CS 446: Machine Learning

Introduction to LBJava:

a Learning Based Programming Language

Writing classifiers

Christos Christodoulopoulos
Parisa Kordjamshidi

Outline

- Back to the Tweeter example
- Advanced LBJava
  - Parameter tuning
  - Constraints and global inference
- Try a new fun task together: Movie Quotes!

One interesting application:

Lets analyse tweets!
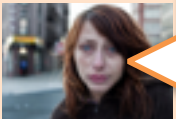
Meta analysis: which location is happier?

Twitter posts

Heard someone sing a Christmas song, in the pub on Friday night. Give
        Place: Illinois, USA, United States

happy tweet

My mom just dragged me to Walgreens and forced me to get a fl
she told me it was just like mother-daughter tattoos #help
        Place: Illinois, USA, United States
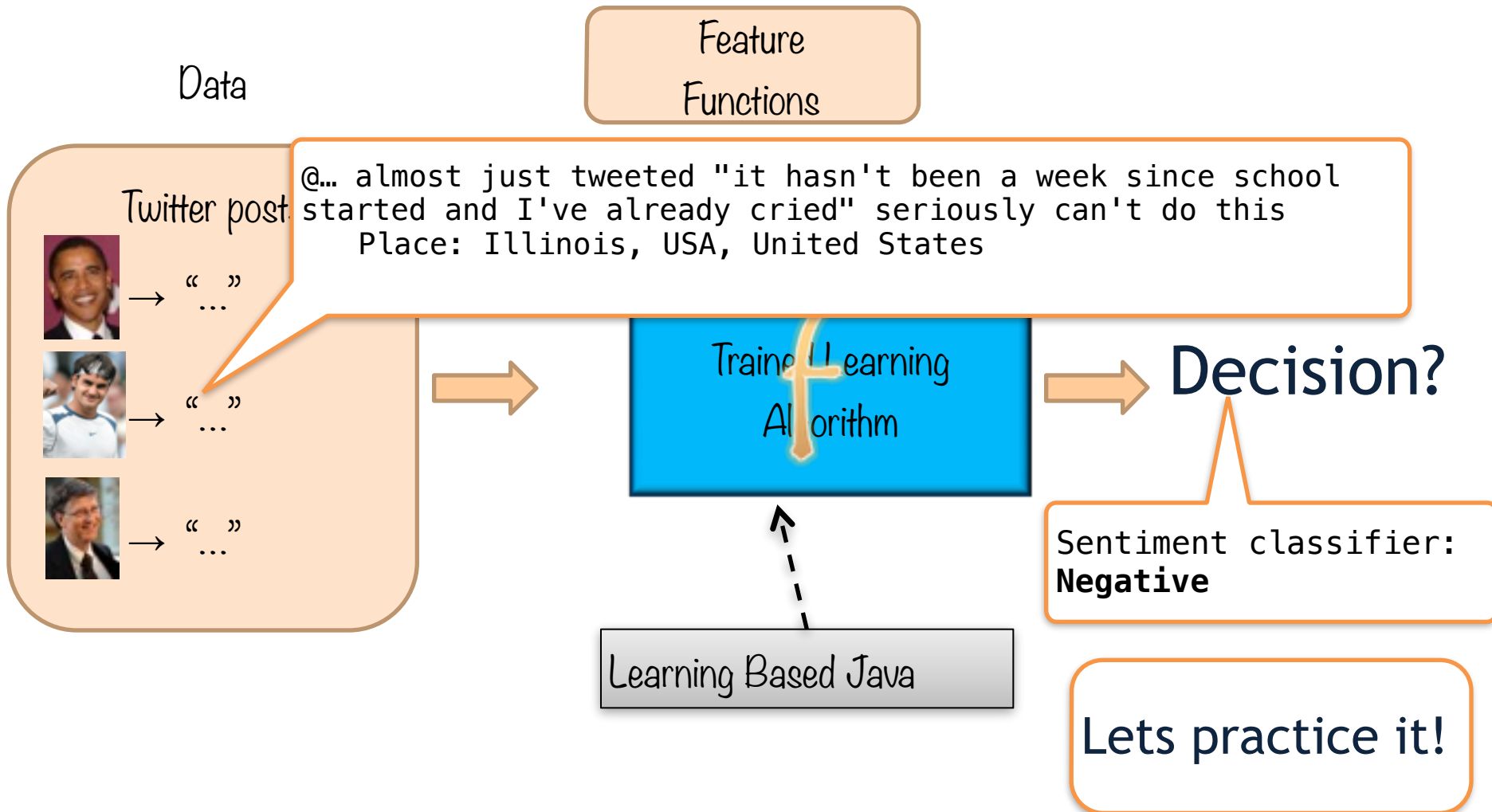
unhappy tweet

