Introduction to LBJava:
a Learning Based Programming Language

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Motivation
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You still have not learnt machine learning algorithms
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- You still have not learnt machine learning algorithms
- But you can do cool things with the existing tools
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But you can do cool things with the existing tools
And even earn money using it ;-)!!
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Google DeepMind!

Yahoo Summly!  Tweeters WhetLab!
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How?
One interesting application: 

Let's analyse tweets!

Data

Twitter posts
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Twitter posts

Heard someone sing a Christmas song, in the pub on Friday night. Give us a break!
Place: Illinois, USA, United States
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- Heard someone sing a Christmas song, in the pub on Friday night. Give us a break!
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- My mom just dragged me to Walgreens and forced me to get a flu shot and then she told me it was just like mother-daughter tattoos #help
  Place: Illinois, USA, United States

happy tweet
One interesting application:

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

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Meta analysis: which location is happier?

Twitter posts:

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

2. 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
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3. Just wanna leave these past in the past and move on
   Place: Edinburgh, Scotland, United Kingdom
Our application

Sentiment analysis of tweets!

What are the steps?
Our application

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- **Look at examples**: Find out the influencing features in realizing the sense of a tweet.
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- **!BTW: Test** the trained model using a subset of your labeled data, don't use that subset for training. You need to see how well your model can work.
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There is already a large number of tweets annotated by human and the data is publicly available. this step is done! Good!
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- **Create examples**: Let’s create examples of tweets with positive/negative labels.
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Represent each tweet simply with contained words. We can learn from these words occurrences, for example cry, sad, horrible, nice, pleasant, etc can tell us the sense of the sentence in many cases.
Our application: Sentiment analysis of tweets!

Create examples: Let’s create examples.

Look at examples: Find out the influencing features in realizing the sense of a tweet.

Learning technique: Apply the technique on the labeled data and build a model.

Use the model: Make predictions on the unlabeled tweets later.

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SVMs? Naive Bayes? Decision trees? Sparse Perceptrons? ...
Our application: Sentiment analysis of tweets!

What are the steps?

- **Create examples**: Let's create examples by getting people to label some tweets with positive/negative labels.

- **Look at examples**: Find out the influencing features in realizing the sense of a tweet.

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- Future tweets also should be represented with the same representation (features) as training.
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What are the steps?

- **Create examples**: Let's create examples by labeling some tweets with positive/negative labels.

- **Look at examples**: Find examples to understand the influencing features in realizing the sense of a tweet.

- **Learning technique**: Choose a learning technique and train a model on the labeled data.

- **Use the model**: Use the trained model to make predictions on the unlabeled tweets.

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Our application: Sentiment analysis of tweets!

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1. **Create examples**: Let’s create examples with positive/negative labels.

2. **Look at examples**: Find out the influencing features in realizing the sense of a tweet.

3. **Learning technique and train**: Apply the technique on the labeled data and build a model.

4. **Use the model**: Make predictions on the unlabeled tweets later.

5. **BTW: Test**

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Use the commonly used evaluation metrics.
Our application

Sentiment analysis of tweets!

Data

Twitter posts

“ ”
...
“ ”
...
“ ”
...

Feature Functions

Learning Algorithm
Our application

Sentiment analysis of tweets!

Data

Twitter posts
  “ ”
  ...
  “ ”
  ...
  “ ”
  ...

Feature Functions

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Sentiment analysis of tweets!

Data

Twitter posts

“…”

 “…”

 “…”

Feature Functions

Learning Algorithm

Learning Based Java

f
Our application

Data

Twitter posts

→ “…”
→ “…”
→ “…”

Feature Functions

Trained Learning Algorithm
Our application

Data

Twitter posts

→ “…”

→ “…”

→ “…”

Feature Functions

Train Learning Algorithm

Transformation
Our application

Data

Twitter posts

→ “…”
→ “…”
→ “…”

→ “…”
→ “…”
→ “…”

Feature Functions

Train Learning Algorithm

Learning Based Java
The diagram illustrates our application, which involves training a learning algorithm with data from Twitter posts. The data includes social media interactions and speech fragments. After training, the algorithm makes decisions based on the learned features. The text highlights the importance of data-driven decision-making in the context of social media analysis.
Our application

Data

Twitter post

→ “…”
→ “…”
→ “…”

Feature Functions

Learning Based Java

Training Learning Algorithm

@… 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

Decision?
Our application

Twitter posts

→ “…”

→ “…”

→ “…”

@... 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

Decision?

