

Practical Learning Algorithms for Structured Prediction Models

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Dream:

Intelligent systems that are able to read, to see, to talk, and to answer questions. Hallo Welt! Hej Värld! Hello World! Ciao Modo ハローワールド! iOlá mundo!世界您好! Salut le Monde!



Personal assistant system

Google Sign in Translate × English Spanish French Chinese - detected ←. English Spanish Arabic Translate 阿拉伯聯合大公國(UAE)今天下令一個F- × United Arab Emirates (UAE) today ordered an 16戰機中隊進駐約旦,支援約旦空襲激進組 F-16 fighter squadron stationed in Jordan, to 織「伊斯蘭國」(IS)。 support Jordan raid militant group "Islamic State" (IS). Ä 🜒 🖉 ☆ ■ 🜒 Wrong? Ālābó liánhé dàgōngguó (UAE) jīntiān xiàling yīgè F-16 zhànjī zhōngduì jìnzhù yuēdàn, zhīyuán yuēdàn kōngxí jījin zůzhī 'yīsīlán guó'(IS).

Translation system

CAUTION WET FLOOR



Carefully Slide

Translate			
English Spanish French Chinese - detected *	+	English Spanish rabic 👻 Tran	slate
小心地滑	×	Carefully slide	
Ä () /		☆ 🔳 🐠	/ Wrong?
Xiǎoxīn dì huá			

CAUTION WET FLOOR



小心: 地滑: Slide Carefully Careful Landslip Wet Floor Take Care Smooth Caution

Translate			×
English Spanish French Chinese - detected -	+	English Spanish Arabic 🕶 Translate	
小心地滑	×	Carefully slide	
Ä •) /		☆ ≣ •)	/ Wrong?
Xiǎoxīn dì huá			

Q: [Chris] = [Mr. Robin] ?

Christopher Robin is alive and well. **He** is the same person that you read about in the book, Winnie the Pooh. As a boy, Chris ived in a pretty home called **Cotchfield Farm**. When **Chris** was three years old, **his father** wrote a poem about **him**. The poem was printed in a magazine for others to read. (Mr. Robin) then wrote a book

Slide modified from Dan Roth

Complex Decision Structure

Christopher Robin is alive and well. He is the same person that you read about in the book, Winnie the Pooh. As a boy, Chris ived in a pretty home called **Cotchfield Farm**. When **Chris** was three years old **his father** wrote a poem about him. The poem was printed in a magazine for others to read. (Mr. Robin) then wrote a book

Co-reference Resolution

Christopher Robin is alive and well. **He** is the same person that you read about in the book, Winnie the Pooh. As a boy, Chris lived in a pretty home called **Cotchfield Farm.** When **Chris** was three years old, **his father** wrote a poem about him. The poem was printed in a magazine for others to read. Mr. Robin then wrote a book

Scalability Issues



Robin is alive and well. He is the same per a coat you read about in the book, Winne the Pooh. As a bey, Chris lived in a pretty nome rabel cotorfield Farm. When Chris was uncertears old, his father wrote a poem about him. The poem was printed in a magazine for others to read. Mr. Robin then wrote a book

Large amount of data

Complex decision structure

Goal: Practical Machine Learning

[Modeling] Expressive and general formulations

[Algorithms] Principled and efficient

[Applications] Support many applications



- LIBLINEAR [ICML08, KDD 08, JMLR 08a, 10a, 10b, 10c]
- Implements our proposed learning algorithms
- Supports binary and multiclass classification Impact: > 60,000 downloads, > 2,600 citations in AI (AAAI, IJCAI), Data Mining (KDD, ICDM), Machine Learning (ICML, NIPS) Computer Vision (ICCV, CVPR), Information Retrieval (WWW, SIGIR), NLP (ACL, EMNLP), Multimedia (ACM-MM), HCI (UIST), System (CCS)



(Selective) Block Minimization [KDD 10, 11, TKDD 12]

Supports learning from large data and streaming data

KDD best paper (2010), Yahoo! KSC award (2011)



Latent Representation for KBs [EMNLP 13b,14]

Tensor methods for completing missing entries in KBs Applications: e.g., entity relation extraction, word relation extraction.



