Introduction to LBJava: a Learning Based Programming Language

Writing classifiers

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CS 446: Machine Learning
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:

Let's analyze tweets!

Meta analysis: which location is happier?

Twitter posts

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

Unhappy tweet:
My mom just dragged me to Walgreens and forced me to get a flu shot; 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
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

Sentiment classifier: Negative

Learning Based Java

Decision?

Lets practice it!
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 \texttt{SpamClassifier}(\texttt{Document d}) \leftarrow
\texttt{learn} \texttt{SpamLabel}
\texttt{using} \texttt{WordFeatures, BigramFeatures}
\texttt{from} \texttt{new DocumentReader(}"\texttt{data/train}\texttt{)}
\texttt{with} \texttt{SparseAveragedPerceptron}
  \begin{align*}
    \texttt{learningRate} &= \{0.1, 1, 1.5\} \\
    \texttt{thickness} &= \{1 \to 3.5: 0.5\}
  \end{align*}
\texttt{testFrom} \texttt{new DocumentReader(}"\texttt{data/test}\texttt{)}
cval 5 "random"
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
NLP task: Given an input text, Entity-Relation extraction aims at identifying:

- Named entities of types: \{ person, location, organization, \ldots \}
- Relations of types: \{ lives-in, works-for, \ldots \}

\begin{itemize}
  \item Obama studied at Occidental College in Los Angeles
\end{itemize}
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: \{ \text{person, location, organization, ...} \}
- Relations of types: \{ \text{lives-in, works-for, bornIn, studiedAt ...} \}

Obama studied at Occidental College in Los Angeles.
ER Classifiers

\[
\text{discrete PersonClassifier}(\text{Phrase } t) \leftarrow \\text{learn PersonLabel using EntityFeatures from new TextReader("InputFile") with SparsePerceptron}
\]

\[
\text{discrete LocationClassifier}(\text{Phrase } t) \leftarrow \\text{learn LocationLabel using EntityFeatures from new TextReader("InputFile") with SparsePerceptron}
\]

\[
\text{discrete BornInClassifier}(\text{Pair } r) \leftarrow \\text{learn BornLabel using PairFeatures from new TextReader("InputFile") with SparsePerceptron}
\]
ER Constrained Classifiers

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

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

**Constraint**

```java
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**

**Inference**

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

**PairPhrase**

```java
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!