Statistical Learning for Text Data Analytics Sequence Labeling and Structured Output Learning: A First Look

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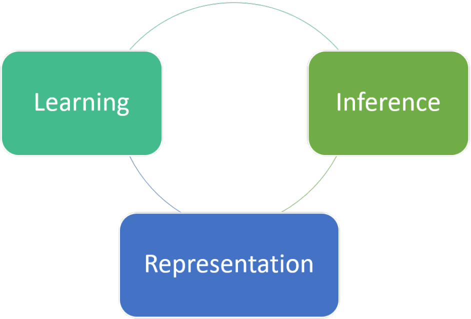
$*$Contents are based on materials created by Dan Roth, Vivek Srikumar, Hongning Wang, Chris Manning

Reference Content

- Dan Roth. CS546: Machine Learning and Natural Language . http://l2r.cs.uiuc.edu/~danr/Teaching/CS546-16/
- Vivek Srikumar. CS 6355 Structured Prediction. https://svivek.com/teaching/structured-prediction/spring2018/
- Hongning Wang. CS6501 Text Mining. http://www.cs.virginia.edu/~hw5x/Course/Text-Mining-2015-Spring/_site/
- Chris Manning. CS 224N/Ling 237. Natural Language Processing. https://web.stanford.edu/class/cs224n/

Course Topics



- Representation: language models, word embeddings, topic models
- Learning: supervised learning, semi-supervised learning, sequence models, deep learning, optimization techniques
- Inference: constraint modeling, joint inference, search algorithms

NLP applications: tasks introduced in Lecture 1

Overview

Overview

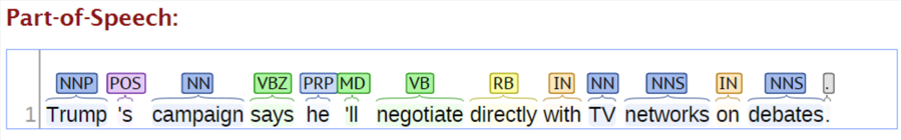
1. Application of Sequence Labeling
2. Application of Structured Output Learning
3. Multiclass as a Structure: A Very Brief Digression
4. Discussion about Structured Prediction

Popular Statistical Machine Learning Algorithms for NLP

- Mid-1970s: Hidden Markov Models (HMMs) for speech recognition $\rightarrow$ probabilistic models
- Early 2000s: Conditional Random Fields (CRFs) for part-of-speech tagging $\rightarrow$ structured prediction
- Early 2000s: Latent Dirichlet Allocation (LDA) for modeling text documents $\rightarrow$ topic modeling
- Mid 2010s: sequence-to-sequence models for machine translation $\rightarrow$ Deep Learning neural networks with memory/state
- Now: ??? for natural language understanding/generation
  - Reinforcement learning?

Sequence Tagging: Part of Speech

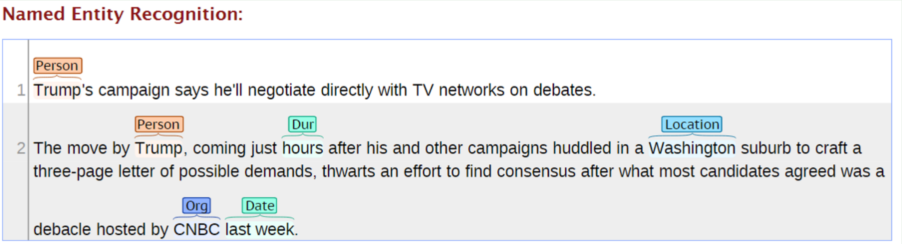
Example (Part of speech)



Tags:

- NN: common noun
- NNP: proper noun
- VB: verb, base form
- VBZ: verb, 3rd person singular
- ...

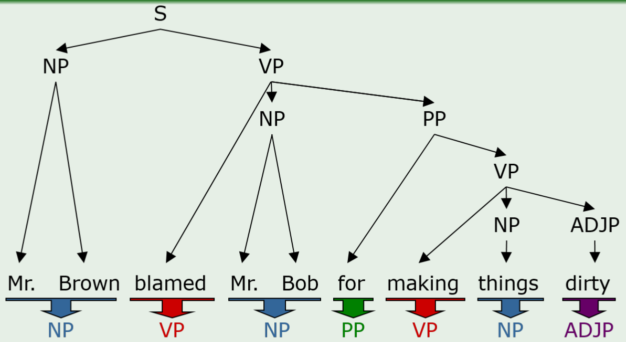
Example (Named Entity Recognition)