Sentiment classifier: Negative

Learning Based Java

Train Learning Algorithm

Feature Functions

Data

LBJava-Tutorial
What is Learning Based Java?
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- A modeling language for learning and inference
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- A modeling language for learning and inference
- Supports
  - Programming using learned models
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  - High level specification of features and constraints between classifiers
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- Learning
  - Classifiers are functions defined in terms of data
What is **Learning Based Java**?

- A modeling language for learning and inference

- **Supports**
  - Programming using learned models
  - High level specification of features and constraints between classifiers
  - Inference with constraints

- **Learning**
  - Classifiers are functions defined in terms of data
  - Learning can happen at compile time
What does LBJava do for you?
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- Abstracts away the feature representation, learning and inference
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- Allows you to write learning based programs
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- Abstracts away the feature representation, learning and inference
- Allows you to write learning based programs
- Application developers can reason about the application at hand
Conference attendees to the 1994 Machine Learning conference were given name badges labeled with + or −.

What function was used to assign these labels?
Why use learning?

We typically use machine learning when the function $f(x)$ we want the system to apply is too complex to program by hand.
Demo1: What’s X for the Badges game?

Possible features:
- Gender/age/country of the person?
- Length of their first or last name?
- Does the name contain letter ‘x’?
- How many vowels does their name contain?
- Is the n-th letter a vowel?

Model this in LBJava, using the following features:
- use the type of the characters in the first 5 positions of name
- use the type of the characters in first 5 positions of the family name.
Demo1: What’s $X$ for the Badges game?

Possible features:
- Gender/age/country of the person?
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- Is the n-th letter a vowel?

Model this in LBJava, using the following features:

For example:
first-character-of-first-name-is-a
first-character-of-first-name-is-b ...
second-character-of-first-name-is-a, ...
Running on linux machine

Step 1: Compile Java code (Readers etc.)
- Need Java version 7 or higher

$ javac -cp "lib/*" -d bin *.java

Step 2: Compile (and train) the LBJava code

$ java -cp "lib/*:bin"
edu.illinois.cs.cogcomp.lbjava.Main -d bin
classifier.lbj
The spam classifier

1. The features
2. The classifier
3. Compiling to train the classifier
Demo2: Spam/noSpam

Don’t LOOK like a spammer!
here are some words to stay away from.

Image courtesy of http://www.wordle.net
Demo2: Spam/noSpam

How a spam looks like? Features!
How a spam looks like? Features!

• Let us simply use features based on occurring words or maybe word frequencies.
How a spam looks like? Features!

- Let us simply use features based on occurring words or maybe word frequencies.
- Write our features and learners using Lbjava.
Demo3: Prediction of Drug Response for Cancer Patients

Input

Patient name
age, race, ...

gene1_Experimental result
gene2_Experimental result
...
genen_Experimental result

Output

If Patient X will response to Drug Y

Drug response is measured and reported as a real value but we can use a threshold and convert it to a binary decision of positive and negative response here.
Exercise

- Tweeter sentiment classification
  - [http://l2r.cs.uiuc.edu/~danr/Teaching/CS446-15/readme-twitter.txt](http://l2r.cs.uiuc.edu/~danr/Teaching/CS446-15/readme-twitter.txt)

- Train a classifier on annotated examples

- Predict sentiment of tweets in real time!
  - Filter by location, search terms, language, etc.
Links

- LBJava Software:
  http://cogcomp.cs.illinois.edu/page/software_view/LBJava

- LBJava Manual:

- Tutorial 2013 code and examples, step by step:
  http://cogcomp.cs.illinois.edu/page/tutorial.201310
See you next time!
See you next time!

Parameter tuning
See you next time!

Parameter tuning

Designing more complex models
See you next time!

Parameter tuning

Designing more complex models

Pipelines
See you next time!

Parameter tuning

Designing more complex models

Inference and Constraints

Pipelines