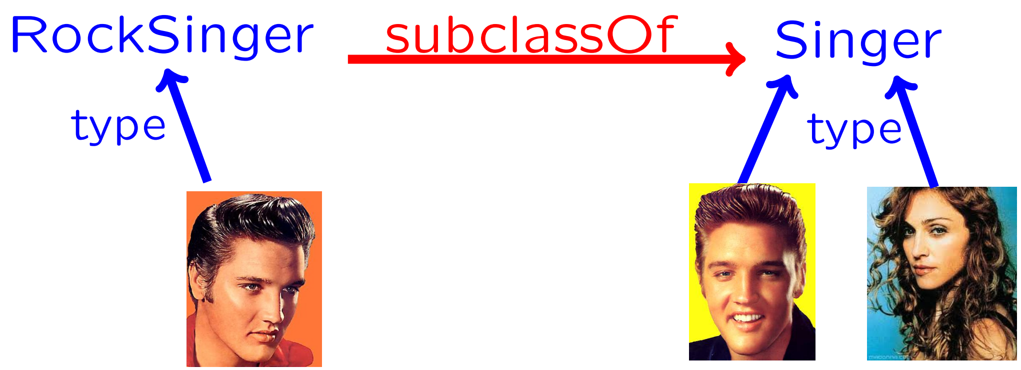

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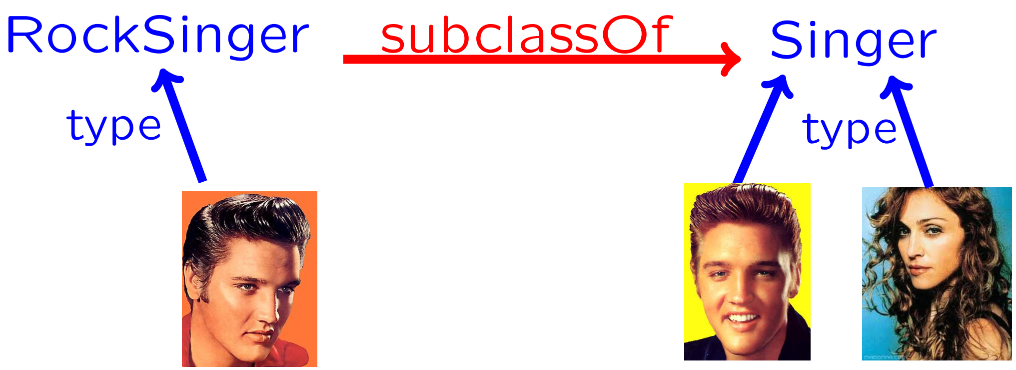

$$Pr(C \subseteq D) = \frac{|C \cap D|}{|C|}$$

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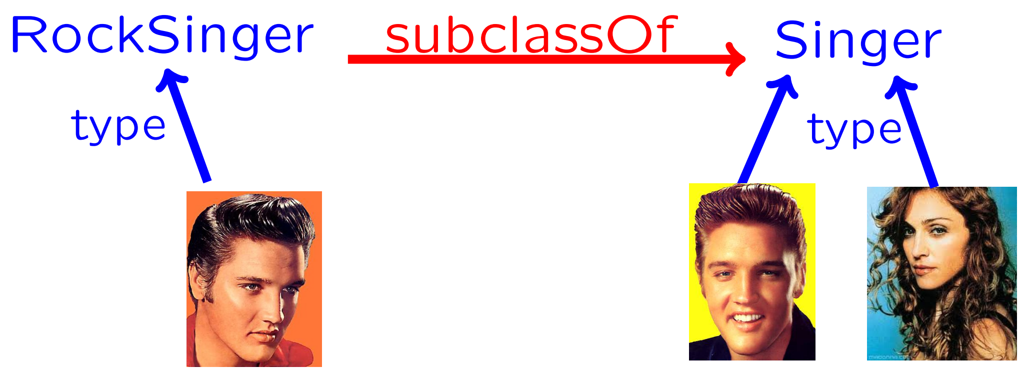

$$Pr(C \subseteq D) = \frac{|C \cap D|}{|C|} = \frac{\sum_{x \in C} Pr(\exists y \in D : x \equiv y)}{|C|}$$

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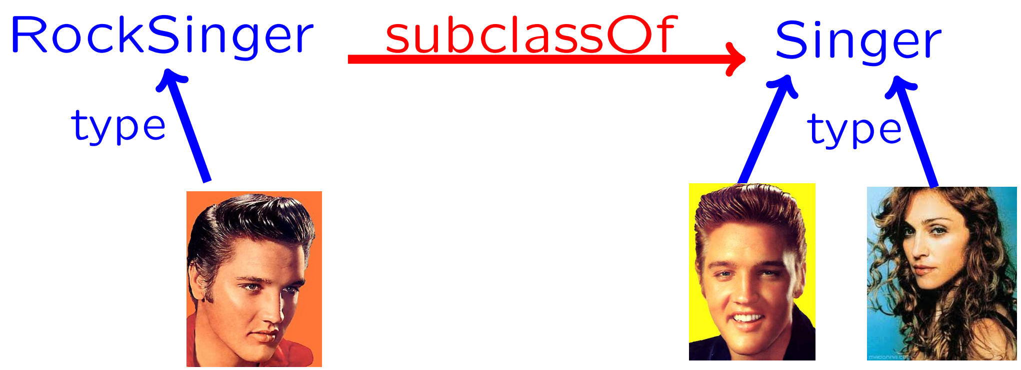
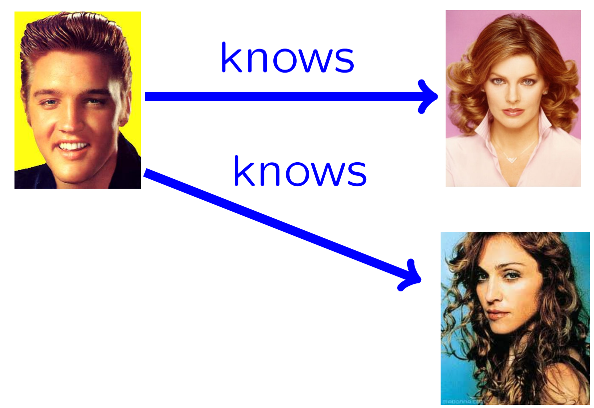


$$Pr(C \subseteq D) = \frac{|C \cap D|}{|C|} \qquad = \frac{\sum_{x \in C} Pr(\exists y \in D : x \equiv y)}{|C|}$$

$$Pr(C \subseteq D) = \frac{\sum_{x \in C}(1 - \prod_{y \in D}(1 - Pr(x \equiv y)))}{|C|}$$

Equality of Relations

If every pair of one relation is a pair of another relation, then the first is a sub-property of the second.



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Can be solved analogously to the subsumption of classes.

Algorithm

1. Fix equalities for literals

Literals: $Pr(x \equiv y) = fixedforliterals$

Algorithm

1. Fix equalities for literals
2. Set equalities for relations to a small initial value

Relations: $Pr(p_1 \subseteq p_2) =$ 0.1

Literals: $Pr(x \equiv y) = fixedforliterals$

Algorithm

1. Fix equalities for literals
2. Set equalities for relations to a small initial value
3. Iterate the estimations for relations and instances to convergence (*)

Iterate

Relations: $Pr(p_1 \subseteq p_2) = \ 13\phi ..$

Instances: $Pr(x \equiv y) = \prod_{42}^{1} \alpha^{\beta} ...$

Literals: $Pr(x \equiv y) = fixedforliterals$

(*) We have no proof for convergence, but it seems to happen

Algorithm

1. Fix equalities for literals
2. Set equalities for relations to a small initial value
3. Iterate the estimations for relations and instances to convergence (*)
4. Compute the estimations for classes