- Pers: Person
- Location
- Org: Organization
- Date/time

Sequence Tagging: Shallow Parsing (Chunking)

Example (Chunking)



- Not all the parse tree information is needed
- By shallow parsing we mean: identifying non-overlapping, non-embedding phrases
- Shallow Parsing = Text Chunking
- Usually text chunking without any further specification follows the definition from CoNLL-2000 shared task

POS Tagging

- POS tagging is (was) a prerequisite for further NLP analysis
  - Syntax parsing
    - Basic unit for parsing
  - Information extraction
    - Indication of names, relations
  - Machine translation
    - The meaning of a particular word depends on its POS tag
  - Sentiment analysis
    - Adjectives are the major opinion holders
    - Good v.s. Bad, Excellent v.s. Terrible

Public Tag Sets in NLP

- Brown corpus (Francis and Kucera 1961)
  - 500 samples, distributed across 15 genres in rough proportion to the amount published in 1961 in each of those genres
  - 87 tags
- Penn Treebank (Marcus et al. 1993)
  - Hand-annotated corpus of Wall Street Journal, 1M words
  - 45 tags, a simplified version of Brown tag set
  - Standard for English now: most statistical POS taggers are trained on this Tagset

Sequence Tagging: Part of Speech

Penn Treebank part-of-speech tags (including punctuation).

Tag	Description	Example	Tag	Description	Example
CC	Coordin. Conjunction	*and, but, or*	SYM	Symbol	*+,%, &*
CD	Cardinal number	*one, two, three*	TO	“to”	*to*
DT	Determiner	*a, the*	UH	Interjection	*ah, oops*
EX	Existential ‘there’	*there*	VB	Verb, base form	*eat*
FW	Foreign word	*mea culpa*	VBD	Verb, past tense	*ate*
IN	Preposition/sub-conj	*of, in, by*	VBG	Verb, gerund	*eating*
JJ	Adjective	*yellow*	VBN	Verb, past participle	*eaten*
JJR	Adj., comparative	*bigger*	VBP	Verb, non-3sg pres	*eat*
JJS	Adj., superlative	*wildest*	VBZ	Verb, 3sg pres	*eats*
LS	List item marker	*1, 2, One*	WDT	Wh-determiner	*which, that*
MD	Modal	*can, should*	WP	Wh-pronoun	*what, who*
NN	Noun, sing. or mass	*llama*	WP$	Possessive wh-	*whose*
NNS	Noun, plural	*llamas*	WRB	Wh-adverb	*how, where*
NNP	Proper noun, singular	*IBM*	$	Dollar sign	*$*
NNPS	Proper noun, plural	*Carolinas*	#	Pound sign	*#*
PDT	Predeterminer	*all, both*	“	Left quote	(‘ or “)
POS	Possessive ending	*’s*	”	Right quote	(’ or ”)
PRP	Personal pronoun	*I, you, he*	(	Left parenthesis	([, (, {, <)
PRP$	Possessive pronoun	*your, one’s*	)	Right parenthesis	( ],), }, >)
RB	Adverb	*quickly, never*	,	Comma	,
RBR	Adverb, comparative	*faster*	.	Sentence-final punc	(. ! ?)
RBS	Adverb, superlative	*fastest*	:	Mid-sentence punc	(: ; ... – -)
RP	Particle	*up, off*			

How much ambiguity is there?

- Statistics of word-tag pair in Brown Corpus and Penn Treebank

		87-tag Original Brown		45-tag Treebank Brown	
Unambiguous (1 tag)		**44,019**	**11%**	**38,857**	**18%**
Ambiguous (2–7 tags)		**5,490**		**8844**	
Details:	2 tags	4,967		6,731	
	3 tags	411		1621	
	4 tags	91		357	
	5 tags	17		90	
	6 tags	2	(*well, beat*)	32	
	7 tags	2	(*still, down*)	6	(*well, set, round, open, fit, down*)
	8 tags			4	(*'s, half, back, a*)
	9 tags			3	(*that, more, in*)