Structured Prediction Models [ECML 13a, 13b, ICML14, CoNLL 11,12, ECML 13a, AAAI15]

- Design tractable, principled, domain specific models
- Speedup general structured models



Structured Prediction

Assign values to a set of interdependent output variables

Task	Input	Output
Part-of-speech Tagging	They operate ships and banks.	Pronoun Verb Noun And Noun
Dependency Parsing	They operate ships and banks.	Root They operate ships and banks .
Segmentation		

Structured Prediction Models

- Learn a scoring function:
 Score (output y | input x, model w)
- Linear model: $S(\mathbf{y} \mid \mathbf{x}, \mathbf{w}) = \sum_i w_i \phi_i(\mathbf{x}, \mathbf{y})$
- Features: e.g., Verb-Noun, Mary-Noun



Features based on both input and output

Inference

- Find the best scoring output given the model argmax Score (output y | input x, model w)
- Output space is usually exponentially large
- Inference algorithms:
 - □ Specific: e.g., Viterbi (linear chain)
 - □ General: Integer linear programming (ILP)
 - Approximate inference algorithms:
 e.g., belief propagation, dual decomposition



Learning Structured Models

- Online, e.g., Structured Perceptron [Collins 02]
- Batch e.g., Structured SVM
 - Cutting plane: [Tsochantaridis+ 05, Joachims+ 09]
 - Dual Coordinate Descent: [Shevade+ 11, Chang+ 13]
 - □ Block-Coordinate Frank-Wolfe: [Lacoste-Julien+ 13]
 - □ Parallel Dual Coordinate Descent: [ECML 13a]



Outline

1. Applications:

Co-reference; ESL Grammar Correction; Word Relation;



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Co-reference Resolution

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Co-reference Resolution

[EMNLP 13a, ICML14, In submission]

Proposed a novel, principled, linguistically motivated model



Stanford
Chen+
Ours (2012)
Martschat+
Ours (2013)
Fernandes+
HOTCoref
Berkeley
Ours (2015)



Co-reference Resolution Demo





http://bit.ly/illinoisCoref



ESL Grammar Error Correction

[CoNLL 13, 14]

They believe that such situation must be avoided.

- × situation
- \checkmark a situation
- \checkmark situations
- × a situations

First place in CoNLL Shared tasks 13' 14'



Identifying Relations between Words

GRE antonym task (no context):

Which word is the opposite of adulterate?(a) renounce(b) forbid(c) purify(d) criticize(e) correct

- Look up in a thesaurus [Encarta]: 56%
- Our tensor method [EMNLP 13b]: 77% (the best result so far)
 Why?

□ Considers multiple word relations simultaneously

e.g., inanimate \leftarrow Ant \rightarrow alive \leftarrow Syn \rightarrow living



Word Relation Demo

http://bit.ly/wordRelation

MEASURE THE DECREE OF RELATION OF TWO	Words	
adulterate renounce -0.014		Word Relation Model
adulterate purify 0.781		WordSim (Wiki) WordSim (LA Times)
adulterate correct -0.004		WordSim (Encarta)
		WordSim (WordNet)
		PILSA (Original)
Antonym of ody	ltarata?	PILSA (S2Net)
Antonym of add	interate?	MRLSA (Antonym)
(a) renounce	-0.014	Voice Search Query
(a) renounce	-0.014	
(b) forbid	0.004	
	0.701	
(c) purify	0.781	
(d) anitiaira	0.004	×
	-0.004	
(e) correct	-0.010	

Outline

1. Applications:

Co-reference; ESL Grammar Correction; Word Relation;





Co-reference Resolution

Christopher Robin is alive and well. **He** is the same person that you read about in the book, Winnie the Pooh. As a boy, Chris lived in a pretty home called **Cotchfield Farm.** When **Chris** was three years old, his father wrote a poem about him. The poem was printed in a magazine for others to read. Mr. Robin then wrote a book