just wanna leave these past in the past and move on
        Place: Edinburgh, Scotland, United Kingdom

unhappy tweet

Our application

Data

Feature
Functions

Twitter post

@... almost just tweeted "it hasn't been a week since school started and I've already cried" seriously can't do this
Place: Illinois, USA, United States

→ " "
...

→ " "
...

→ " "
...

Trained Learning Algorithm

Decision?

Learning Based Java

Sentiment classifier:
Negative

Lets practice it!
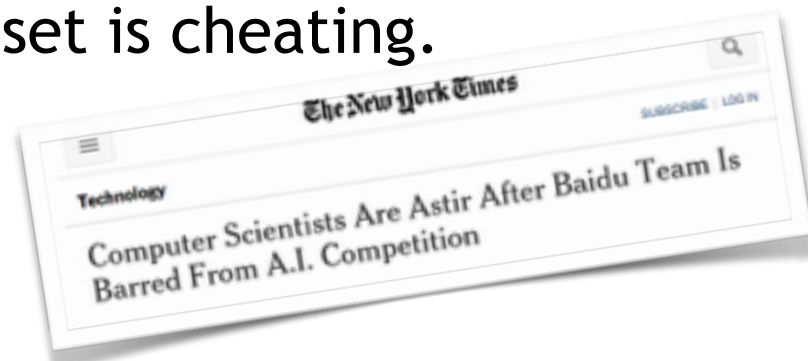
Advanced Learning Based Java

- **Parameter tuning**
  - Very important step for a production system
  - Free parameters that you can set based on
    - Your background and instincts about the problem domain.
    - Your computational and memory capacities.
  - Development set
    - Need a way to check lots of parameter values
    - Tuning on the test set is cheating.

Parameter Tuning

```
discrete SpamClassifier(Document d) <-
learn SpamLabel
  using WordFeatures, BigramFeatures
  from new Document
  with SparseAverage
    learningRate = 0.1;
    thickness =3.5;

testFrom new DocumentReader("data/test")
end
```

learningRate = {{0.1,1,1.5}}

thickness = {{1->3.5:0.5}}

cval 5 "random"

Parameter Tuning

```
discrete SpamClassifier(Document d) <-
learn SpamLabel
  using WordFeatures, BigramFeatures
  from new DocumentReader("data/train")
  with SparseAveragedPerceptron {
    learningRate = {{0.1,1,1.5}};
    thickness = {{1->3.5:0.5}};
  cval 5 "random"
testFrom new DocumentReader("data/test")
end
```

Advanced Learning Based Java
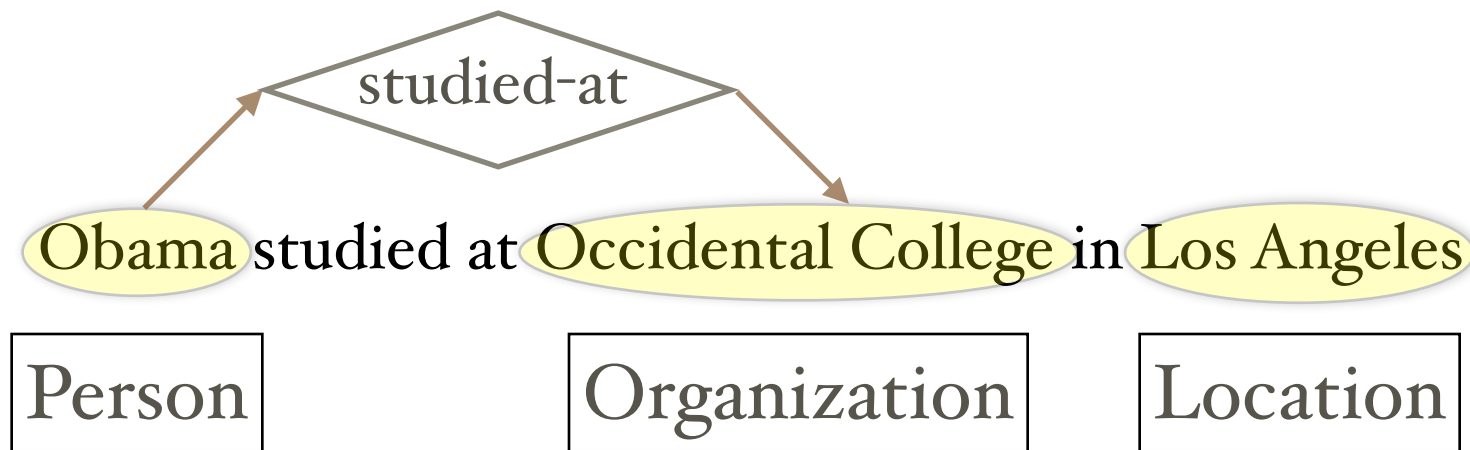
- Combining Classifiers
    - Learning models as "black boxes" (primitives)
    - Used to build more complex applications

