Cognitive Computation Group
University of Illinois at Urbana-Champaign

# Learning Based Programming:

## Facilitating the Programming of Data Driven Software Systems

Dan Roth

Department of Computer Science

University of Illinois at Urbana—Champaign

**June 2014**
**ICML AutoML Workshop**

Cognitive Computation Group
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With thanks to:

Collaborators: **Nick Rizzolo, Ming-Wei Chang, Kai-Wei Chang, Scott Yih, Parisa Kordjamshidi; Many others**

Funding: NSF; DHS; NIH; DARPA; IARPA, ARL, ONR
DASH Optimization (Xpress-MP); Gurobi.

# A Hypothetical Surveillance Program

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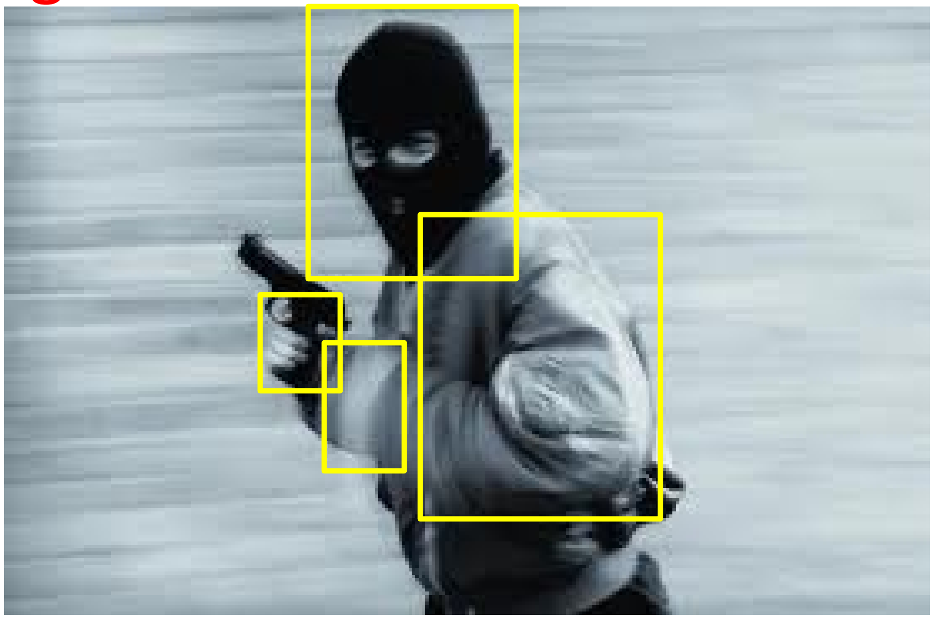
All hard problems

All just predicates
that break problem down

# Common Approach: Breaking it Down

- Person detection:
  - **Detect head**
  - **Detect arms**
  - **Detect hands**
  - **Detect legs**



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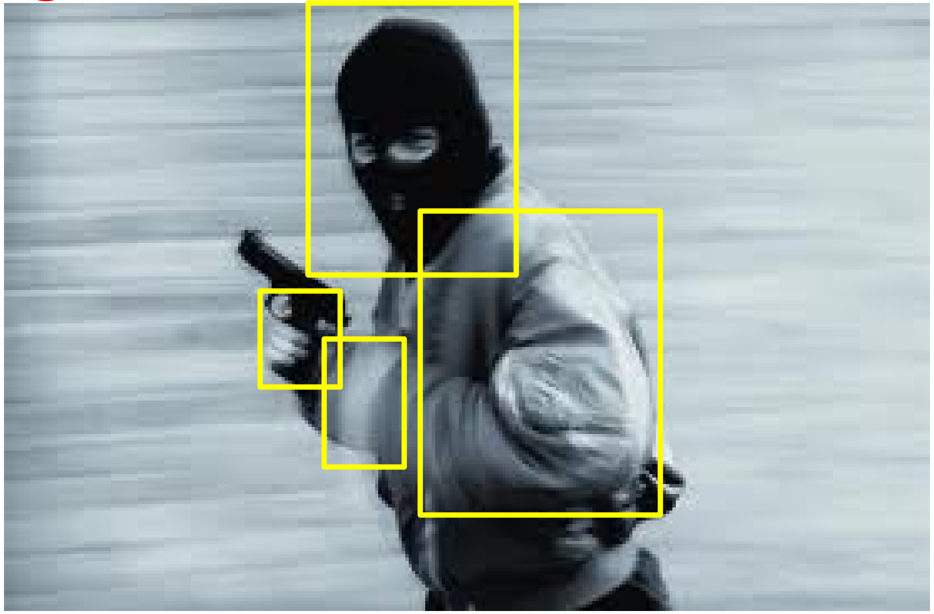

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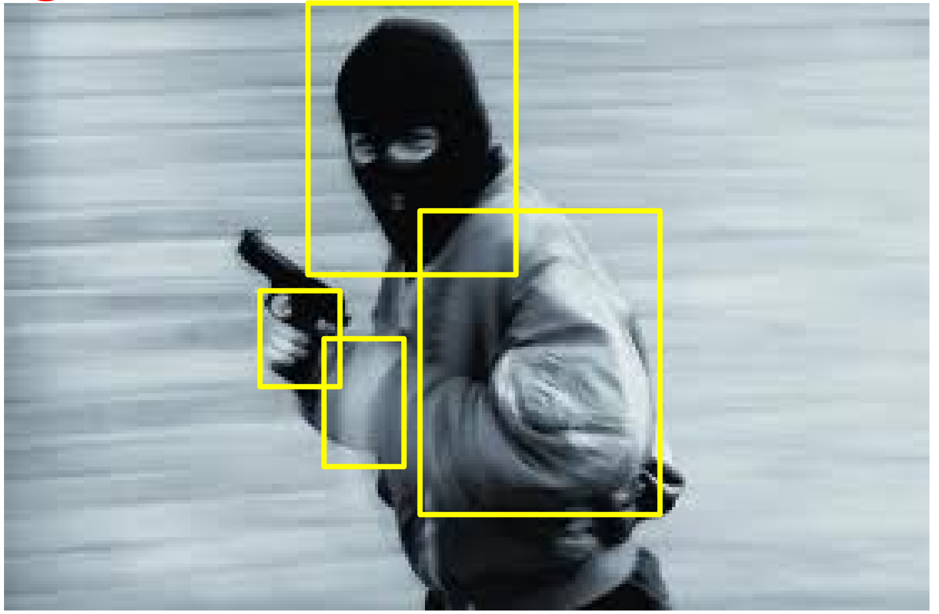