General Sequence Labeling Problem

VBG	NN	IN	DT	NN	IN	NN
Chasing	opportunity	in	an	age	of	upheaval

POS tagging

B	B	I	I	B	I	B	I	B	B
而	相	对	于	这	些	品	牌	的	价

Word segmentation

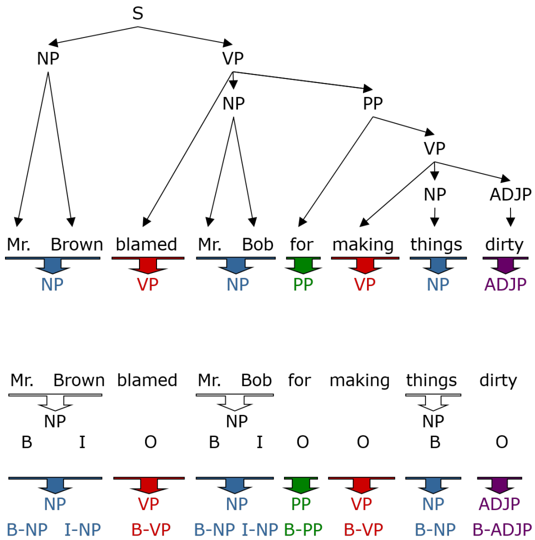
PERS	O	O	O	ORG	ORG
Murdoch	discusses	future	of	News	Corp.

Named entity recognition

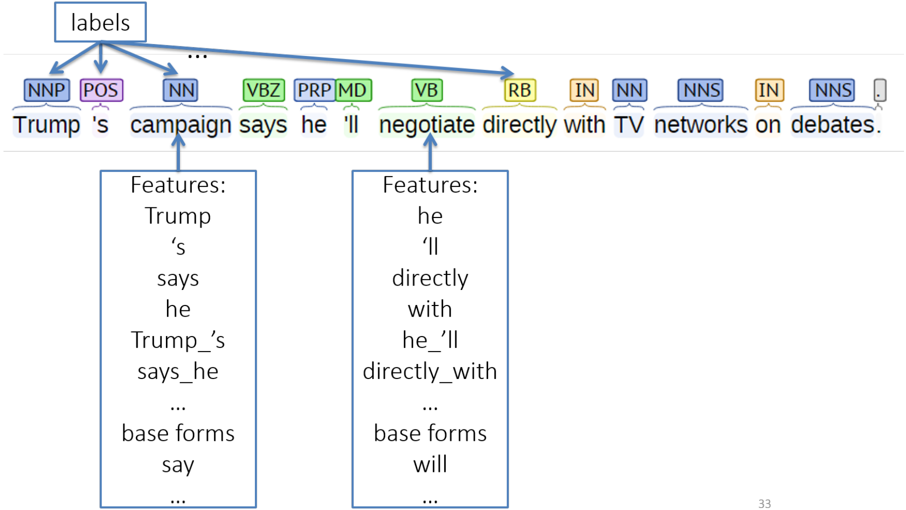
Text segmentation

- The BIO encoding
  - B-NP: beginning of a noun phrase chunk
  - I-NP: inside of a noun phrase chunk
  - O: outside of a noun phrase chunk

General Sequence Labeling Problem

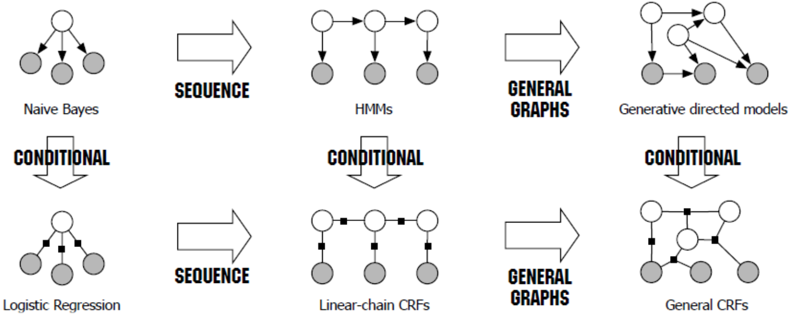


Classification Problem



Classifiers Feasible for Sequence Labeling

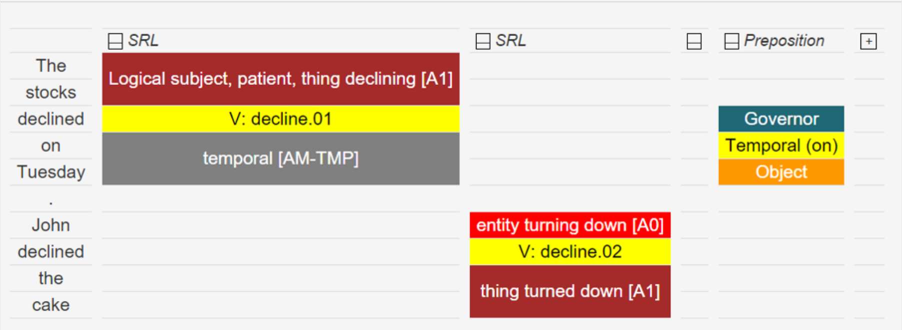
- Generative
  - Naive Bayes
  - Hidden Markov model (HMM)
- Discriminative models
  - Maximum entropy, logistic regression
  - Maximum Entropy Markov Model (MMEM)
  - Conditional random field (CRF)