Co-reference Resolution

- Learn a pairwise similarity measure (local predictor)
 - Example features:
 - □ same sub-string?
 - positions in the paragraph
 - \Box other 30+ feature types
 - Key questions:
 - How to learn the similarity function
 - How to do clustering

Christopher Robipis alive and well. He is the same person that you read about in the book, Winnie the **Pooh**. As a **boy**, Chris lived in a pretty home called Cotchfield Farm. When Chris was three years old, his father wrote a poem about him. The poem was printed in a magazine for others to read. Mr. Robin then wrote a book



Decoupling Approach

A heuristic to learn the model [Soon+ 01, Bengtson+ 08, CoNLL11]
Decouple learning and inference:



Cluster based on this function



Decoupling Approach-Learning

As a boy, $Chris_1$ lived in a pretty home called CotchfieldFarm. When $Chris_2$ was three years old, his father₃ wrote a poem about him₄. The poem was printed in a magazine for others to read. Mr. Robin₅ then wrote a book

Positive Samples (Chris₁, him₄) (Chris₂, him₄) (Chris₁, Chris₂) (his father₃, Mr. Robin₅) Negative Samples (Chris₁, his father₃) (Chris₂, his father₃) (him₄, his father₃) (Chris₁, Mr. Robin₅) (Chris₂, Mr. Robin₅) (him₄, Mr. Robin₅)



[Bill Clinton], recently elected as the [President of the USA], has been invited by the [Russian President], [Vladin Putin], to visit [Russia]. [President Clinton] said that [he] looks forward to strengthening ties between [USA] and [Russia].



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[Soon+01, Bengtson+08, CoNLL11]

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Challenges

Decoupling may lose information

Christopher Robin is alive and well. He is the same person that you read about in the book, **Winnie the Pooh**. As a **boy**, **Chris** lived in a pretty home called **Cotchfield Farm**. When **Chris** was three years old, **his father** wrote a poem about **him**. The poem was printed in a magazine for others to read. **Mr. Robin** then wrote a book



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Challenges

In addition, we need world knowledge



Complexity: need an efficient algorithm
 Modeling: learn the metric while clustering
 Knowledge: augment with knowledge



Structured Learning Approach

Update the similarity function

Cluster based on this function.

Learn the similarity function while clustering



Attempt: All-Links Clustering

[Mccallum+ 03, CoNLL 11]

- Define a global scoring function: Attempt: using all within-cluster pairs:
 - □ Inference problem is too hard

Christopher Robin is alive and well. He is the same person that you read about in the book, Winnie the Pool. As a boy, Chris lived in a pretty home called Cotchfield Farm. When Chris was three years old, his father wrote a poem about him. The poem was printed in a magazine for others to read. Mr. Robin then wrote a book



Latent Left-Linking Model (L3M)

Score (a clustering C)

- = Score (the best left-linking forest that is consistent with C)
- $= \sum$ Score of edges in the forests

Christopher Robin is alive and well. **He** is the same person that you read about in the book, **Winnie the Poeh**. As a **hoy**, **Chris** lived in a pretty home called **Cotchfield Farm**. When **Chris** was three years old, **his father** wrote a poem about **him**. The poem was printed in a magazine for others to read. **Mr. Robin** then wrote a book

Linguistic Constraints

- Must-link constraints:
 - □E.g., SameProperName, ...
- Cannot-link constraints:
 - □E.g., ModifierMismatch, ...

[Bill Clinton], recently elected as the [President of the USA], has been invited by the [Russian President], [Vladimir Putin], to visit [Russia]. [President Clinton] said that [he] looks forward to strengthening ties between [USA] and [Russia].



Inference in L3M [ICML 14, EMNLP 13]

 Solved by a greedy algorithm or formulated as an Integer Linear Program (ILP)





Learning L3M (simplified version)[ICML 14, EMNLP 13a]

[Bill Clinton], recently elected as the [President of the USA], has been invited by the [Russian President], [Vladimir Putin], to visit [Russia]. [President Clinton] said that [he] looks forward to strengthening ties

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predicted forest

[Bill Clinton], recently elected as the [President of the USA], has been invited by the [Russian President], [Vladimir Putin], to visit [Russia]. [President Clinton] said that [he] looks forward to strengthening ties

between [USA] and [Russia].