Iterate

Relations: $Pr(p_1 \subseteq p_2) = \; 13\phi\cdot..$

Instances: $Pr(x \equiv y) = \prod_{42}^{1} \alpha^{\beta}...$

Literals: $Pr(x \equiv y) = fixedforliterals$

final step

Classes: $Pr(c_1 \subseteq c_2) = \pi m c^2...$

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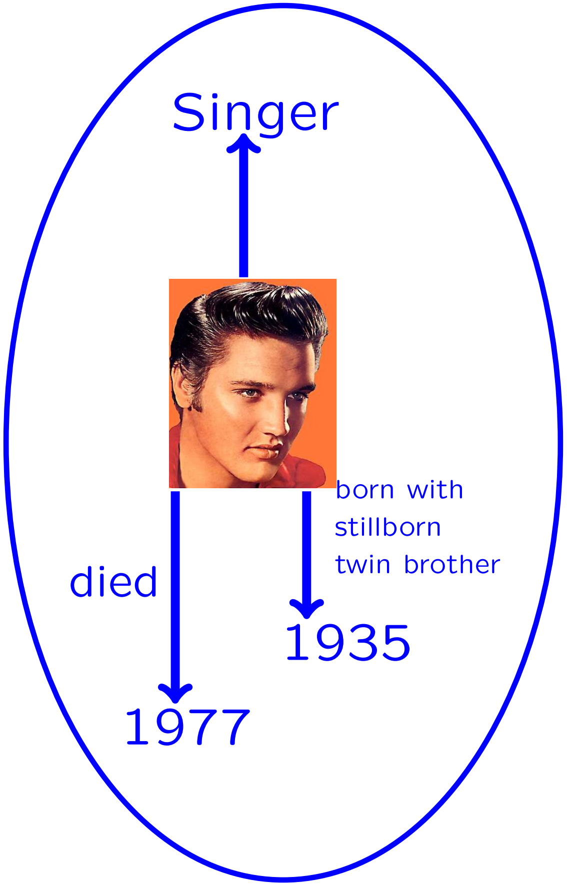
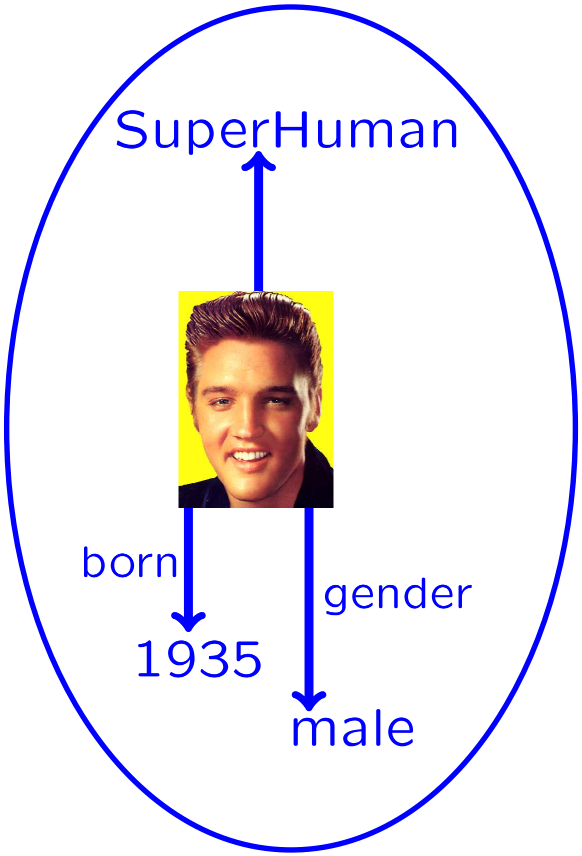
Experiment: YAGO and DBpedia