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    - ***Functions defined via data***
- A PhD Thesis…
- Download some libraries
  - **Learning algorithms**
  - **Inference algorithms**
  - **Other researchers' detectors**
- Write some feature extractors
- Write some scripts to run everything

# A (Realistic) Knowledge Management Program

```
Corpus c = ReadCollection()
List   LikedPeople = ReadPeople()
List   DisLikedBPeople = ReadPeople()
for (Email e in c):
      for (Person p in body(e)):
            Like = isLike(p)
            if Like and (not in LikedPeople)
                  LikedPeople +v p
            if (not Like) and (not in DisLikedPeople)
                  DisLikedPeople +v p
Update Likedpeople, DisLikedPeople
```

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# Discriminative Example: Semantic Role Labeling

[Punyakanok, et.al., CL'08]

**I *left* my pearls to my daughter in my will .**

**[I]$_{A0}$ *left* [my pearls]$_{A1}$ [to my daughter]$_{A2}$ [in my will]$_{AM\text{-}LOC}$ .**

- ***A0*** Leaver
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# Our Learning Based Programming Thesis

- Existing programming languages are not designed to deal with real-world messy data, and to describe the central components of modern learning-based programs:
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- Present the Constrained Conditional Model (CCM), a computation model for learning and inference that is
  - **Expressive enough to capture a large class of problems**
  - **Provides the abstraction for our language**

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- Present the Constrained Conditional Model (CCM), a computation model for learning and inference that is
  - **Expressive enough to capture a large class of problems**
  - **Provides the abstraction for our language**
- Demonstrate 2 CCM-based LBP languages that compile their efficient implementation from data.
  - **LBJava http://cogcomp.cs.illinois.edu/page/software_view/11**
  - **Our 2nd generation language, CCMP**

# Principles of Learning Based Programming

- An LBP language provides:
  - **High level primitives**
    - **for feature extraction, learning, inference, and their combinations**
  - **Relational features (a.k.a. *structure*)**
    - **Features involving multiple output variables**
  - **Infinite feature space**
    - **Cannot assume a priori how many or which features will be present**
  - **Customizable objective function**
    - **Model can't be a black box**

# Principles of Learning Based Programming (2)

- An LBP language provides:
  - **Model composability**
    - **Encapsulate model in a name; re-use in larger models**
  - **Training & Inference decomposability**
    - **Facilitate tailored inference solutions via access to structure**
    - **In particular, support of reusability of models, pipelines, etc.**
  - **Algorithm independence**

# Roadmap

- Introduction
  - **Desiderata**
- Constrained Conditional Models
  - **A general, discriminative inference framework**
- Learning Based Java
  - **A discriminative modeling language**
- CCMP: Constraint Conditional Model Processing Language
  - **LBP with structure**
  - **Developing flexible programs over models**
    - **Example**
    - **Program structure: all you need is the paper…**

# Constrained Conditional Models [Roth & Yih ‘04, 07; Chang, et.al.,’08,’12]

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- Prediction function: assign values that maximize objective

$$f(\mathbf{x}) = \operatorname*{argmax}_{\mathbf{y} \in \mathcal{Y}(\mathbf{x})} z(\mathbf{x}, \mathbf{y})$$

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- Objective is linear in features and constraints

$$z(\mathbf{x}, \mathbf{y}) = \left( \sum_{i=1}^{n_\phi} w_i \phi_i(\mathbf{x}, \mathbf{y}) \right) - \left( \sum_{j=1}^{n_c} \rho_j c_j(\mathbf{x}, \mathbf{y}) \right)$$

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- Accommodates both probabilistic *and* discriminative techniques

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- Any discrete MPE problem can be formulated this way.
- Solution: Use ILP packages for an exact solution; Cutting Planes, Dual Decomposition & other search techniques for approximate solutions

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## Learning

- Training is learning the objective function
- **Decoupling** Left from Right allows incorporating independently trained models, pipelines, etc.
- Model decomposition facilitates more flexible and efficient computation.

# Examples: CCM Formulations

$$\underset{y}{\operatorname{argmax}}\, \boldsymbol{\lambda} \cdot F(x, y) - \sum_{i=1}^{K} \rho_i d(y, 1_{C_i(x)})$$

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Formulate NLP Problems as ILP problems (inference may be done otherwise)

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**Sequential Prediction**

HMM/CRF based:

Argmax $\sum \lambda_{ij} x_{ij}$

**Linguistics Constraints**

Cannot have both A states and B states in an output sequence.

