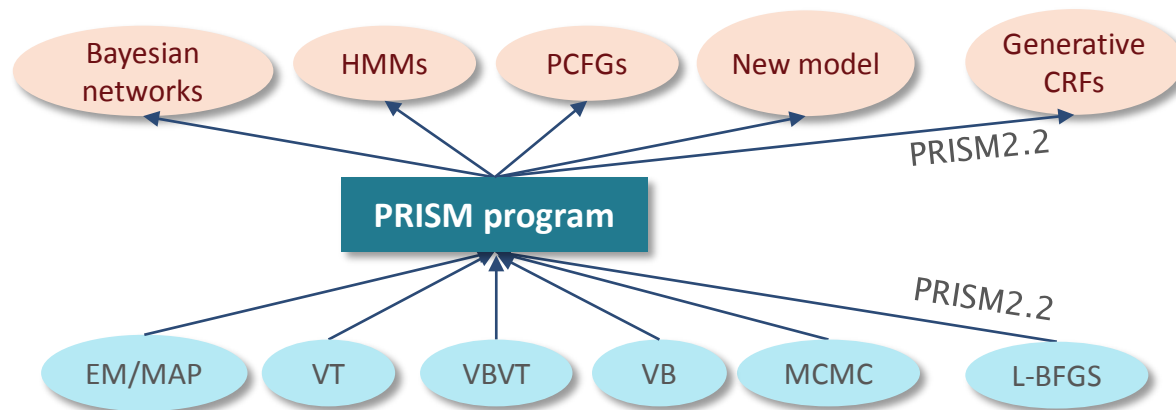


Goal recognition from incomplete action sequences by probabilistic grammars

Ryosuke Kojima & Taisuke Sato
Tokyo Institute of Technology

PRISM2.2

- ▶ PRISM [Sato et al. '97] (<http://sato-www.cs.titech.ac.jp/prism/>)
 - Probabilistic Prolog for machine and subsumes BN,HMM,PCFG,...



- ▶ PRISM2.2 has two new features
 - Learn and compute **generative conditional random fields** (G-CRFs)
 - logistic regression, linear-chain CRFs, CRF-CFGs
 - Can compute **an infinite sum of probabilities** ← Today's topic
 - Markov chains, prefix and infix prob. in PCFGs

Probability computation in PRISM

- ▶ Goal → expl. graph → probs

PCFG₁
 $S \rightarrow a:0.5 \mid b:0.3 \mid SS:0.2$

```
values(s,[[a],[b],[s,s]],
set@[0.5,0.3,0.2]).
```

```
pcfg(L):- pcfg([s],L,[]).
pcfg([A|R],L0,L2):-
  ( nonterminal(A) →
    msw(A,RHS),
    pcfg(RHS,L0,L1)
  ; L0=[A|L1] ),
pcfg(R,L1,L2).
pcfg([],L,L).
```

PCFG program

?- prob(pcfg([s],[a,b],[]),P)

↓ Tabled search

```
pcfg([s],[a,b],[])
  ⇔ pcfg([s,s],[a,b],[]) & pcfg([],[],[]) & msw(s,[s,s])
pcfg([s,s],[a,b],[])
  ⇔ pcfg([a],[a,b],[b]) & pcfg([s],[b],[]) & msw(s,[a])
pcfg([s],[b],[])
  ⇔ pcfg([b],[b],[]) & pcfg([],[],[]) & msw(s,[b])
pcfg([b],[b],[]) ⇔ pcfg([],[],[])
pcfg([],[],[])
pcfg([a],[a,b],[b]) ⇔ pcfg([],[b],[b])
pcfg([],[b],[b])
```

0.2
0.5
0.3

↑ G-I/O comp. by DP

↓

$$P = 0.5 \times 0.3 \times 0.2 = 0.03$$

ILP 2014

Probabilities are automatically learned from data by learn/1 in PRISM

New feature: infinite sum

–Prefix probability computation

- ▶ Prefix u : uw is a sentence for some w
- ▶ $P_{\text{prefix}}(u) = \sum_{uw:\text{sentence}} P(uw)$
- ▶ PCFG₁ (probabilistic context free grammar)

$S \rightarrow a:0.5 \mid b:0.3 \mid S S:0.2$

$$P_{\text{cfg}}([a,b]) = P\left(\begin{array}{c} S \\ \swarrow \quad \searrow \\ S \quad S \\ | \quad | \\ a \quad b \end{array}\right) = P(S \xrightarrow{0.2} S S)P(S \xrightarrow{0.5} a)P(S \xrightarrow{0.3} b)$$

$$P_{\text{prefix}}([a,b]) = P\left(\begin{array}{c} S \\ \swarrow \quad \searrow \\ S \quad S \\ | \quad | \\ a \quad b \end{array}\right) + P\left(\begin{array}{c} S \\ \swarrow \quad \searrow \\ S \quad S \\ | \quad \swarrow \quad \searrow \\ a \quad S \quad S \\ \quad | \quad | \\ \quad b \quad b \end{array}\right) + \dots$$