DBpedia



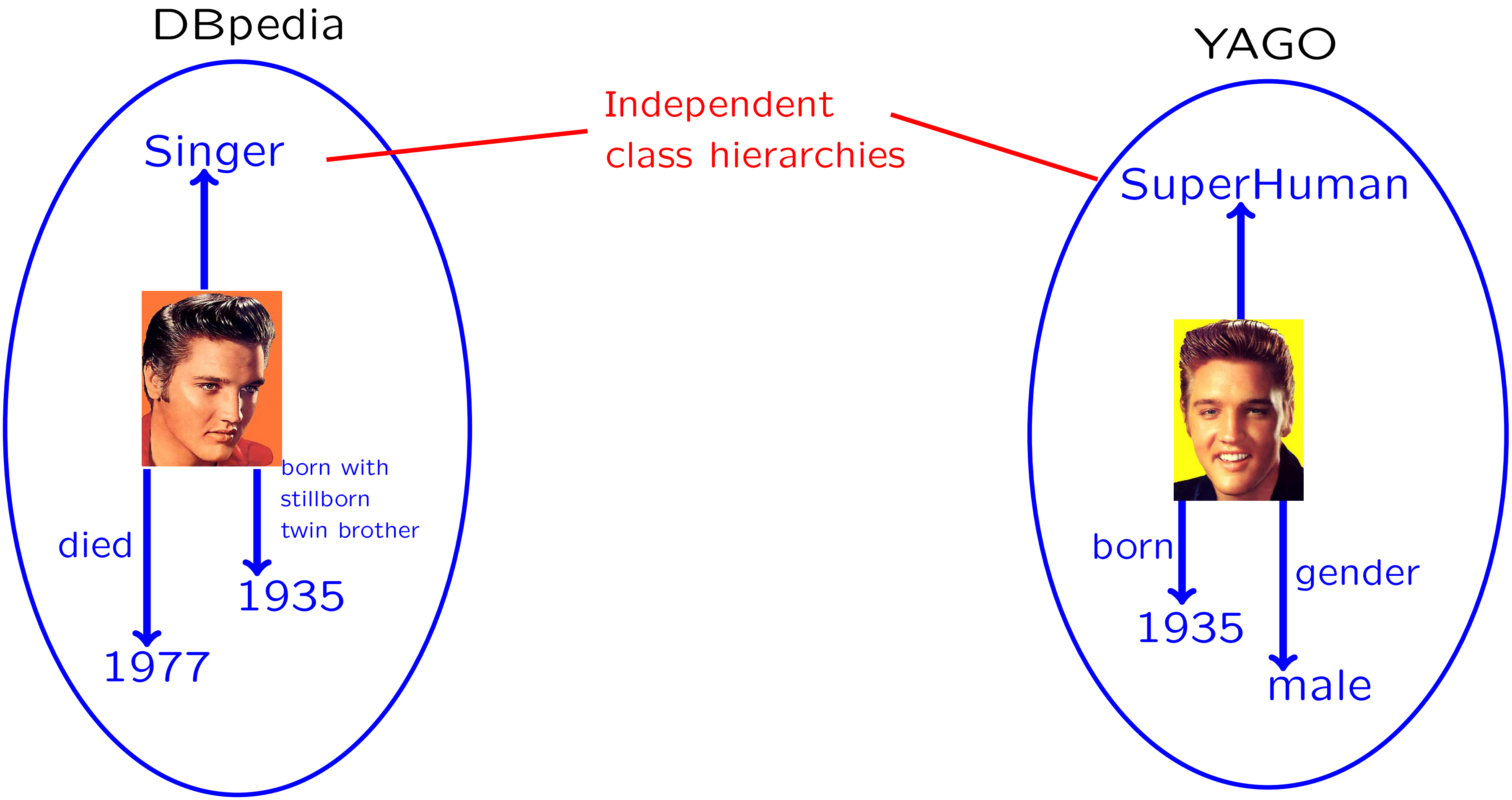
1.7 million instances
19 million facts

YAGO



2.6 million instances
18 million facts

Experiment: YAGO and DBpedia



1.7 million instances
19 million facts

2.6 million instances
18 million facts

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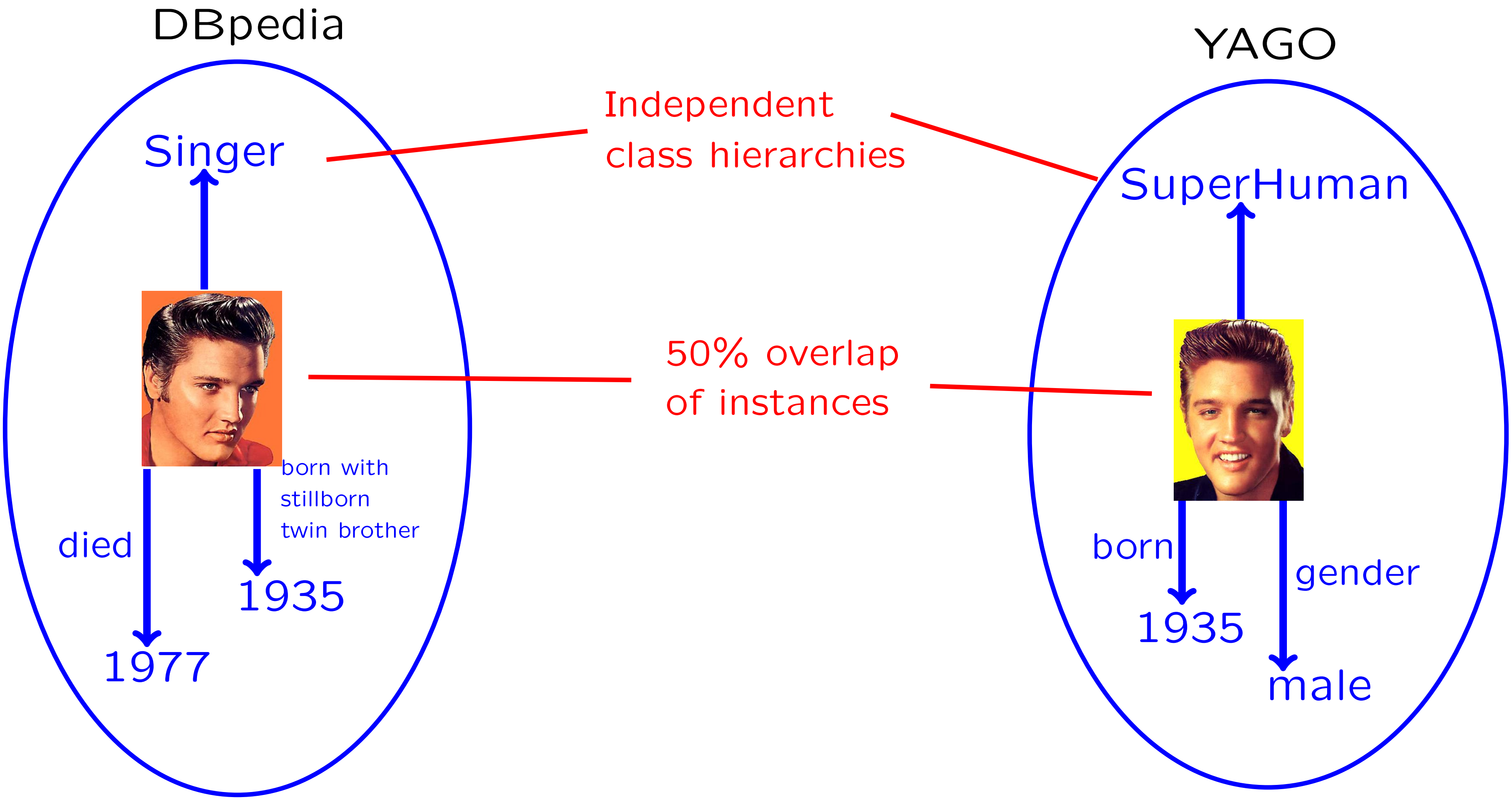

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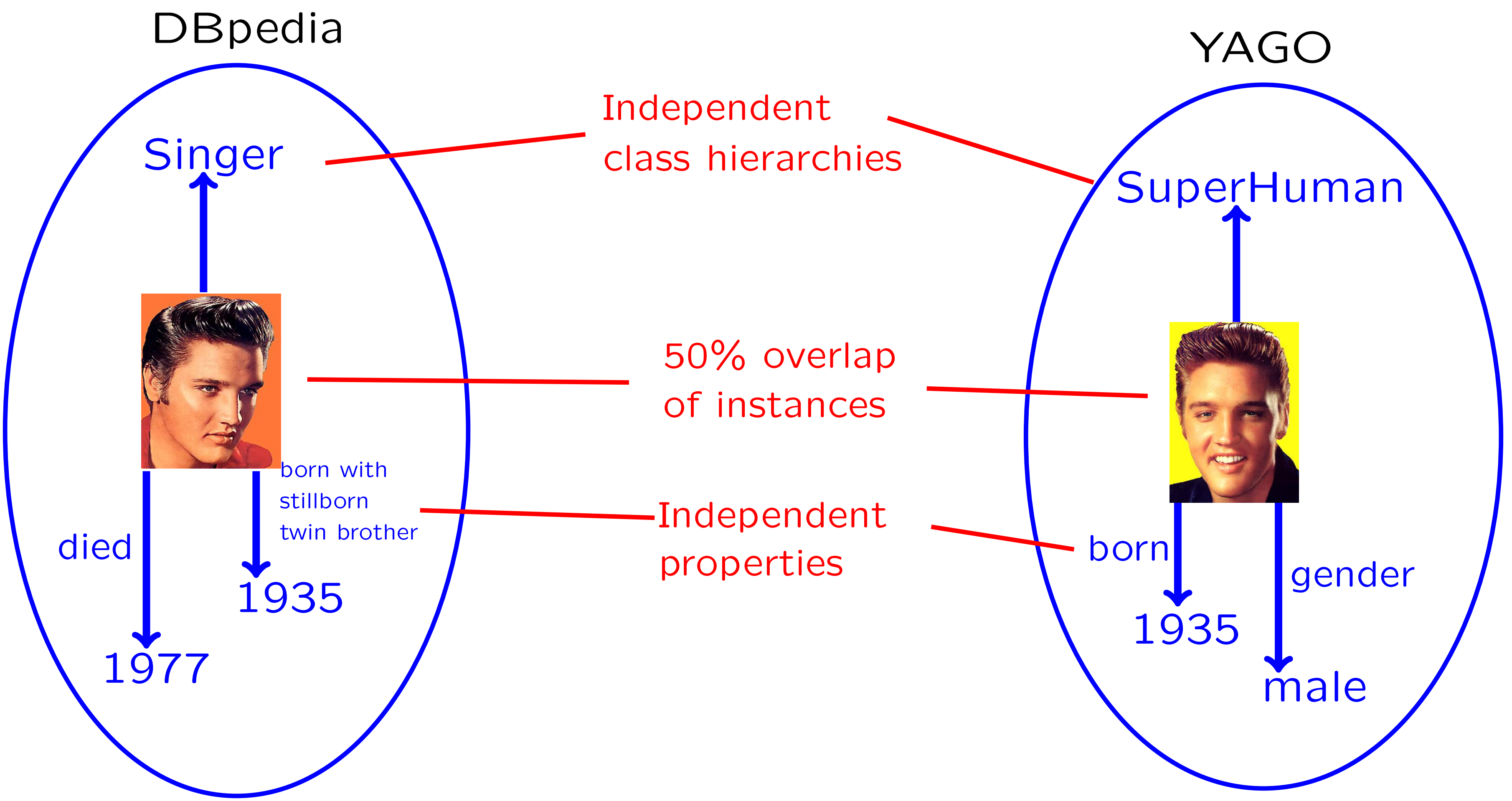