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Sentence Compression/Summarization:

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Constrained Conditional Models Allow:

- Learning a simple model (or multiple; or pipelines)
- Make decisions with a more complex model
- Accomplished by directly incorporating constraints to bias/re-rank global decisions composed of simpler models' decisions
- More sophisticated algorithmic approaches exist to bias the output
  [CoDL: Cheng et. al 07,12; PR: Ganchev et. al. 10; DecL, UEM: Samdani et. al 12]

# Discriminative Example: Semantic Role Labeling

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# SRL: Discriminative Decomposition

- Identify argument candidates
  - Pruning Heuristics
  - Argument Identifier
    - Binary classification
- Classify argument candidates
  - Multi-class classification
  - Can choose to "trust" output of identifier
- Inference
  - Use the estimated probability distribution given by the argument classifier
  - Use structural and linguistic constraints
  - Infer the optimal global output

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candidate arguments

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$$\phi_i^F(\mathbf{x},\mathbf{y}) = \sum_{a=1}^{\mathcal{A}} y_a^F \ x_i^F$$

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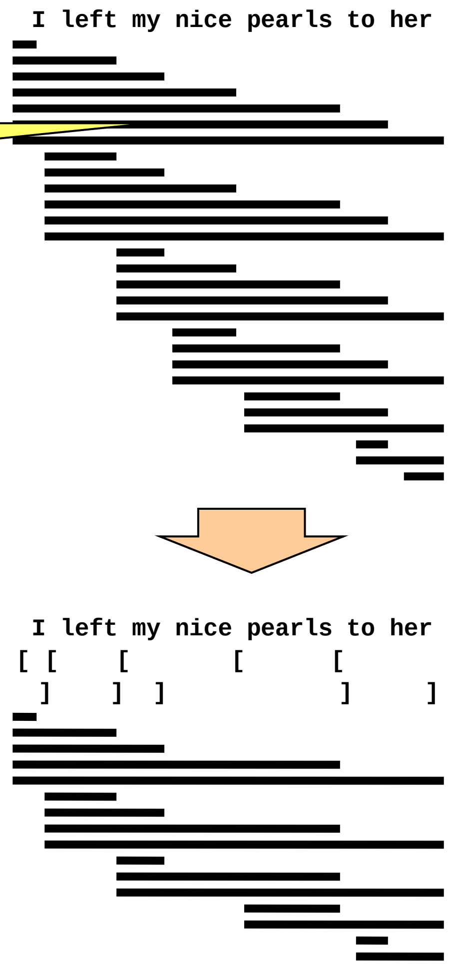

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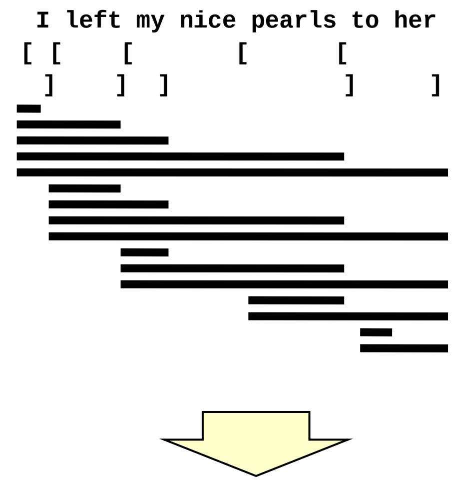


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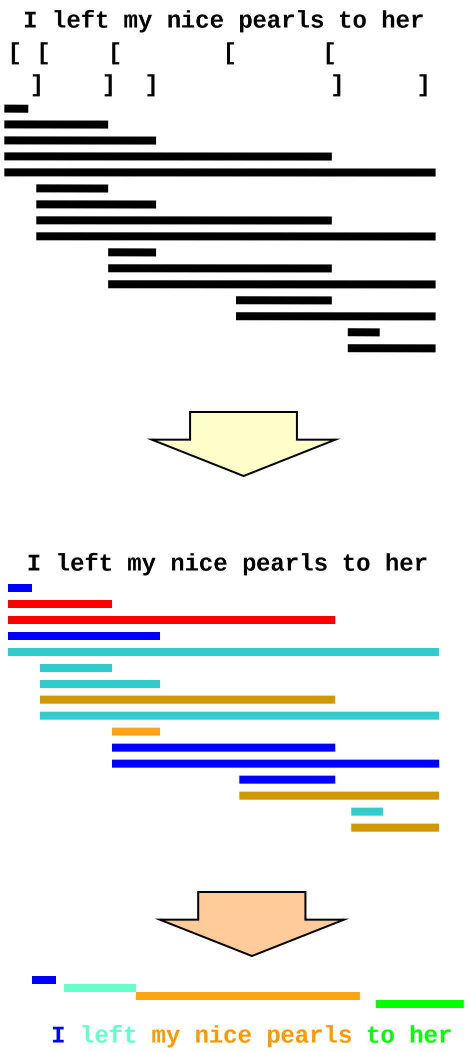

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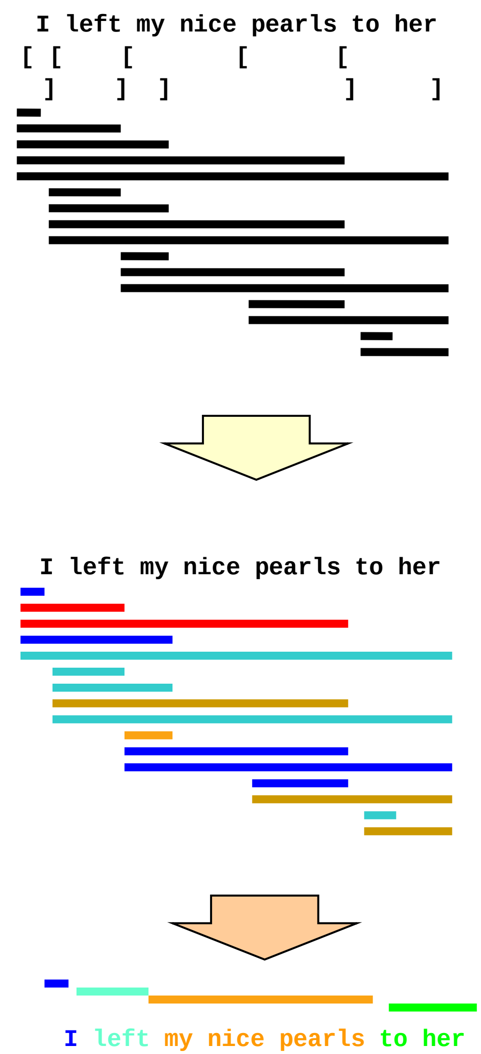
One inference problem for each verb predicate.