0.030.0108

Cyclic explanation graph

- ▶ Goal → expl. graph → SCCs → linear eqs → probs

PCFG₂
 S → a:0.4 | b:0.3 | S S:0.2 | S:0.1

```

values(s,[[a],[b],[s,s],[s]],
      set@[0.4,0.3,0.2,0.1]).
pre_pcfg(L):-
  pre_pcfg([s],L,[]).
pre_pcfg([A|R],L0,L2):-
  ( nonterminal(A) →
    msw(A,RHS),
    pre_pcfg(RHS,L0,L1)
  ; L0=[A|L1] ),
  ( L1=[] → L2=[]
  ; pre_pcfg(R,L1,L2) ).
pre_pcfg([],L,L).
  
```

prefix parser

?- lin_prob(pre_pcfg([s],[a,b],[]),P)

prefix
↙

↓ Tabled search

pre_pcfg([s],[a,b],[])

↔ pre_pcfg([s,s],[a,b],[]) & msw(s,[s,s])
 v pre_pcfg([s],[a,b],[]) & msw(s,[s])

pre_pcfg([s,s],[a,b],[])

↔ pre_pcfg([a],[a,b],[b]) & pre_pcfg([s],[b],[]) & msw(s,[a])
 v pre_pcfg([s,s],[a,b],[]) & msw(s,[s,s])
 v pre_pcfg([s],[a,b],[b]) & pre_pcfg([s],[b],[]) & msw(s,[s])
 v pre_pcfg([s],[a,b],[]) & msw(s,[s])

...

Cyclic dependency!

↓ Solving linear equations

P = 0.05

SCCs (strongly connected components)

- ▶ SCCs are partially ordered → DP possible

SCC



SCC



SCC

$pre_pcfg([s],[a,b],[])$

$\Leftrightarrow pre_pcfg([s,s],[a,b],[]) \ \& \ msw(s,[s,s]) \ \vee \ pre_pcfg([s],[a,b],[]) \ \& \ msw(s,[s])$

$pre_pcfg([s,s],[a,b],[])$

$\Leftrightarrow pre_pcfg([a],[a,b],[b]) \ \& \ pre_pcfg([s],[b],[]) \ \& \ msw(s,[a])$

$\vee \ pre_pcfg([s,s],[a,b],[]) \ \& \ msw(s,[s,s])$

$\vee \ pre_pcfg([s],[a,b],[b]) \ \& \ pre_pcfg([s],[b],[]) \ \& \ msw(s,[s])$

$\vee \ pre_pcfg([s],[a,b],[]) \ \& \ msw(s,[s])$

$pre_pcfg([s],[b],[])$

$\Leftrightarrow pre_pcfg([b],[b],[]) \ \& \ msw(s,[b]) \ \vee \ pre_pcfg([s,s],[b],[]) \ \& \ msw(s,[s,s])$

$\vee \ pre_pcfg([s],[b],[]) \ \& \ msw(s,[s])$

$pre_pcfg([s,s],[b],[])$

$\Leftrightarrow pre_pcfg([b],[b],[]) \ \& \ msw(s,[b]) \ \vee \ pre_pcfg([s,s],[b],[]) \ \& \ msw(s,[s,s])$