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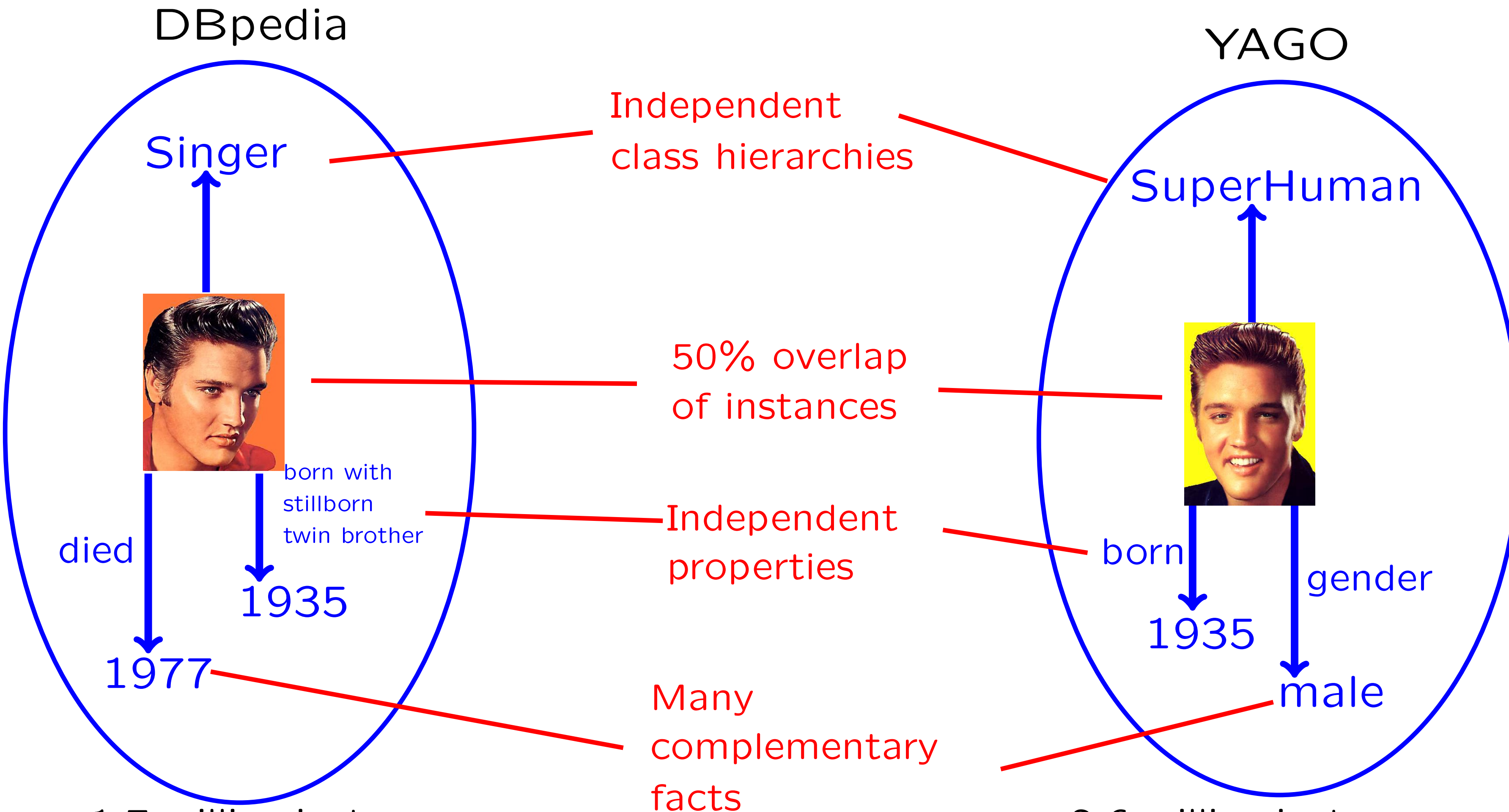

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Experiment: YAGO and DBpedia

Matching the instances:

Iteration	Change	Time	Precision	Recall
1	–	4:04h	86%	69%
2	12%	5:06h	89%	73%
3	1%	5:00h	90%	73%
4	0.3%	5:30h	90%	73%

F-Measure increases

Experiment: YAGO and DBpedia

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Matching the classes:

Precision: 74%
Aligns roughly half of DBpedia's classes

Experiment: YAGO and DBpedia

Matching the relations:

yago:actedIn = dbpedia:starring-inv
yago:hasChild = dbpedia:child
yago:hasChild = dbpedia:parent-inv
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... and many more. Precision: 96%

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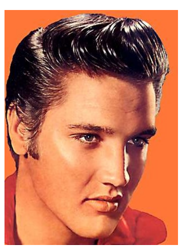
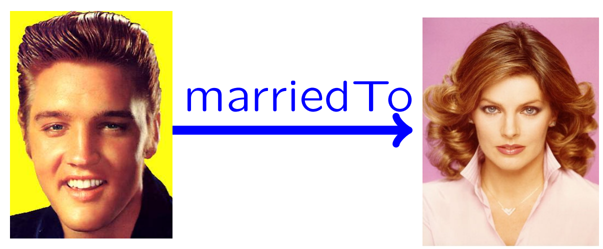
All experiments run with the same settings.
No parameter tuning.

Conclusion

- PARIS matches relations, instances and schema holistically
- PARIS has no parameters to tune
- PARIS shows high precision and recall





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- PARIS has no parameters to tune
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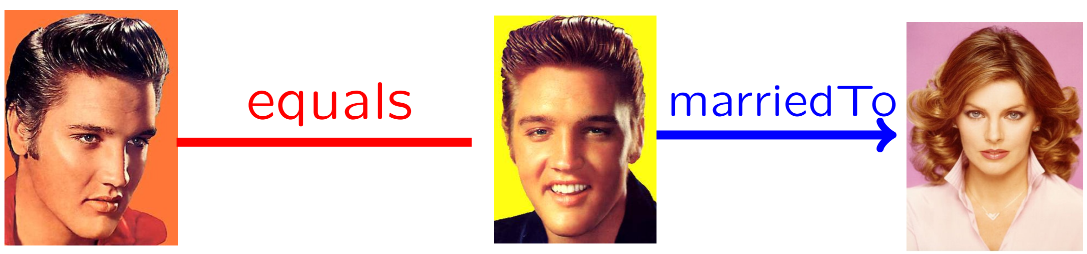
- PARIS allows the YAGO Elvis to marry the DBpedia Priscilla



Happy End

Slides done with PowerLine, the free graphical SVG slide editor with Latex support

Backup Slides

with more details

Equality of Instances

x and x' shall be matched if

$\exists r, y, y' with r(x, y), r(x', y') : y \equiv y' \wedge ifun(r) large$

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Let's compute the probability of this happening,

$$Pr(\neg \bigwedge_{r,y,y' with r(x,y),r(x',y')} \neg(y \equiv y' \wedge ifun(r)))$$

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(under independence assumptions)

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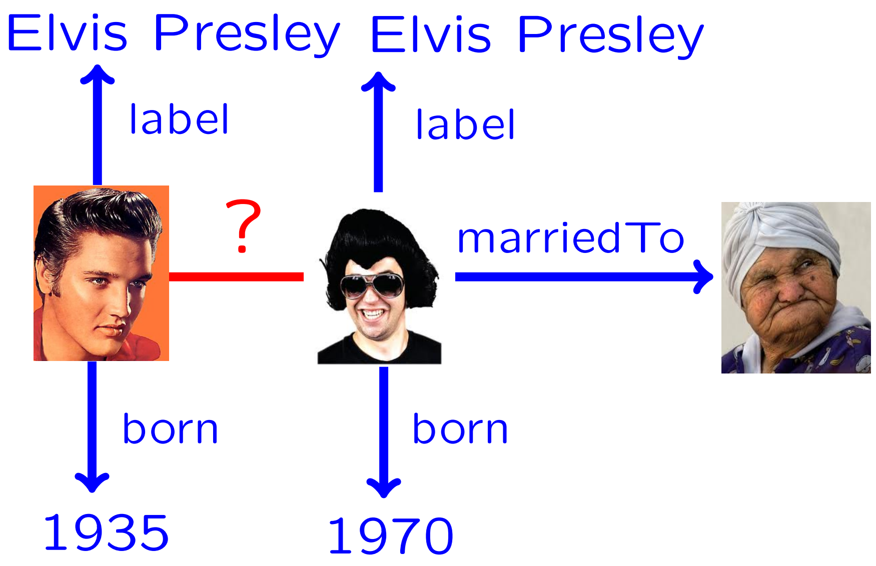
$$= Pr(x \equiv x')$$

Unequality of Instances

How do we guard against inequalities?



Unequality of Instances

How do we guard against inequalities?

These cannot be equal,
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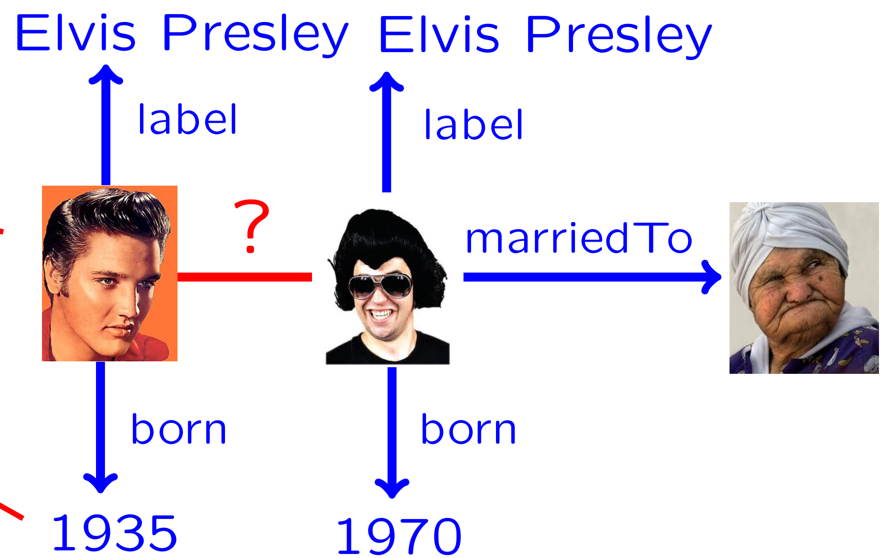