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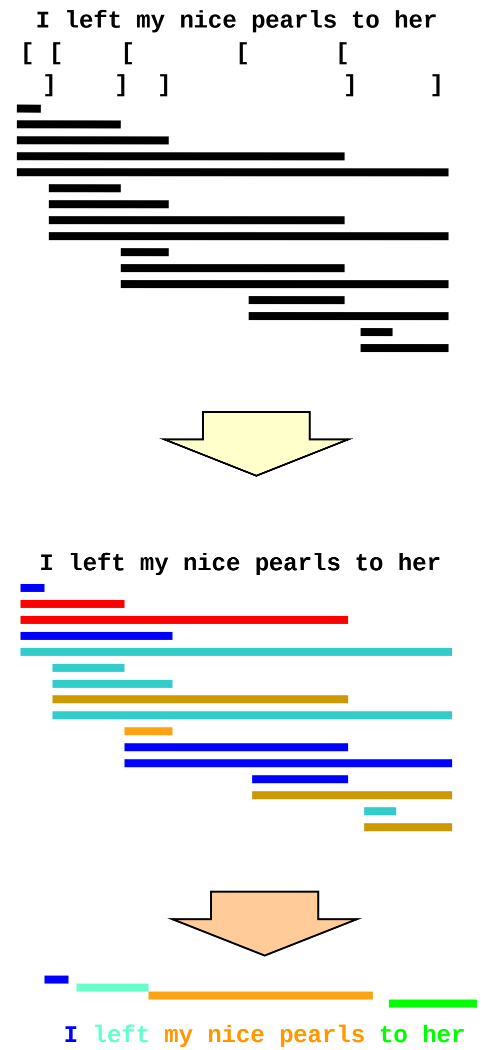
- argmax $\sum_{a,t} y^{a,t} c^{a,t} = \sum_{a,t} 1_{a=t}\, c_{a=t}$

  Subject to:
  - One label per argument: $\sum_{t} y^{a,t} = 1$
  - No overlapping or embedding
  - Relations between verbs and arguments,....



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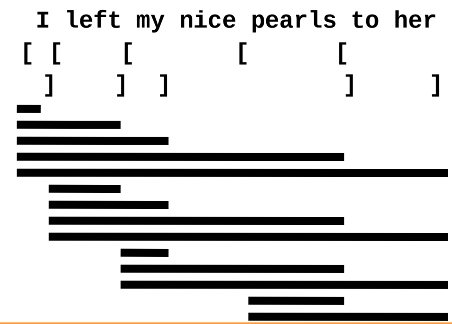


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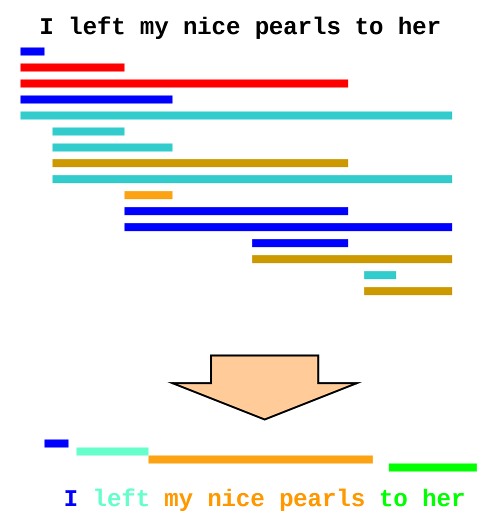
Variable $y^{a,t}$ indicates whether candidate argument $a$ is assigned a label $t$.
$c^{a,t}$ is the corresponding model score

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# SRL: Discriminative Decomp

No duplicate argument classes $\forall i, \sum_{y \in \mathcal{Y}} 1_{\{y_i = y\}} = 1$

Unique labels $\forall y \in \mathcal{Y}, \sum_{i=0}^{n-1} 1_{\{y_i = y\}} \le 1$

$$\forall y \in \mathcal{Y}_R, \sum_{i=0}^{n-1} 1_{\{y_i = y = \text{“R-Ax”}\}} \le \sum_{i=0}^{n-1} 1_{\{y_i = \text{“Ax”}\}}$$

$$\forall j, y \in \mathcal{Y}_C, 1_{\{y_j = y = \text{“C-Ax”}\}} \le \sum_{i=0}^{j} 1_{\{y_i = \text{“Ax”}\}}$$

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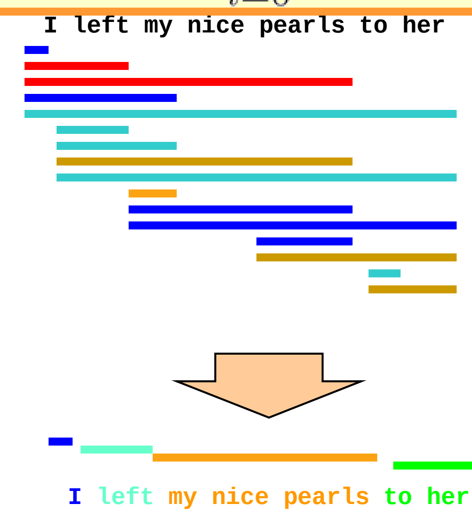

# SRL: Discriminative Decomposition

Learning Based Java: allows a developer to encode constraints in First Order Logic; these are compiled into linear inequalities automatically.