$\vee \ pre_pcfg([s],[b],[]) \ \& \ msw(s,[s])$

$pre_pcfg([b],[b],[])$

$pre_pcfg([s],[a,b],[b])$

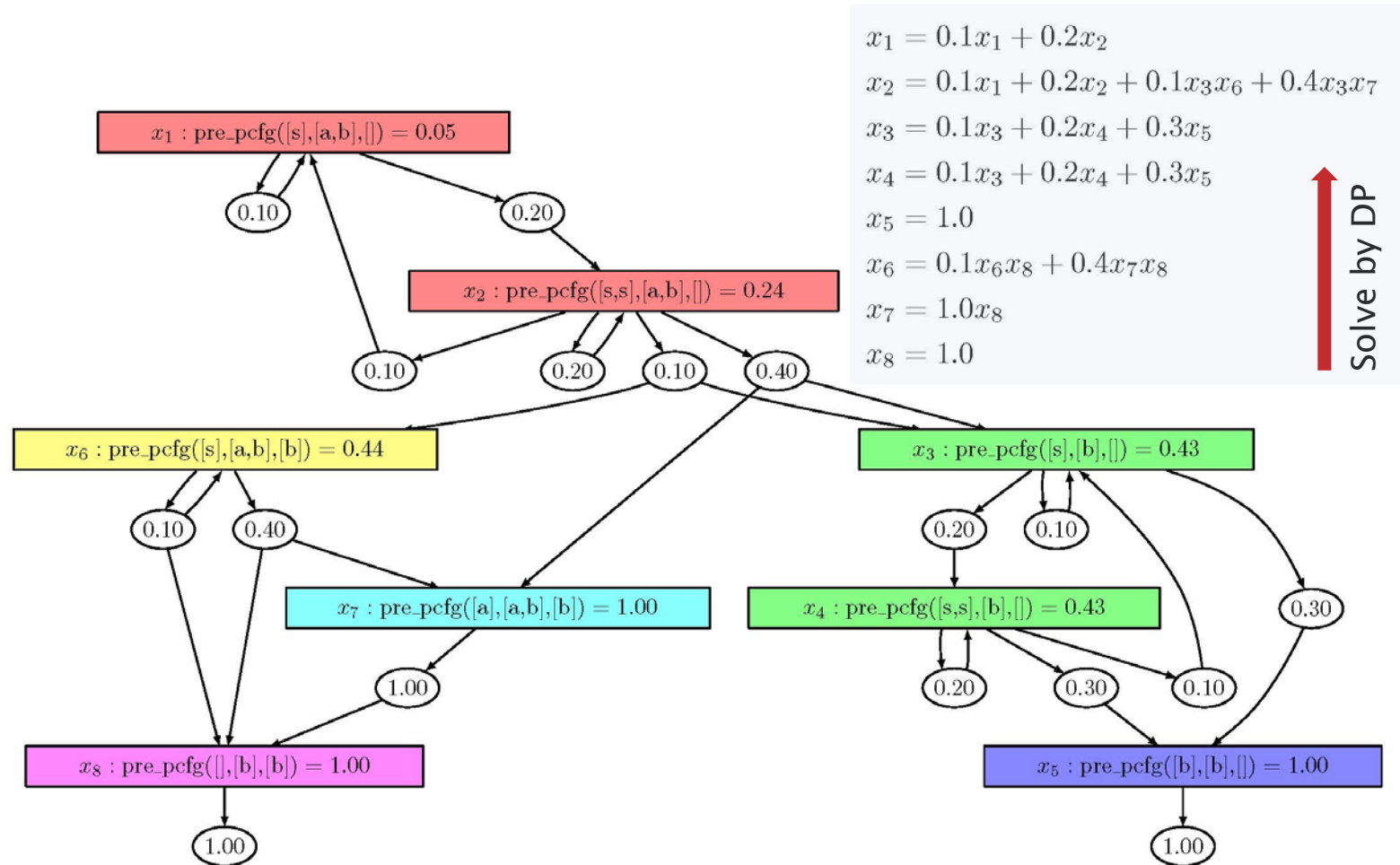
$\Leftrightarrow pre_pcfg([a],[a,b],[b]) \ \& \ pre_pcfg([], [b],[b]) \ \& \ msw(s,[a])$

$\vee \ pre_pcfg([s],[a,b],[b]) \ \& \ pre_pcfg([], [b],[b]) \ \& \ msw(s,[s])$

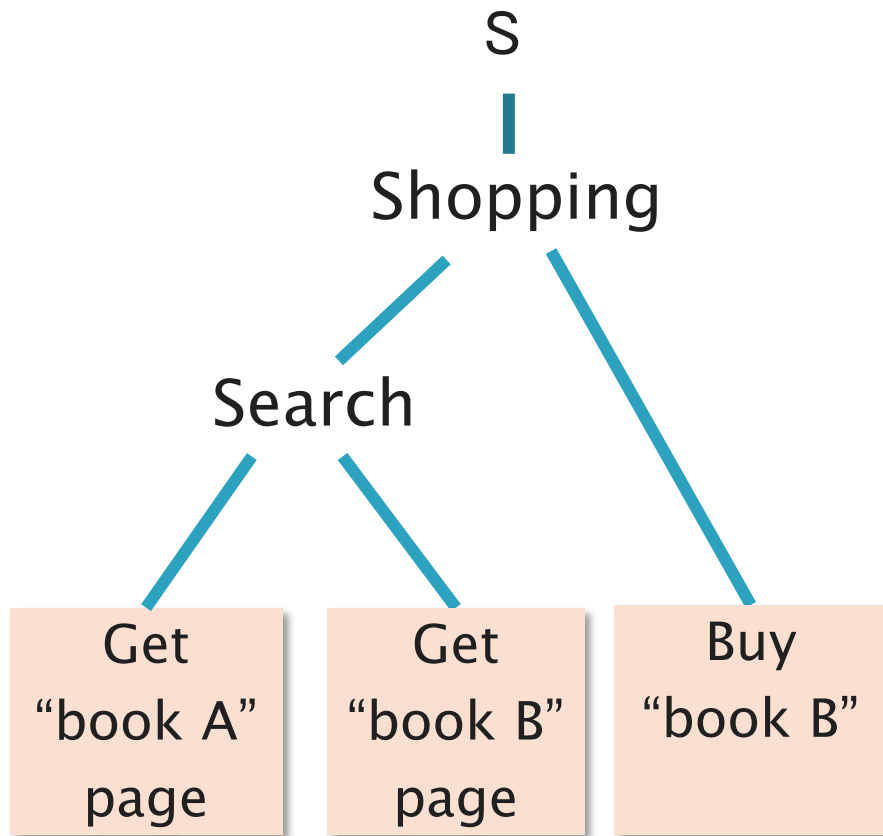
$pre_pcfg([a],[a,b],[b]) \ \Leftrightarrow \ pre_pcfg([], [b],[b])$