- Making global decisions
    - **Constraining** classifier choices to be related

Entity-Relation (ER) Task

- NLP task: Given an input text, **Entity-Relation extraction** aims at identifying:
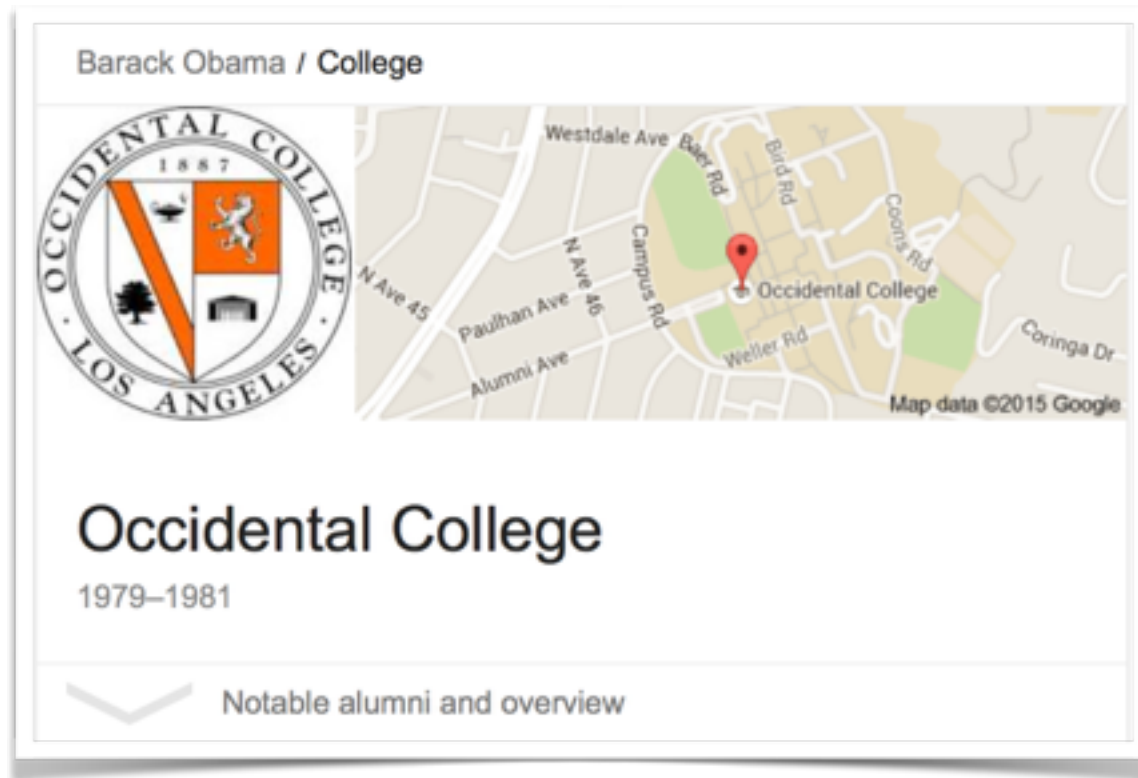
  Named entities of types: { **person, location, organization,…** }

  Relations of types:{ **lives-in, works-for,…** }

studied-at

Obama studied at Occidental College in Los Angeles

Person   Organization   Location

Why ER is useful?

Ask Google: Where did Obama study?

Why ER is useful?

- Populating Google's knowledge graph

Why ER is useful?