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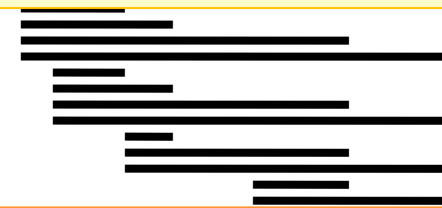

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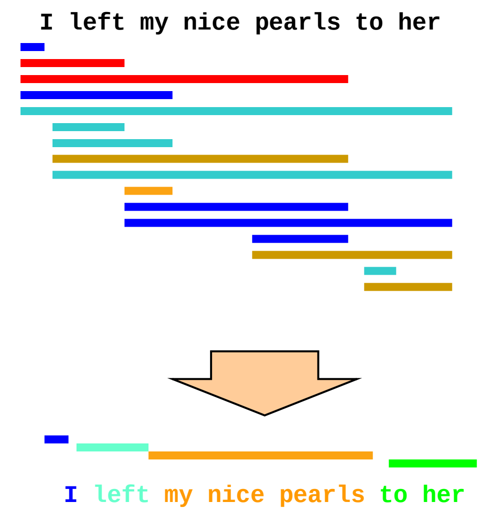
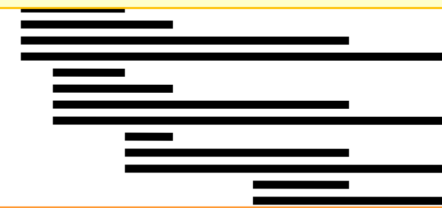
  - One label per argument: $\sum_t y^{a,t} = 1$
  - No overlapping or embedding
  - Relations between verbs and arguments,….



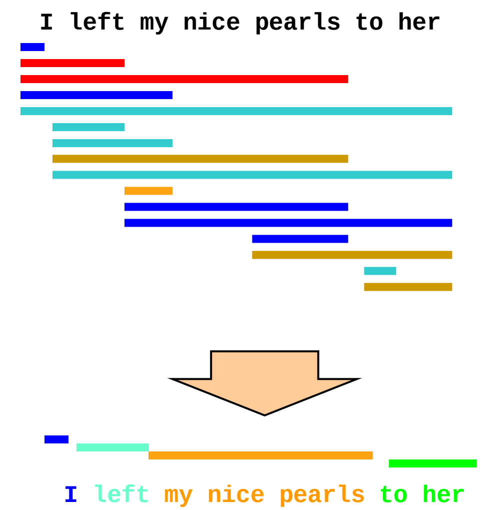
# SRL: Discriminative Decomposition

Learning Based Java: allows a developer to encode constraints in First Order Logic; these are compiled into linear inequalities automatically.

- Identify argument candidates
  - **Pruning Heuristics**
  - **Argument Identifier**
    - **Binary classification**
- Classify argument candidates
  - **Multi-class classification**
  - **Can choose to "trust" output of identifier**



Variable $y^{a,t}$ indicates whether candidate argument $a$ is assigned a label $t$.
$c^{a,t}$ is the corresponding model score

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  - Relations between verbs and arguments,….

Use the **pipeline architecture's simplicity** while **maintaining uncertainty**: keep probability distributions over decisions & use global inference at decision time.

# Constrained Conditional Models—ILP Formulations

- **Have been shown useful in the context of many NLP problems**
- [Roth&Yih, 04,07: Entities and Relations; Punyakanok et. al: SRL …]
  - **Summarization; Co-reference; Information & Relation Extraction; Event Identifications and causality ; Transliteration; Textual Entailment; Knowledge Acquisition; Sentiments; Temporal Reasoning, Parsing,…**
- Some theoretical work on training paradigms [Punyakanok et. al., 05 more; Constraints Driven Learning, PR, Constrained EM…]
- Some work on Inference, mostly approximations, bringing back ideas on Lagrangian relaxation, etc.

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- Some work on Inference, mostly approximations, bringing back ideas on Lagrangian relaxation, etc.
- Good summary and description of training paradigms
  - **[Chang, Ratinov & Roth, Machine Learning Journal 2012]**
- **Summary of work & a bibliography: http://L2R.cs.uiuc.edu/tutorials.html**

# Roadmap

- Introduction
  - **Desiderata**
- Constrained Conditional Models
  - **A general, discriminative inference framework**
- Learning Based Java
  - **A discriminative modeling language**
- CCMP: Constraint Conditional Model Processing Language
  - **LBP with structure**
  - **Developing flexible programs over models**
    - **Example**
    - **Program structure: all you need is the paper…**

# Learning Based Java [Rizzolo & Roth, ICSC'07, LREC'10]

- LBP design principles:
  - **High level primitives**
  - **Relational features**
  - **Infinite feature space**
  - **Customizable objective function**
  - **Model composability**
  - **Inference decomposability** *(not flexible enough)*
  - **Algorithm independence** *(learning; not inference)*

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# Learning Based Java [Rizzolo & Roth, ICSC'07]

- Describes a particular type of CCM
  - **Collection of (optionally normalized) multi-class CCMs**
  - **User-defined feature functions**

$$\mathbf{y}_k \equiv \{y_t \mid t \in \mathcal{T}_k,\ y_t \in \{0,1\}\}$$

$$z_k(\mathbf{x},\mathbf{y}) = \left(\sum_{t \in \mathcal{T}_k} \sigma_k(\mathbf{w}_t, \Phi_k(\mathbf{x}))y_t\right) - \infty\, c_k^D(\mathbf{x},\mathbf{y})$$

$$\sigma_k(\mathbf{w},\mathbf{x}) = g_k(\mathbf{w} \cdot \mathbf{x})$$

  - **User-defined constraints (only hard constraints)**
- How to represent constraints / perform inference?
  - **First order logic → translate to ILP**
- How to integrate with user's application?