Learning L3M (simplified version)[ICML 14, EMNLP 13a]



Loop until stopping condition is met: For each (x_i, y_i) pair: $\overline{y}, \overline{h} = \arg \max_{y,h} w^T \phi(x_i, y, h)$ $\mathbf{h}_i = \arg \max_h w^T \phi(x_i, y_i, h)$ $w \leftarrow w + \eta(\phi(x_i, y_i, h_i) - \phi(x_i, \overline{y}, \overline{h})), \eta$: learning rate



Extension: Probabilistic L3M

[ICML 14, EMNLP 13a]

Define a log-linear model

Pr [a clustering C] = \sum Pr [forests that are consistent with C] = $\sum \sum$ Pr [edges in the forest]

 $\Pr\left[\text{edge}\right] \sim \Pr\left[\sum_{j \in e} \exp(\mathbf{w} \cdot \phi(i, j) / \gamma)\right] \quad (^{\circ}: \text{a parameter})$

Regularized Maximum Likelihood Estimation:

$$\min_{\mathbf{w}} LL(\mathbf{w}) = \beta ||\mathbf{w}||^2 + \sum_d \log Z_d(\mathbf{w})$$
$$- \sum_d \sum_i \log(\sum_{j < i} \exp(\mathbf{w} \cdot \phi(i, j) / \gamma) C_d(i, j))$$



Coreference: OntoNotes-5.0 (with gold mentions)





Latent Left-Linking Model (L3M)

Advantages:

- Complexity: Very efficient
- Modeling: Learn the metric while clustering
- Knowledge: Easy to incorporate constraints (must-link or cannot-link)

Can be applied to other supervised clustering problems! e.g., the posts in a forum, error reports from users ...

Outline





Learning Structured Models

- Online, e.g., Structured Perceptron [Collins 02]
- Batch e.g., Structured SVM
 - Cutting plane: [Tsochantaridis+ 05, Joachims+ 09]
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Redundancy in Learning Phase

[AAAI 15]

Recognizing Entities and Relations Task





Redundancy of Solutions[Kundu+13]

S1	POS	POS	S2
He	Pronoun	Pronoun	She
is	VerbZ	VerbZ	is
reading	VerbG	VerbG	watching
a	Det	Det	a
book	Noun	Noun	movie

Although the inference problems are different, their solutions might be the same



Fewer Inference Calls [AAAI 15]

Recognizing Entities and Relations Task

Obtain the same model with fewer inference calls





Learning with Amortized Inference

- A general inference framework
 - ... to represent inference problems
- A condition
 - ... to check if two problems have the same solution

If CONDITION (problem <i>cache, new proble</i>	<i>∋m)</i>		
then (no need to call the solver)	0.04 ms		
SOLUTION (<i>new problem</i>) = old solut	ion		
Else			
Call base solver and update <i>cache</i>			
End 2 ms			



A General Inference Framework

Integer Linear Programming (ILP) $\arg \max_{y} \sum_{c} S_{c} y_{c} \quad s.t \quad Ay \leq b; \ y_{c} \in \{0,1\}$

- Widely used in NLP & Vision tasks [Roth+04]
 E.g., Dependency Parsing, Sentence Compression
- Any MAP problem w.r.t. any probabilistic model, can be formulated as an ILP [Roth+ 04, Sontag 10]
- Only used for verifying amortized conditions



Amortized Inference Theorem[Kundu+13]

- Theorem 1: If the following conditions are satisfied
 - 1. Same # variables & same constraints

2.
$$\forall i$$
, $(2x_{p,i}^* - 1)(c_{Q,i} - c_{P,i}) \ge 0$

(The solution is not sensitive to the changes of the coefficients.)