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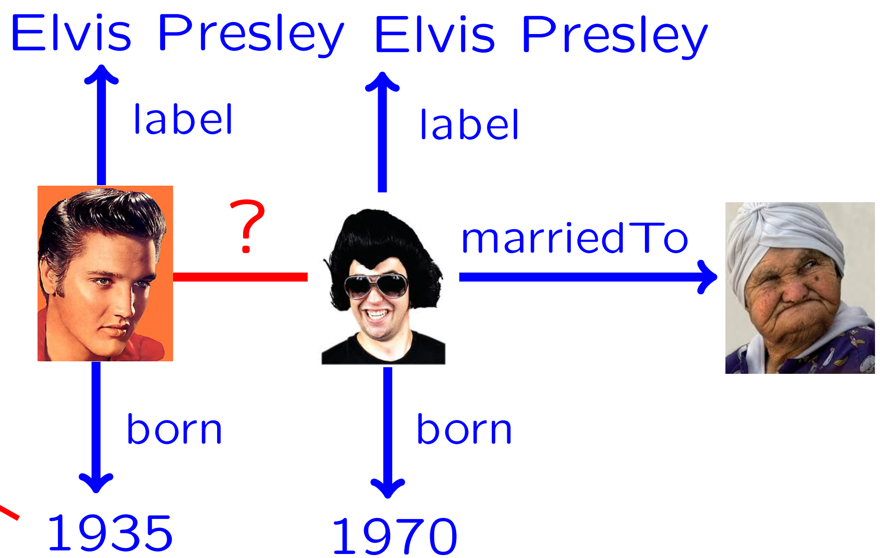

The functionality is defined analogously to the inverse functionality.

$$fun(bornIn) = 1$$

Unequality of Instances

Every value in one ontology should have a pendant in the other, weighted by the functionality:

$$Pr(x \equiv x') = \ldots \prod_{r(x,y)} (1 - fun(r) \prod_{r(x',y')} Pr(y \not\equiv y'))$$

This factor makes sure that
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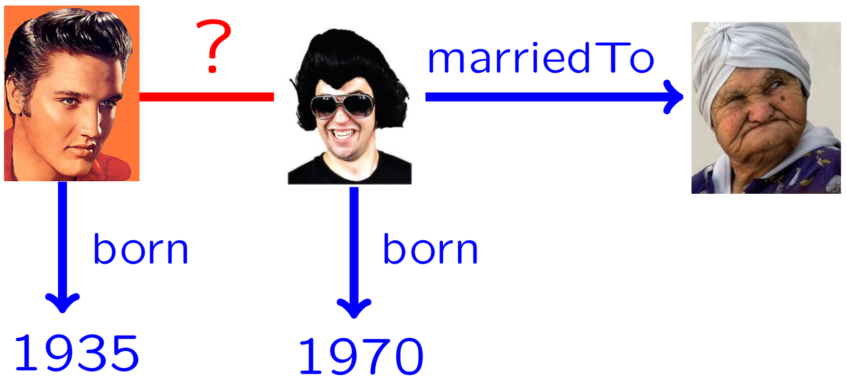

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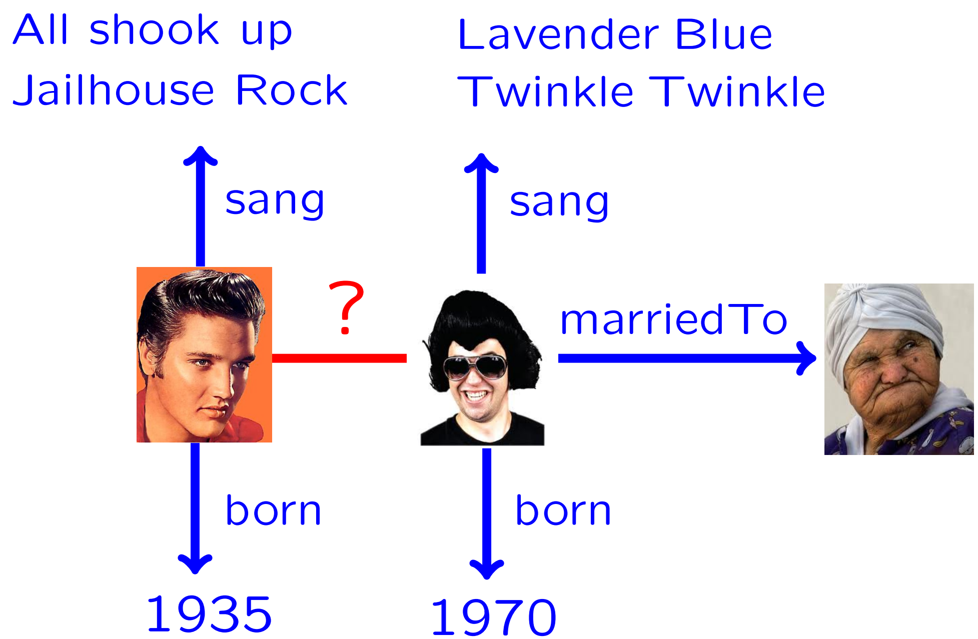
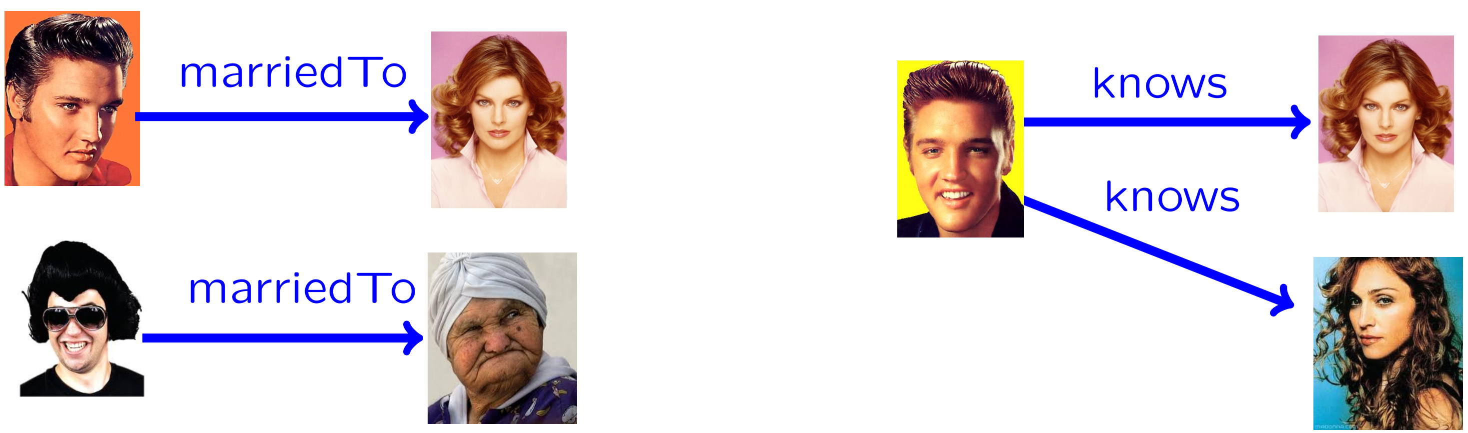


Equality of Relations

If every pair of one relation is a pair of another relation, then the first is a sub-property of the second.