Overview

Frame based Semantics

Example (Semantic Role Labeling)



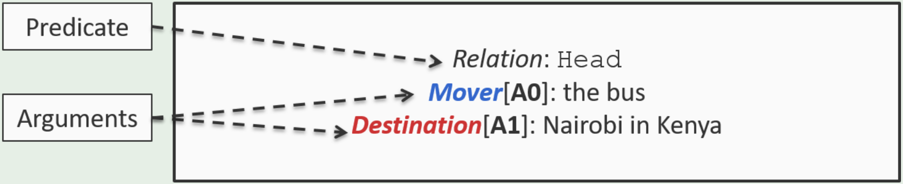
- Predicates
- Arguments
- Senses

Semantic Role Labeling

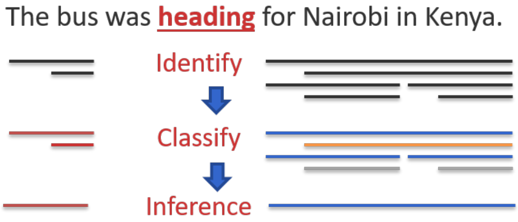
- Based on the dataset PropBank (Palmer et al. (2005))
  - Large human-annotated corpus of verb semantic relations
- The task: To predict arguments of verbs

Example ("The bus was heading for Nairobi in Kenya")

Given the sentence, identifies who does what to whom, where and when.