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# Example: Semantic Role Labeling

```
discrete{false, true} ArgumentIdentifier(Argument a) <-
learn ArgumentIdentifierLabel
  using CandidateFeatures,
        PredicatePOS && PhraseType, PredicatePOS && HeadWordAndTag,
        PredicatePOS && ParsePosition, VerbNegated && LinearPosition,
        VerbNegated && Path, ContainsModal && LinearPosition,
        ContainsModal && Path
  with new SparseAveragedPerceptron(.1, 0, 4)
  from new FilterParser(Constants.chunkTrainingData) 50 rounds
end
```

- Classifiers take user's objects as input; produce features
  - **Can be hard-coded or learned**
  - **Learned classifiers use other classifiers to extract features**
    - **Those can be learned too: model composability**
- LBJava compiler:
  - **Indexes features for fast training / testing**
  - **Generates a Java class for every classifier**

# Constraints

```
constraint References(SRLSentence sentence)
{
  for (int i = 0; i < sentence.verbCount(); ++i)
  {
    ParseTreeWord verb = sentence.getVerb(i);
    LinkedList forVerb = sentence.getCandidates(verb);

    (exists (Argument a in forVerb) ArgumentTypeLearner(a) :: "R-A0")
      => (exists (Argument a in forVerb) ArgumentTypeLearner(a) :: "A0");
    (exists (Argument a in forVerb) ArgumentTypeLearner(a) :: "R-A1")
      => (exists (Argument a in forVerb) ArgumentTypeLearner(a) :: "A1");
```

$$(\exists a \in \mathcal{A},\ y_{a,\text{“R-A0”}}) \Rightarrow (\exists a \in \mathcal{A},\ y_{a,\text{“A0”}})$$

“If there’s a reference to an A0, there must be an A0.”

- Declarative, FOL-style constraints
  - **Learned classifiers appear as functions**
  - **Applied directly over user’s Java objects**
  - **Interspersed with arbitrary Java code**
  - **New quantifiers: `atleast` and `atmost`**

# Inference Problems

```
inference SRLInference head SRLSentence sentence
{
  Argument a      { return a.getConstituent().getSentence(); }
  ParseTreeWord w { return w.getSentence(); }
  subjectto
  {
     @NoOverlaps(sentence) /\ @NoDuplicates(sentence) /\ @VA1CV(sentence)
       /\ @References(sentence) /\ @Continuences(sentence)
       /\ @LegalArguments(sentence);
  }
  with new GLPK()
}

discrete ArgumentType(Argument a) <- SRLInference(ArgumentTypeLearner)
```

- "Head" object represents entire inference problem
- At run-time
  - **Constraints translated to linear inequalities**
  - **ILP inference solves problem**
    - **Used broadly in NLP applications**

# LBJava: Success Stories

- Multiple state-of-the-art Natural Language Processing Tools
  - **Part-of-speech tagger; Named Entity Recognition**
  - **Co-Reference Resolution; Relation and Event Extraction,…**
  - **Recognizing authority in dialogue [Mayfield & Rose, ACL'11]**

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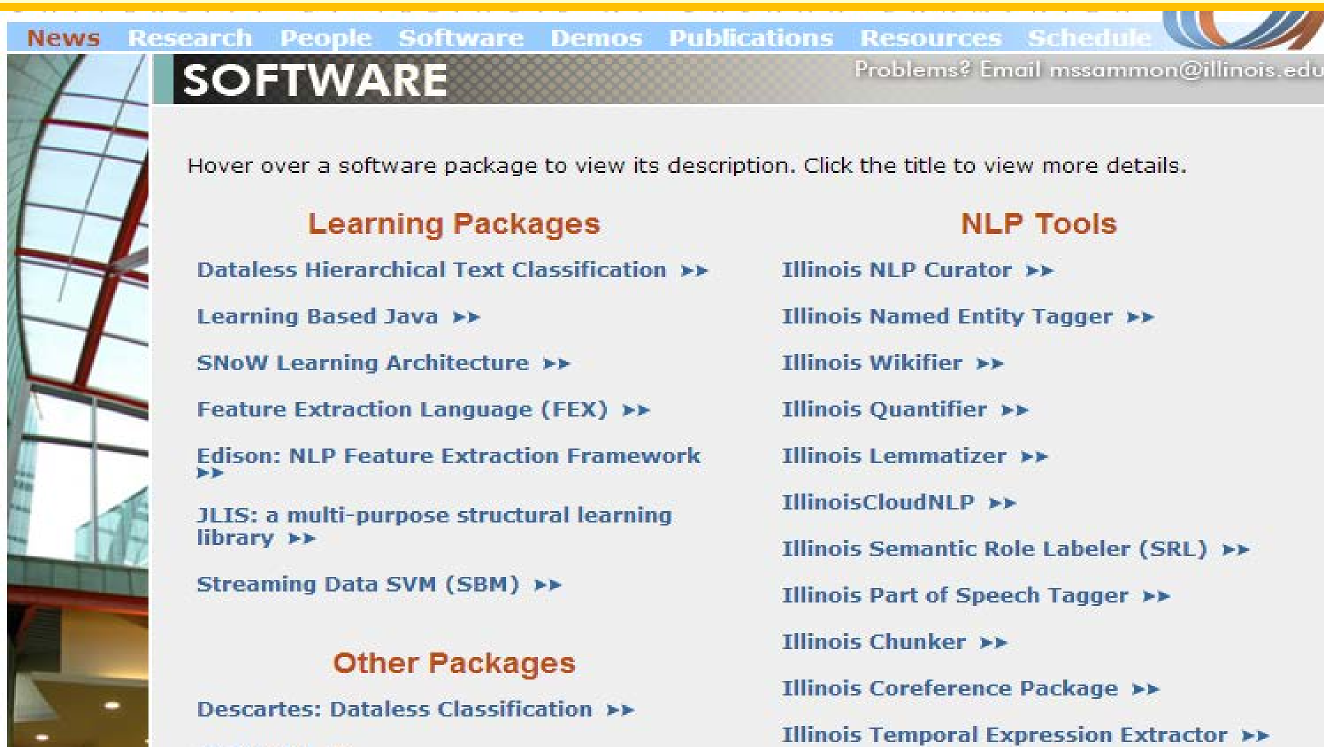