marriedTo $\xrightarrow{\text{subpropertyOf}}$ knows

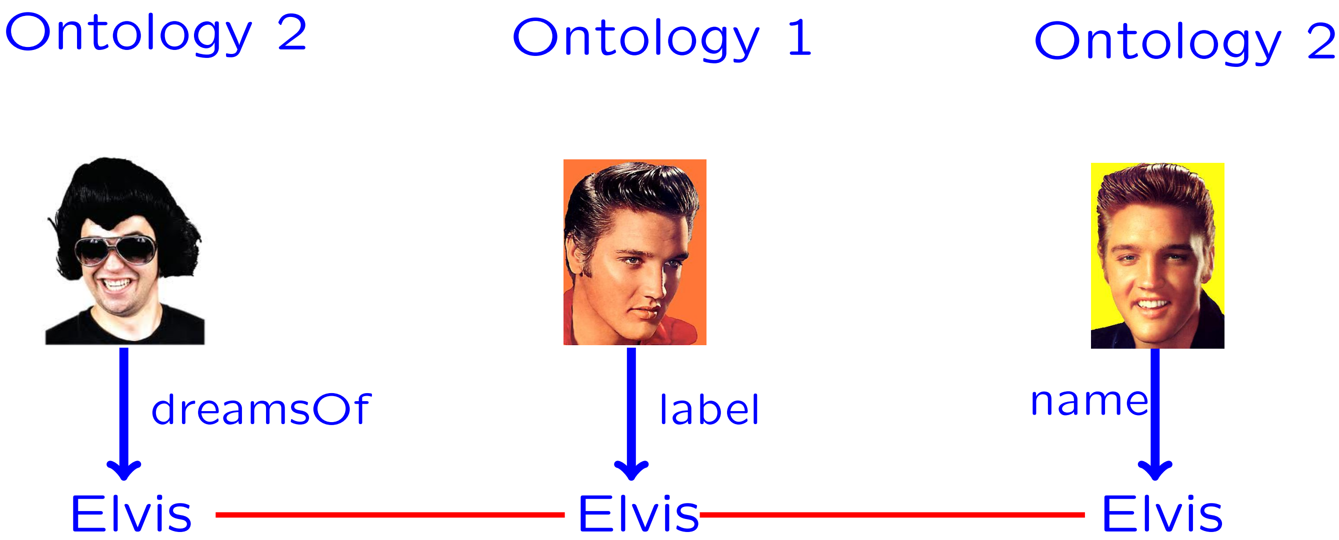


(Those in the intersection)

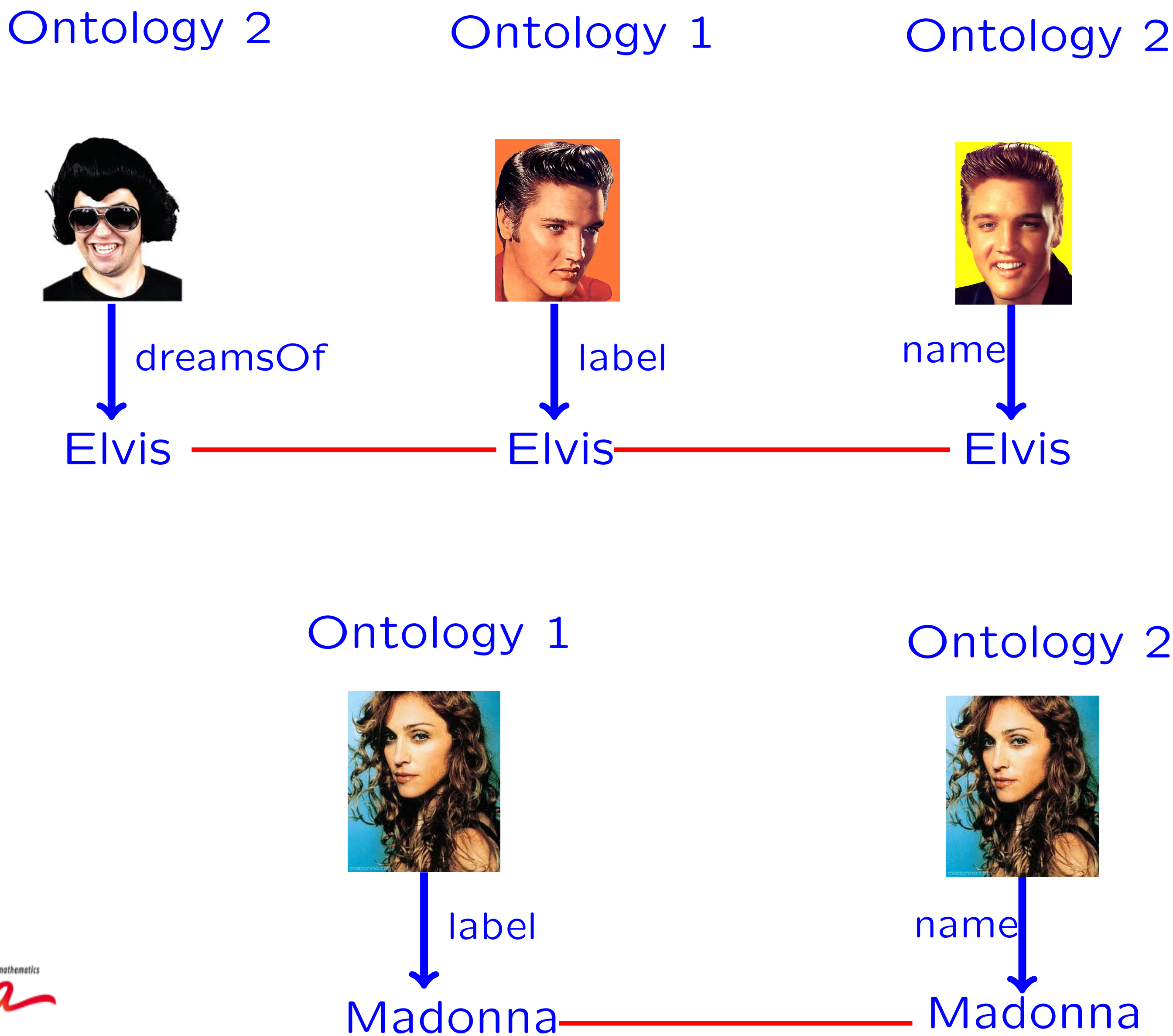
$$Pr(r \subseteq r') = \frac{\sum_{r(x,y)}(1-\prod_{r'(x',y')}(1-Pr(x\equiv x')\cdot Pr(y\equiv y')))}{\sum_{r(x,y)}(1-\prod_{x',y'}(1-Pr(x\equiv x')\cdot Pr(y\equiv y')))}$$

(Those that have a pendant)