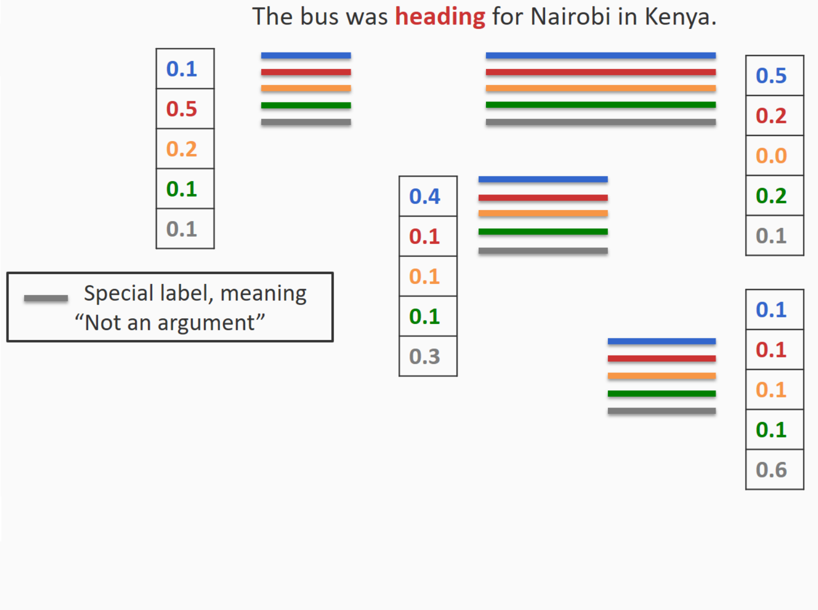


Predicting Verb Arguments

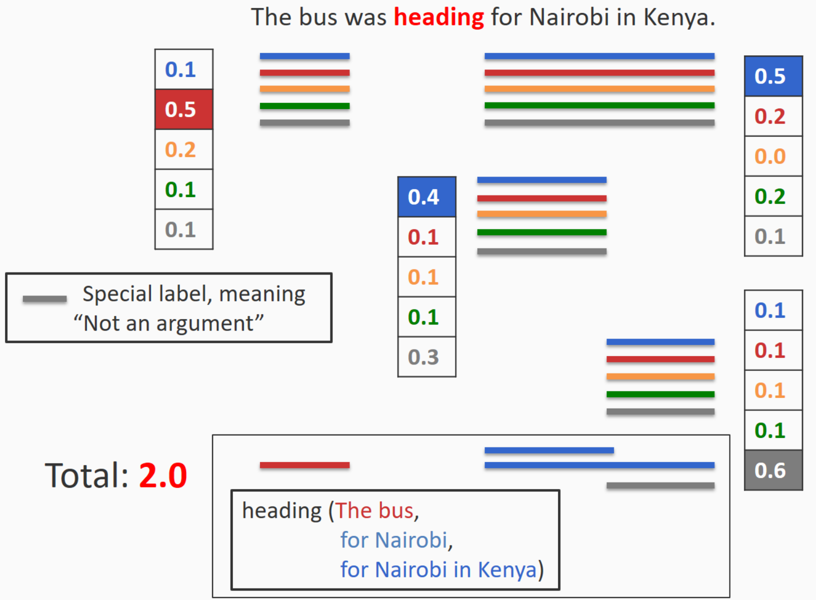


- Identify candidate arguments for verb using parse tree
  - Filtered using a binary classifier
- Classify argument candidates
  - Multi-class classifier (one of multiple labels per candidate)
- Inference
  - Using probability estimates from argument classifier
  - Must respect structural and linguistic constraints, e.g., no overlapping arguments

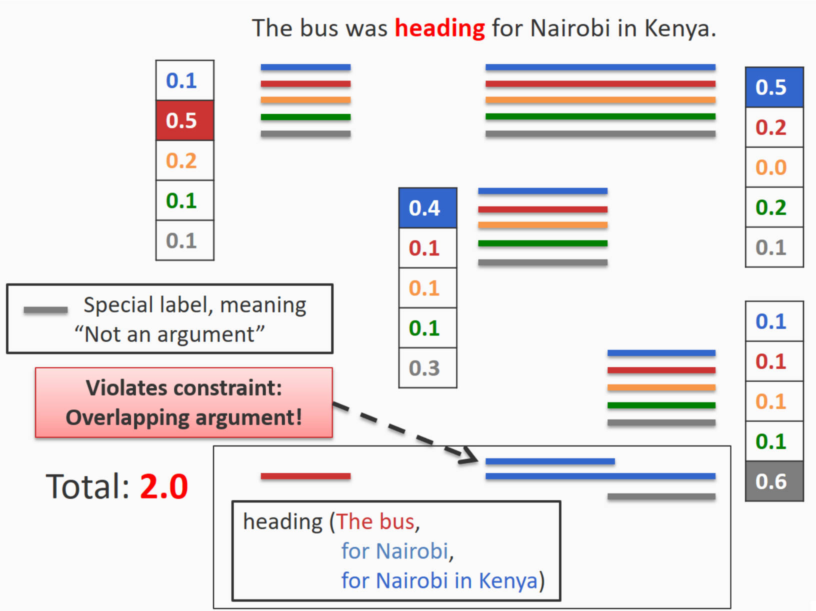
Inference: Verb Arguments



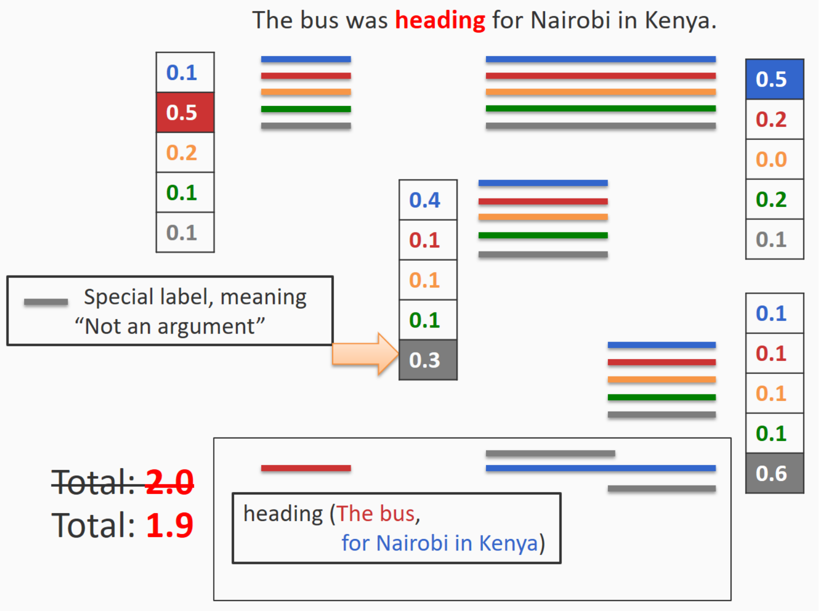
Inference: Verb Arguments



Inference: Verb Arguments



Inference: Verb Arguments

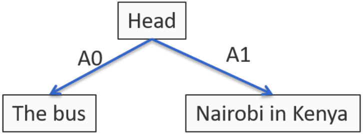


Structured output is...