Where did Obama study?

Barack Obama - Biography.com
www.biography.com/people/barack-**obama**-12782369 ▾
As a child, **Obama did** not have a relationship with his father. ... After high school, **Obama studied** at **Occidental College** in Los Angeles for two ... Returning from Kenya with a sense of renewal, **Obama** entered **Harvard Law School** in 1988.
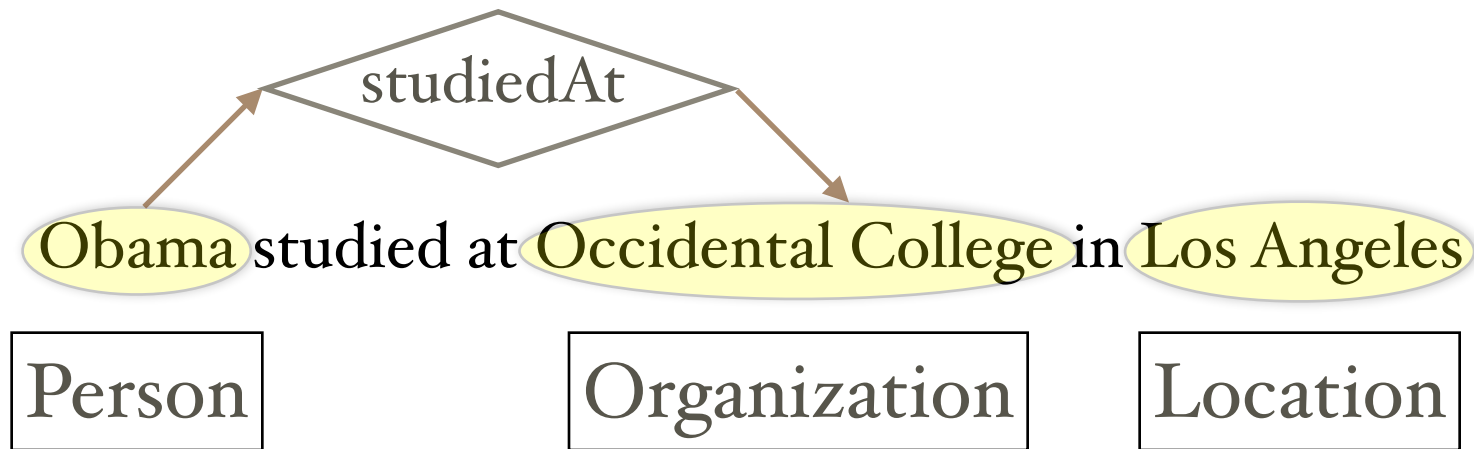
Google is doing Entity-Relations **extraction** here!

Entity-Relation (ER) Task

- Named entities of types: { **person, location, organization,...** }
  Relations of types:{ **lives-in, works-for,bornIn,studiedAt...** }