Example


Ontology 2
Ontology 1
Ontology 2
dreamsOf
label
name
Elvis
Elvis
Elvis

Example



Ontology 2
Ontology 1
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dreamsOf
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Elvis
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label
name
Madonna
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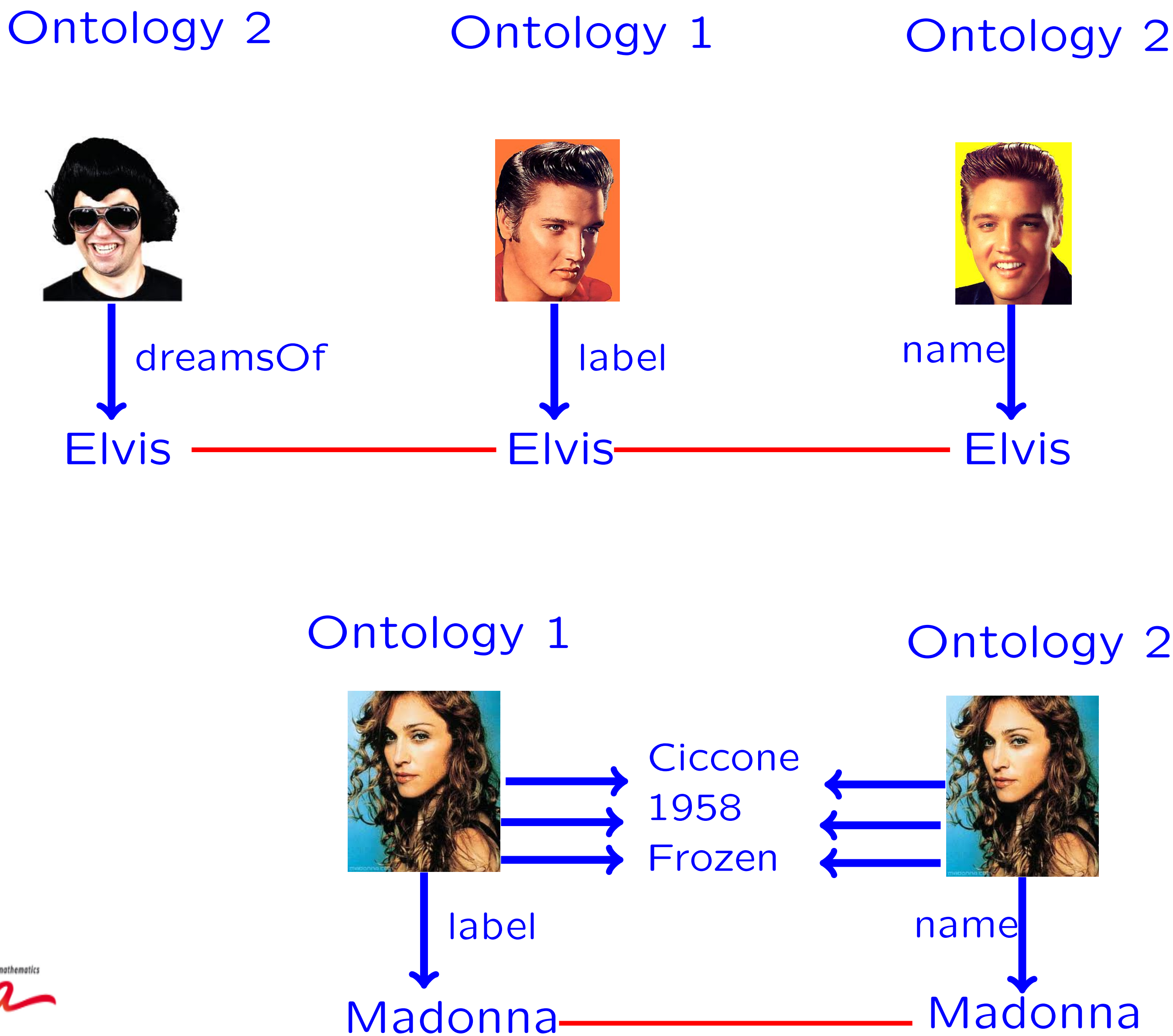
Ontology 2
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Ontology 1