- A data structure with a pre-defined schema
  - Eg: SRL converts raw text into a record in a database

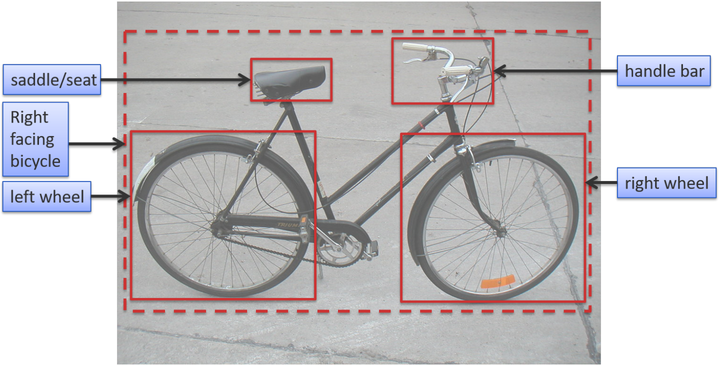
Predicate	A0	A1	Location
Head	The bus	Nairobi in Kenya	-

- Equivalently, a graph
  - Often restricted to be a specific family of graphs: chains, trees, etc

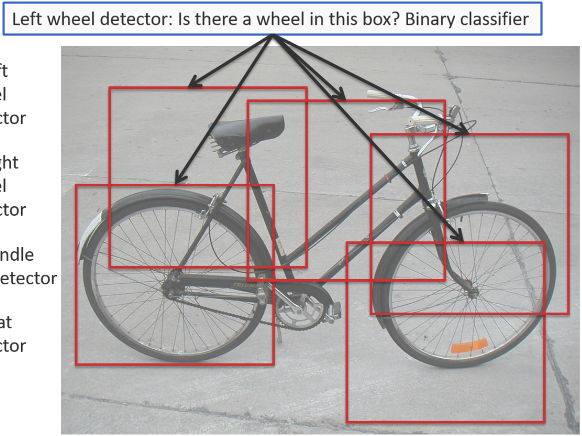


Object Detection

- How would you design a predictor that labels all the parts using the tools we have seen so far?

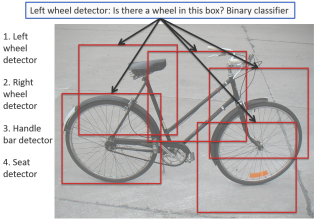


Object Detection



1. Left wheel detector
2. Right wheel detector
3. Handle bar detector
4. Seat detector

Object Detection



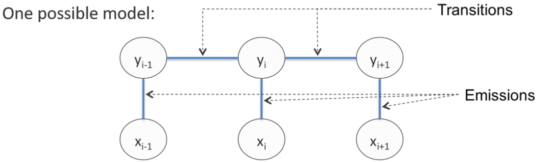
- Final output: Combine the predictions of these individual classifiers (local classifiers)
- The predictions interact with each other
- Eg: The same box can not be both a left wheel and a right wheel, handle bar does not overlap with seat, etc.
- Need inference to compose the output

How about this?

Li Fei-Fei and Li-Jia Li. What, Where and Who? Telling the Story of an Image by Activity Classification, Scene Recognition and Object Categorization

Sequence Labeling as a Special Structured Output Learning Problem

- Input: A sequence of tokens (like words)
- Output: A sequence of labels of same length as input
- Given a word, its label depends on :
  - The identity and characteristics of the word
    - E.g., Raises is a Verb because it ends in es (among other reasons)
  - Its grammatical context
    - Fed in "The Fed" is a Noun because it follows a Determiner
    - Fed in "I fed the.." is a Verb because it follows a Pronoun



Structured output is...

- A graph, possibly labeled and/or directed (representation)
  - Possibly from a restricted family, such as chains, trees, etc.
  - A discrete representation of input
    - E.g., A table, the SRL frame output, a sequence of labels etc.
- A collection of inter-dependent decisions
  - E.g., The sequence of decisions used to construct the output
- The result of a combinatorial optimization problem $\arg\max_{\mathbf{y}} \text{score}(\mathbf{x}, \mathbf{y})$
  - We have seen something similar before in the context of multiclass
  - Question: Why can't we treat each output as a label and train/predict as multiclass?