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# 2nd Generation: From LBJava to CCMP

- What's missing?

- Expressivity:
  - **Structures over output variables**

- Ease of use: from paper to program
  - **Declarative definition of models**
    - **Declarative ways to define training and inference preferences**
  - **Procedural building of an application**

# Constrained Conditional Model Processing (CCMP)

- General purpose language; Turing complete
- Fully supports CCMs
- Modular design, decomposed and reusable models
- Flexible and expressive training and inference paradigms
- LBP design principles:
  - **High level primitives**
  - **Relational features**
  - **Infinite feature space**
  - **Customizable objective function**
  - **Model composability**
  - **Inference decomposability**
  - **Algorithm independence**

# CCMP's Unified Formalism

- *Features*, *sparse vectors*, *examples*, and *models* are all primitive data types.
- Provided operators break them down and build them up.
- Models are modular
  - **Previously learned models can be imported, constrained, etc.**
  - **Instances store**
    - **learned parameters**
    - **feature functions**
    - **pointers to other models**
- *Supports a variety of learning and inference protocols*

# From Paper* to Program

- The goal of CCMP is to (almost) automatically generate a program from the application/model described in your paper
- Some code is generated automatically
  - **But can be modified by the programmer**

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Information crucial to the development of an application is often omitted; CCMP abstractions reveal these gaps.

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- The program has five components:
  - **Data**
  - **Y Space Definition  (the variables you want to assign values to)**
  - **Representation (features; constraints)**
  - **Prediction (inference) Paradigm**
  - **Training Paradigm**

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- Decoupling decision time prediction and training facilitates reusable models, various decompositions, and pipelines

# Recognizing Entities and Relations [Roth&Yih'04,07]

$\boxed{\text{Dole}}$ 's wife, $\boxed{\text{Elizabeth}}$ , is a native of $\boxed{\text{N.C.}}$

$$E_1 \xrightarrow[R_{12}]{} E_2 \xrightarrow[R_{23}]{} E_3$$

# Recognizing Entities and Relations [Roth&Yih'04,07]

| | |
|---|---|
| other | 0.05 |
| per | 0.85 |
| loc | 0.10 |

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

# Prediction Paradigms

$$\min \sum_{E\in\mathcal{E}} \sum_{e\in\mathcal{L}_\mathcal{E}} c_E(e)\cdot x_{\{E,e\}} + \sum_{R\in\mathcal{R}} \sum_{r\in\mathcal{L}_\mathcal{R}} c_R(r)\cdot x_{\{R,r\}}$$

$$+ \sum_{\substack{E_i,E_j\in\mathcal{E}\\ E_i\neq E_j}} \left[ \sum_{r\in\mathcal{L}_\mathcal{R}} \sum_{e_1\in\mathcal{L}_\mathcal{E}} d^1(r,e_1)\cdot x_{\{R_{ij},r,E_i,e_1\}} + \sum_{r\in\mathcal{L}_\mathcal{R}} \sum_{e_2\in\mathcal{L}_\mathcal{E}} d^2(r,e_2)\cdot x_{\{R_{ij},r,E_j,e_2\}} \right]$$

subject to:

$$\sum_{e\in\mathcal{L}_\mathcal{E}} x_{\{E,e\}} = 1 \qquad \forall E\in\mathcal{E} \tag{2}$$

$$\sum_{r\in\mathcal{L}_\mathcal{R}} x_{\{R,r\}} = 1 \qquad \forall R\in\mathcal{R} \tag{3}$$

$$x_{\{E,e\}} = \sum_{r\in\mathcal{L}_\mathcal{R}} x_{\{R,r,E,e\}} \qquad \forall E\in\mathcal{E} \text{ and } \forall R\in\{R: E=\mathcal{N}^1(R) \text{ or } R: E=\mathcal{N}^2(R)\} \tag{4}$$

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# Prediction Paradigms

Variable indicating E takes value e.

Variable indicating R takes value r.

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Model weight

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Constraint weight

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$$\min \sum_{E\in\mathcal{E}}\sum_{e\in\mathcal{L}_{\mathcal{E}}} c_E(e)\cdot x_{\{E,e\}} + \sum_{R\in\mathcal{R}}\sum_{r\in\mathcal{L}_{\mathcal{R}}} c_R(r)\cdot x_{\{R,r\}}$$

Model weight

$$+ \sum_{\substack{E_i,E_j\in\mathcal{E}\\ E_i\neq E_j}} \left[\sum_{r\in\mathcal{L}_{\mathcal{R}}}\sum_{e_1\in\mathcal{L}_{\mathcal{E}}} d^1(r,e_1)\cdot x_{\{R_{ij},r,E_i,e_1\}} + \sum_{r\in\mathcal{L}_{\mathcal{R}}}\sum_{e_2\in\mathcal{L}_{\mathcal{E}}} d^2(r,e_2)\cdot x_{\{R_{ij},r,E_j,e_2\}}\right]$$