studiedAt

Obama studied at Occidental College in Los Angeles

Person   Organization   Location
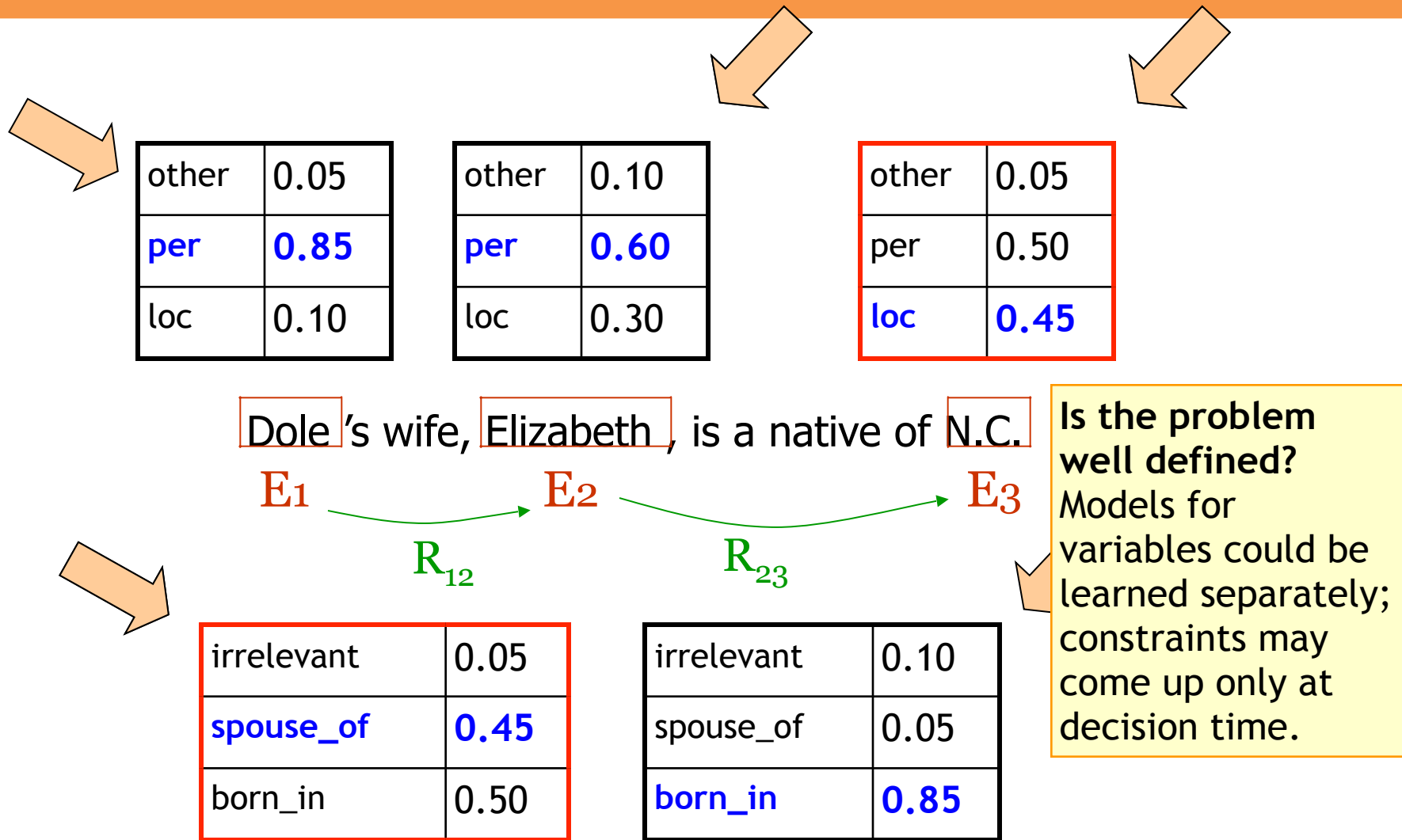
ER Classifiers

```
discrete PersonClassifier(Phrase t) <-
  learn PersonLabel
  using EntityFeatures
  from new TextReader("InputFile")
  with SparsePerceptron
end
```

```
discrete BornInClassifier(Pair r) <-
  learn BornLabel
  using PairFeatures
  from new TextReader("InputFile")
  with SparsePerceptron
end
```

```
discrete LocationClassifie
  learn LocationLabel
  using EntityFeatures
  from new TextReader("InputFile")
  with SparsePerceptron
 end
```

ER Constrained Classifiers

other	0.05
per	**0.85**
loc	0.10

other	0.10
per	**0.60**
loc	0.30

other	0.05
per	0.50
loc	**0.45**

Dole 's wife, Elizabeth , is a native of N.C.

E_1 $\longrightarrow$ E_2 $\longrightarrow$ E_3

R_{12} $\qquad$ R_{23}

irrelevant	0.05
spouse_of	**0.45**
born_in	0.50

irrelevant	0.10
spouse_of	0.05
born_in	**0.85**

Is the problem well defined? Models for variables could be learned separately; constraints may come up only at decision time.

ER Constrained Classifiers

```
constraint BornIn (PairPhrase r) <- {
  BornInClassifier(r)::"true" =>
    PersonClassifier(r.firstArgument)::"true" /\
  LocationClassifier(r.secondArgument)::"true";
}
```

A **born-in** relation can only exist between a
PERSON and a **LOCATION**

```
discrete GlobalRelationClassifier(PairPhrase r) <-
    GlobalER(BornInClassifier)
```

```
inference
    PairPhrase r  { return r; }
    subjectto { @BornIn }
    with new ILPInference(new GurobiHook())
}
```

Demo2: Movie Quotes

- A classifier that guesses the movie from a quote
  1. The features
  2. The classifier
  3. Compiling to train the classifier
  4. Use the classifier

See you next time!