Challenges with Structured Output

- Two challenges
  - We cannot train a separate weight vector for each possible inference outcome
    - For multiclass, we could train one weight vector for each label
  - We cannot enumerate all possible structures for inference
    - Inference for multiclass was easy
- Solution
  - Decompose the output into parts that are labeled
  - Define
    - how the parts interact with each other
    - how labels are scored for each part
    - an inference algorithm to assign labels to all the parts

Overview

Multiclass as a Structured Output

- A graph (in general, hypergraph), possibly labeled and/or directed
- A collection of inter-dependent decisions
- The output of a combinatorial optimization problem
  $\arg\max_{\mathbf{y}} \text{score}(\mathbf{x}, \mathbf{y})$

- A graph with one node and no edges: Node label is the output
- Can be composed via multiple decisions
- Winner-take-all
  $label = \arg\max_i \mathbf{w}_i^\top \mathbf{x}$

Multiclass is a Structure: Implications

- A lot of the ideas from multiclass may be generalized to structures
    - Not always trivial, but useful to keep in mind
- Broad statements about structured learning must apply to multiclass classification
    - Useful for sanity check, also for understanding
- Binary classification is the most trivial form of structured classification
    - Multiclass with two classes

Overview

Decomposing the Output

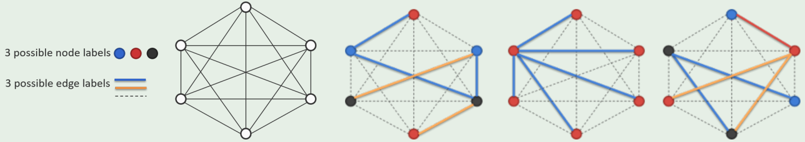
- We need to produce a graph
  - We cannot enumerate all possible graphs for the argmax
- Solution: Think of the graph as combination of many smaller parts
  - The parts should agree with each other in the final output
  - Each part has a score
  - The total score for the graph is the sum of scores of each part
- Decomposition of the output into parts also helps generalization
  - Why?

Decomposing the Output: Example

- The scoring function (via the weight vector) scores outputs
- For generalization and ease of inference, break the output into parts and score each part
- The score for the structure is the sum of the part scores
- What is the best way to do this decomposition? Depends...

Example (Decomposing the Output)

- Nodes and edges are labeled and the blue and orange edges form a tree
- Goal: Find the highest scoring tree



- The output **y** is a labeled assignment of the nodes and edges
- The input x not shown here

Decomposing the Output: Example

- Goal:

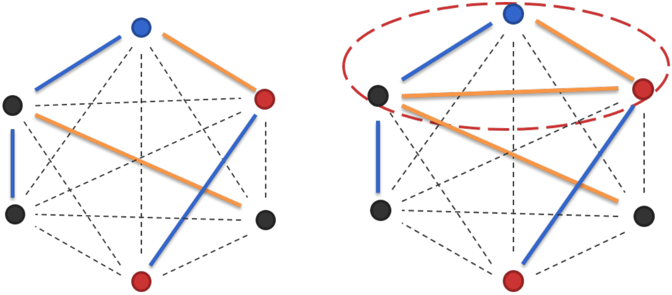
$$\text{score}(\mathbf{x}, \mathbf{y}) = \sum_{n \in \text{nodes}(\mathbf{x},\mathbf{y})} \text{score}(n) + \sum_{e \in \text{edges}(\mathbf{x},\mathbf{y})} \text{score}(e)$$

- Option 1: Decompose fully. All nodes and edges are independently scored
  - Still need to ensure that the colored edges form a valid output (i.e. a tree)
  - Prediction:

$$\begin{array}{ll} \arg\max_y & \sum_{n \in \text{nodes}(\mathbf{x},\mathbf{y})} \text{score}(\mathbf{x}, \mathbf{y}) \\ s.t. & \mathbf{y} \text{ forms a tree} \end{array}$$

Decomposing the Output: Example

- Still need to ensure that the colored edges form a valid output (i.e. a tree)

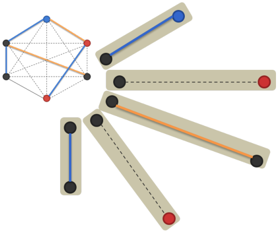


- Right: This is invalid output!
- Even this simple decomposition requires inference to ensure validity