Constraint weight

Variable relating E and R

subject to:

$$\sum_{e\in\mathcal{L}_{\mathcal{E}}} x_{\{E,e\}} = 1 \qquad \forall E\in\mathcal{E} \tag{2}$$

$$\sum_{r\in\mathcal{L}_{\mathcal{R}}} x_{\{R,r\}} = 1 \qquad \forall R\in\mathcal{R} \tag{3}$$

$$x_{\{E,e\}} = \sum_{r\in\mathcal{L}_{\mathcal{R}}} x_{\{R,r,E,e\}} \qquad \forall E\in\mathcal{E} \text{ and } \forall R\in\{R: E=\mathcal{N}^1(R) \text{ or } R: E=\mathcal{N}^2(R)\} \tag{4}$$

$$x_{\{R,r\}} = \sum_{e\in\mathcal{L}_{\mathcal{E}}} x_{\{R,r,E,e\}} \qquad \forall R\in\mathcal{R} \text{ and } \forall E=\mathcal{N}^1(R) \text{ or } E=\mathcal{N}^2(R) \tag{5}$$

Consistency Constraints

$$x_{\{E,e\}} \in \{0,1\} \qquad \forall E\in\mathcal{E}, e\in\mathcal{L}_{\mathcal{E}} \tag{6}$$

$$x_{\{R,r\}} \in \{0,1\} \qquad \forall R\in\mathcal{R}, r\in\mathcal{L}_{\mathcal{R}} \tag{7}$$

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# CCMP: Declarative Specification of Problem and Solution

- 1. Data
  - **Readers into CCMP data structures; Edison for NLP**
- 2. Defining the output space (Y)
  - **The variables we need to assign values to**
  - **Y = { Entity(Phrase) $\in$ {PER, LOC, ORG} ;**
  - **Relation(Phrase, Phrase) $\in$ {LivesIn, WorksFor } }**
- 3. Representation
  - **Features and Constraints**
  - **Most are generated automatically, but can be modified**
- 4. Learning
  - **Defining the decomposition in Training**
- 5. Inference
  - **Decision Time Prediction**

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**The ability to define Learning and Inference paradigm independently is key in CCMP**

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- $\sum_e W_e X_e + \sum_r W_r X_r$
- Subject to
  - $X_{r=LivesIn} \rightarrow X_{e1=PER}$
  - ....

# Inference Paradigms

- There are multiple ways to assign values to target variables

- {E(Phrase)}; {R(Phrase, Phrase)}
  - **Mode decisions with respect to individual variables.**

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```
//Here is default input structure
  Corpus(id:Corpus)
  Document(id1:Document,id2:Corpus)
  Paragraph(id1:Paragraph,id2:Document)
  Sentence(id1:Sentence,id2:Paragraph)
  Phrase(id1:Phrase,id2:Word)
```

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//Here is default output definition

// Entity Aux Variables

$E_i = \{B_i, I_i, L_i, U_i, O\}$

// Phrase Construction Procedure:

Phrase = BIOLU(S)

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//Here is default FEX
Lexical-form(id:phrase,[0,1])
parse-path(id1:phrase,id2:after(id1))
…..

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# CCMP Also Provides Low Level Access

- Access to vector "slices" and individual elements
- Access to FGFs, constraints, and sub-models
  - **Enables learning and inference that was hard or impossible in LBJava**

- Break an FGF down to see operators and sub-formulae
  - **Enables translation to ILP**
  - **Will be useful for other inference algorithms as well**

# CCMP Status: 1st prototype define via Maude & K

- Maude: a language of *rewriting logic* [Meseguer, '92]
  - **Define logical functions and rewrite rules**
  - **Functions represent language syntax; rules give the semantics**
  - **Terms are programs + input; Maude deduces the output**
  - ***Executional semantics***
- K: semantics via *continuations* [Rosu & Serbanuta, '10]
  - **Arrange program state into a *configuration* of *cells***
  - **Arrange computation as stack of continuations**
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- Current version is being implemented in Scala

# Before Conclusion: Cloud NLP

[Wu et. al. LREC'14]

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**A related – save my time – effort**

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A related – save my time – effort

- Researcher as well as small/medium-sized organizations sometimes need to analyze large document collections.
- They want to apply a lot of rich Natural Language Processing (NLP) analytics to the document text, but
  - **They don't have expertise developing them**
  - **They may not have peak-time computing power**
  - **They may not have expertise and time to install 3rd party versions.**
- How do you make it really easy to periodically process large sets of documents with rich NLP analytics…
  - **…in a short time**
  - **…at reasonable cost**
  - **…with minimal local compute power?**
- (HINT: IllinoisCloudNLP)

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Illinois CloudNLP  (shortly on: http://cogcomp.cs.illinois.edu/page/software)

- **On-demand processing of large corpora**
- **Using state-of-the art Illinois NLP components**
- **Training and application of text classifiers**
- **Maximum user privacy & user control over data**
- **User runs client software from local machine**
- **Client software applies NLP analytics in the cloud**

# Conclusions

- Learning Based Programming
  - **LBP is the study of programming language abstractions for machine learning representations and techniques.**
  - **A platform for defining and combining decision making models.**
    - **Discriminative or probabilistic; Trained jointly or independently; Exact or approximate inference**
    - **All of these can be left to the programmer to decide**
- An LBP language makes the programmer's life easier
  - **Abstracts away details that distract from the main goal**
  - **Shortens the development cycle**
- Presented the case, and some details of two languages.
  - **LBJava: a mature, easy to use, language that supports learning individual models and joint inference at decision time**
  - **CCMP: an in development declarative language that support the whole LBP development cycle**

Thank You!

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