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Ciccone
1958
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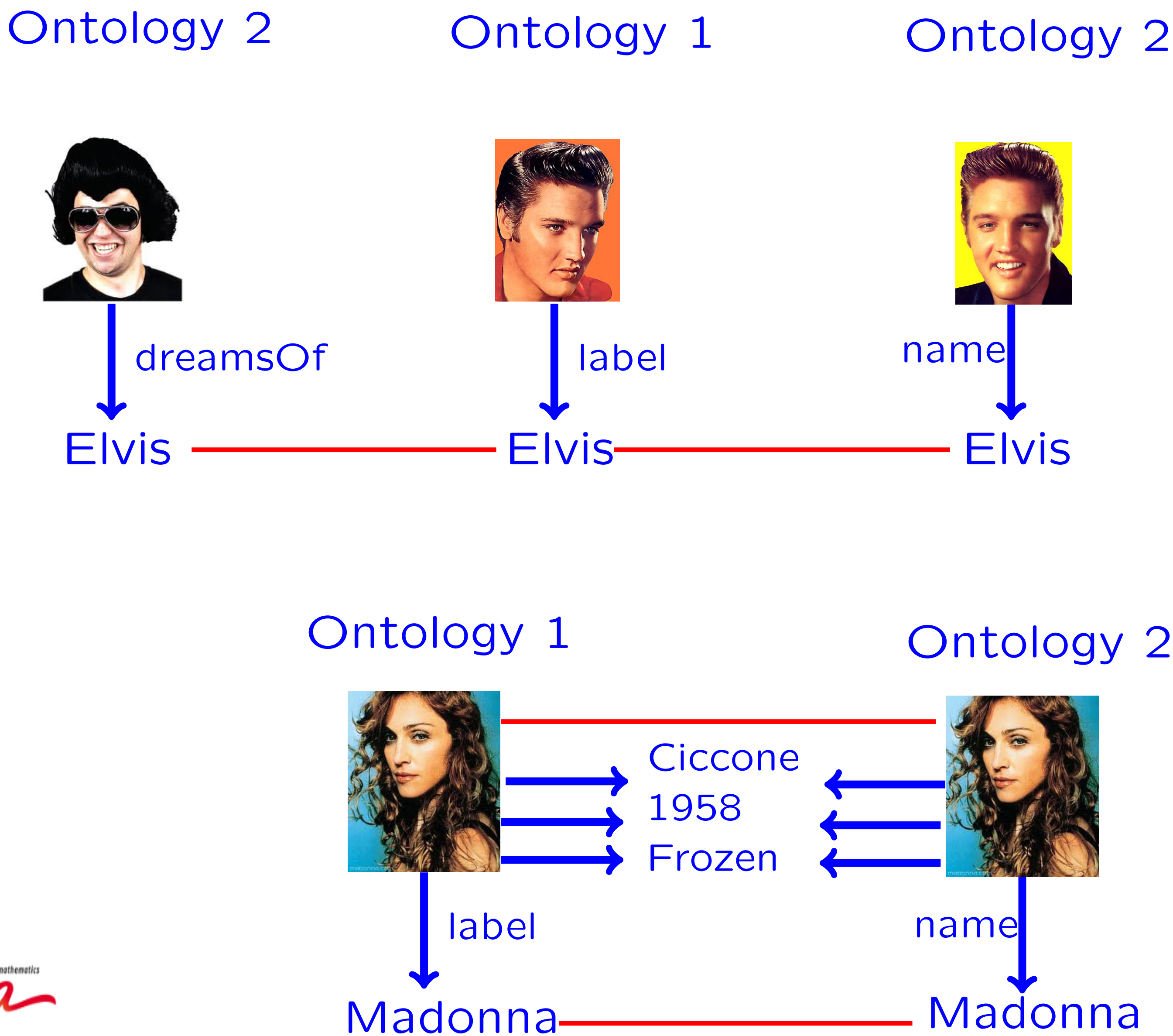
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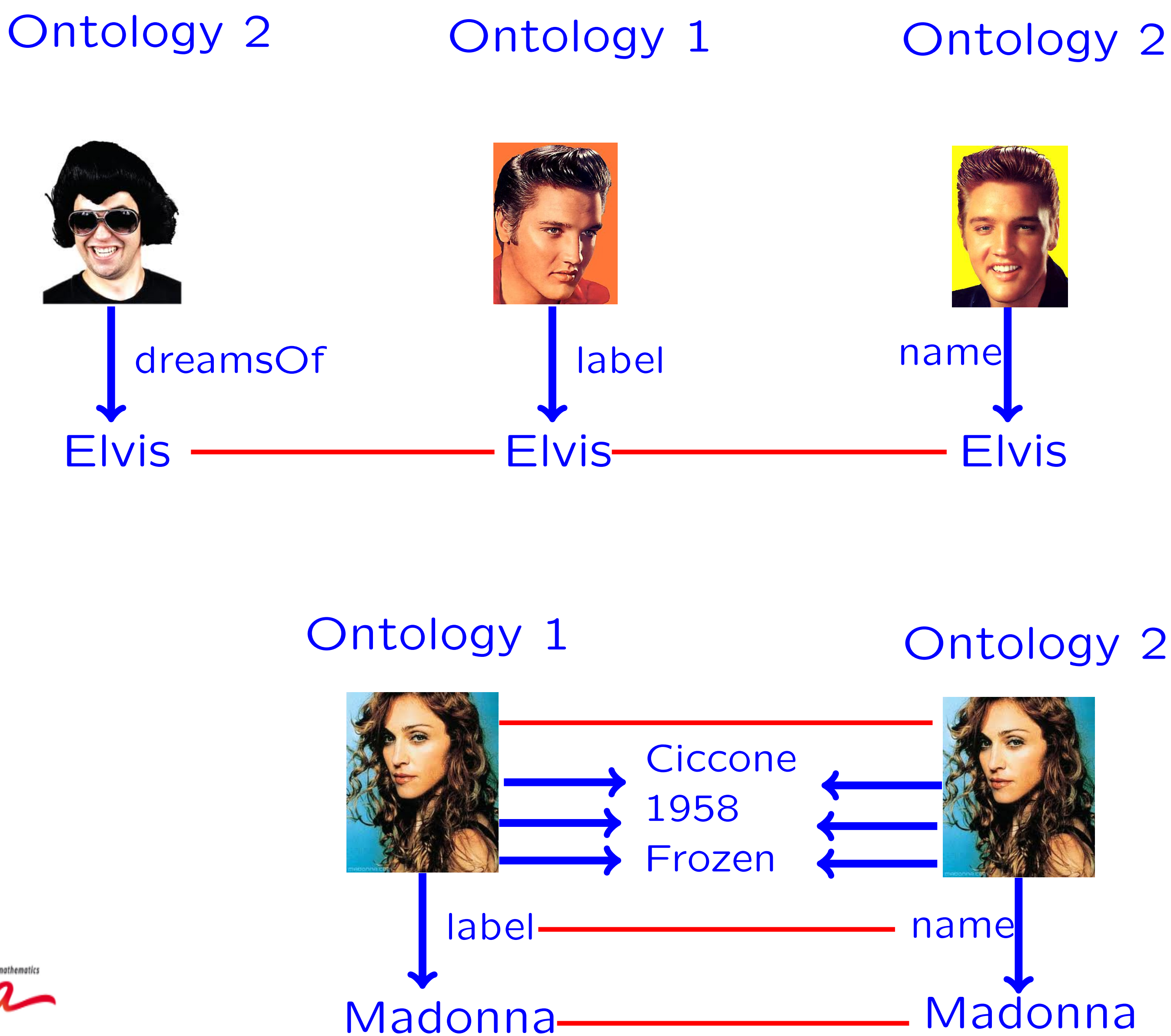
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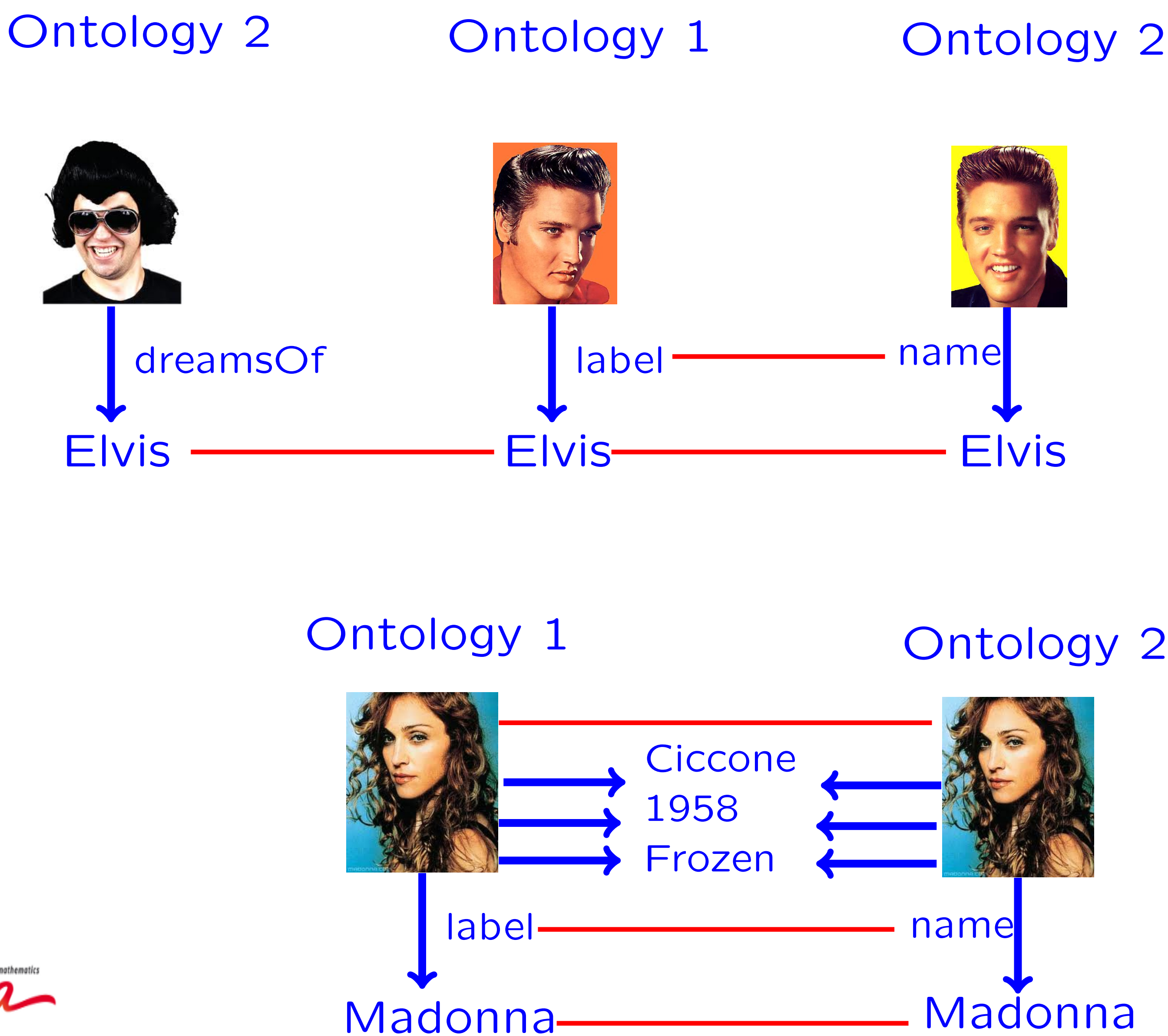
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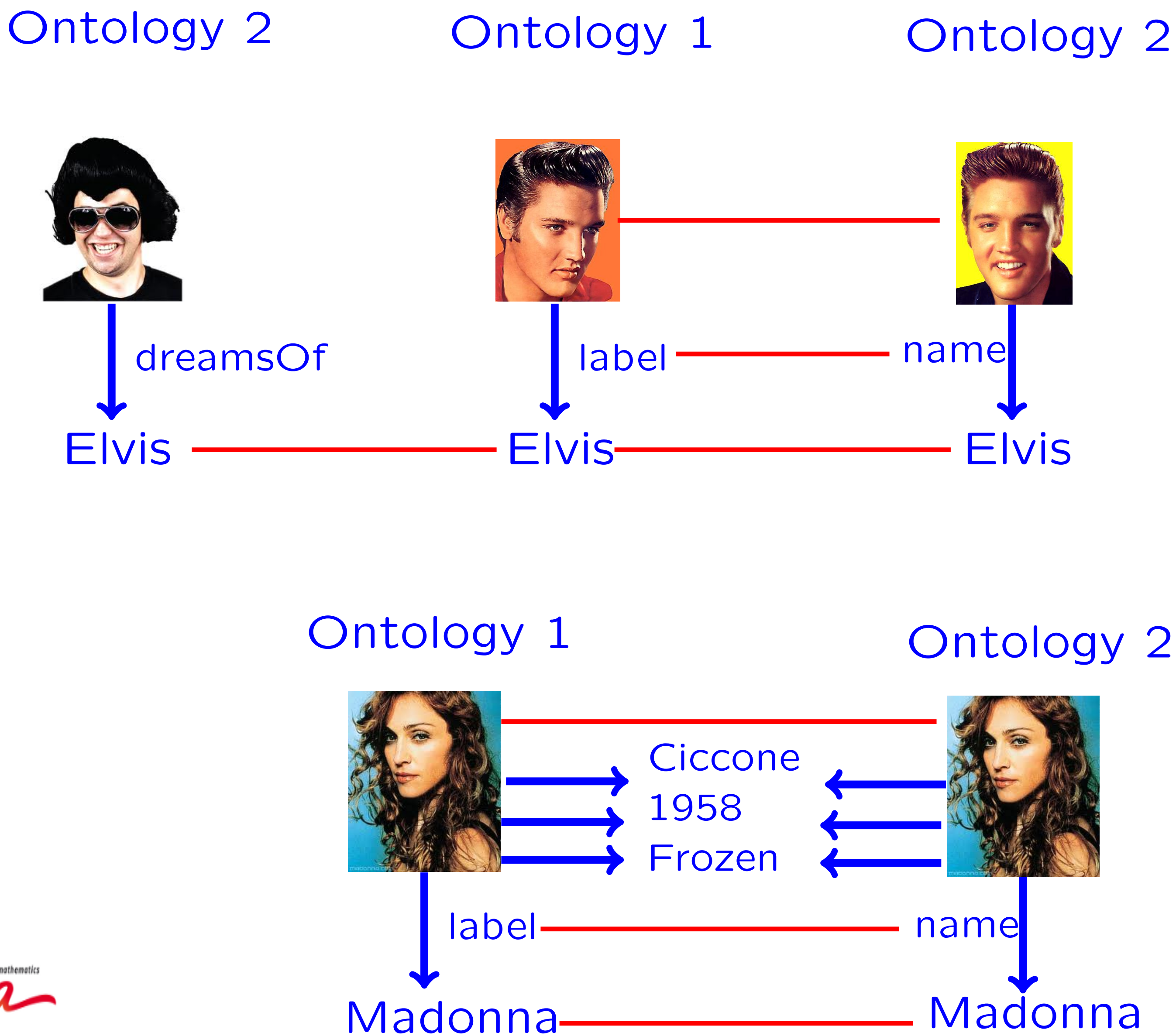

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