Decomposing the Output: Example

- Option 2: Score each edge and its nodes together

$$\text{score}(\mathbf{x},\mathbf{y}) = \sum_{\substack{n_1,n_2 \in \text{nodes}(\mathbf{x},\mathbf{y}) \\ \forall e \in \text{edges}(\mathbf{x},\mathbf{y})}} \text{score}(n_1, n_2, e)$$



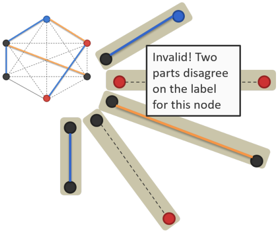
Inference should ensure that

- The output is a tree, and
- Shared nodes have the same label in all the parts

Decomposing the Output: Example

- Option 2: Score each edge and its nodes together

$$\text{score}(\mathbf{x}, \mathbf{y}) = \sum_{\substack{n_1, n_2 \in \text{nodes}(\mathbf{x},\mathbf{y}) \\ \forall e \in \text{edges}(\mathbf{x},\mathbf{y})}} \text{score}(n_1, n_2, e)$$



Inference should ensure that

- The output is a tree, and
- Shared nodes have the same label in all the parts

Decomposing the Output: Example

- Many other decompositions possible
- In general, we need a learning phase (learn the parameters of a model) and a inference phase (to decide the labels for an example)

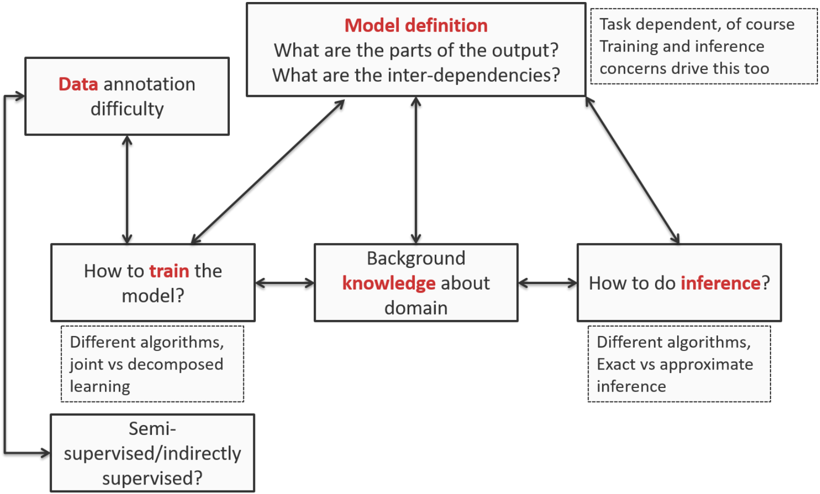
Inference

- Each part is scored independently
  - Key observation: Number of possible inference outcomes for each part may not be large
  - Even if the number of possible structures might be large
- Inference: How to glue together the pieces to build a valid output?
  - Depends on the "shape" of the output
- Computational complexity of inference is important
  - Worst case: intractable
  - With assumptions about the output, polynomial algorithms exist
    - Predicting sequence chains: Viterbi algorithm
    - To parse a sentence into a tree: CKY algorithm
    - In general, might have to either live with intractability or approximate

Training Regimes

- Decomposition of outputs gives two approaches for training
  - Decomposed training/learning without inference
    - Learning algorithm does not use the prediction procedure during training
  - Global training/Joint training/Inference-based training
    - Learning algorithm uses the final prediction procedure during training
- Similar to the two strategies we had before with multiclass
  - One-vs.-all
  - Kesler construction
- Inference complexity often an important consideration in choice of modeling and training
  - Especially so if full inference plays a part during training
  - Ease of training smaller/less complex models could give intermediate training strategies between fully decomposed and fully joint

Computational Issues: Reprise



Summary

- We saw several examples of structured output (structures are graphs)
  - Sometimes useful to think of them as a sequence of decisions
  - Also useful to think of them as data structures
- Multiclass is the simplest type of structure
  - Lessons from multiclass are useful
- Modeling outputs as structures
  - Decomposition of the output, inference, training

References

Palmer, M., Kingsbury, P., and Gildea, D. (2005). The proposition bank: An annotated corpus of semantic roles. *Computational Linguistics*, 31(1):71–106.