then the optimal solution of Q is x_p^*

- x_P^* : the solution to P
- **c**: the coefficients of ILPs



Amortized Inference Theorem[Kundu+13]

Theorem 1: If the following conditions are satisfied

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Amortized Inference Theorem[Kundu+13]

Theorem 1: If the following conditions are satisfied

1. Same # variables & same constraints

2.
$$\forall i, \quad (2x_{p,i}^* - 1)(c_{Q,i} - c_{P,i}) \ge 0$$

if $x_{p,i}^* = 1$ then $(c_{Q,i} - c_{P,i}) \ge 0$
if $x_{p,i}^* = 0$ then $(c_{Q,i} - c_{P,i}) \le 0$

then the optimal solution of Q is x_p^*

- x_P^* : the solution to P
- **c**: the coefficients of ILPs



Approx. Amortized Inference [AAAI 15]

• Theorem 2: If the following conditions are satisfied

1. Same # variables & same constraints

2.
$$\forall i, (2x_{p,i}^* - 1)(c_{Q,i} - c_{P,i}) \ge -\epsilon |c_{Q,i}|$$

then x_P^* is a $(\frac{1}{1+M\epsilon})$ -approximate solution to Q

- x_P^* : the solution to P
- M: a constant
- **c**: the coefficients of ILPs



Approx. Amortized Inference [AAAI 15]

• Theorem 2: If the following conditions are satisfied

1. Same # variables & same constraints

2.
$$\forall i, (2x_{p,i}^* - 1)(c_{Q,i} - c_{P,i}) \ge -\epsilon |c_{Q,i}|$$

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Corollary 1:

Learning Structured SVM with approximate amortized inference gives a model with bounded empirical risk



Approx. Amortized Inference [AAAI 15]

• Theorem 2: If the following conditions are satisfied

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Corollary 2:

Dual coordinate descent for structured SVM can still return an exact model even if approx. amortized inference is used.

Solver Calls (Entity-Relation Extraction) Exact Exact Better 100 Ent F1: 87.7 80 Rel F1: 47.6 % Solver Calls 60 Ent F1: 87.3 40 Rel F1: 47.8 20 Baseline Our-approx. Our

Outline

1. Applications:

Co-reference; ESL Grammar Correction; Word Relation;



Other Related Work

1. Applications: Co-reference; ESL Grammar Correction; Word Relation; Dependency Parsing [Arxiv 15 b]; Multi-label Classification [ECML13]



2. Modeling: Supervised Clustering Model Semi-Supervised Learning[ECML 13a] Search-Based Model [Arxiv 15 a]

3. Algorithms: Learning with Amortized Inference Parallel learning algorithms [ECML 13b]



Future Work: Practical Machine Learning

1. Applications: More applications, easy access tools



2. Modeling: Learning from heterogeneous information

3. Algorithms: Handle large & complex data

Learning From World Knowledge

Go beyond supervised learning
 Learning from indirect supervision signals

After the vessel suffered a catastrophic torpedo detonation, Kursk sank in the waters of Barents Sea with all hands lost.

Learning From World Knowledge

Massive textual data on the Internet

- □ Wikipedia: 4.7 M English articles 35M in total
- □ Tweets: 500 M per day & 200 Billion per year

Learn world knowledge to support target tasks

- □ Extract knowledge from free text [EMNLP 13a, 14, ICML 14]
- □ Handle large-scale data

- [Liblinear, KDD 12]
- □ Inference on knowledge bases

[EMNLP 14b, 14]

Applications & Tools

- LIBLINEAR: library for classification
- Streaming Data SVM:
 - □ Support training on very large data
- Illinois-SL: library for structured prediction
 - \Box Support various algorithms; parallel \Rightarrow very fast

Provide a nice platform

- for developing novel methods
- for collaboration
- for education

More easy-access tools; More collaborations

Conclusion

Goal: Practical Machine Learning

- [Modeling] Expressive and general formulations
- [Algorithms] Principled and efficient
- [Applications] Support many applications

Code and Demos:

http://www.illinois.edu/~kchang10