$pre_pcfg([], [b],[b])$

A set of probability equations



Plan recognition [Kautz+ 91, Vilain 90]



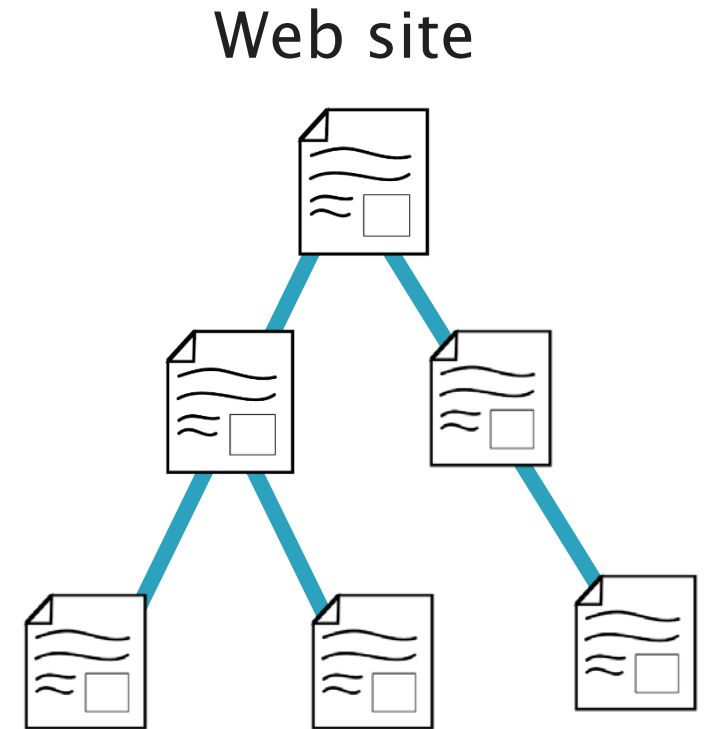
Plan	Parse tree in a PCFG
action	word
action seq	word seq
completed action seq	sentence

Web surfing

– capturing the user's intension online

up : climb up
down : down
sibling : visit sibling page
revisit : visit same page
move : others

We observe an action sequence as a prefix in a PCFG and infer its underlying plan as a most-likely nonterminal using prefix probability



path:

[/en/publication/](/en/publication/index.html)index.html

Experiment

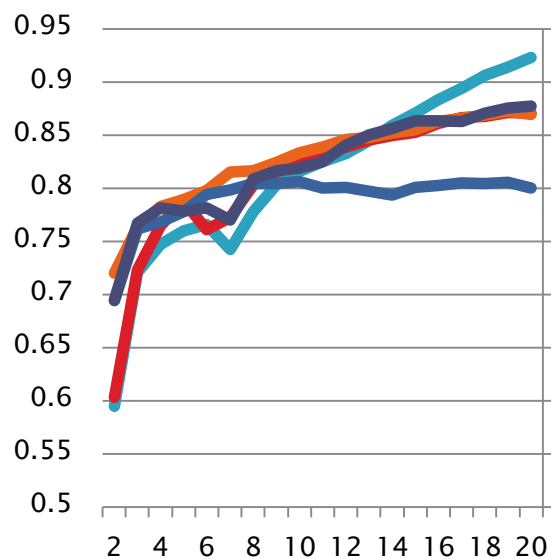
- ▶ Web data:
 - access log (action sequences) from the Internet Traffic Archive (NASA(2014), ClarkNet(4523), U of S(652))
- ▶ Task:
 - to classify prefixes of access log data into five plans (survey,news,...)
 - Four methods (HMM, **Prefix**, LR,SVM) used
generative discriminative

Gold standard

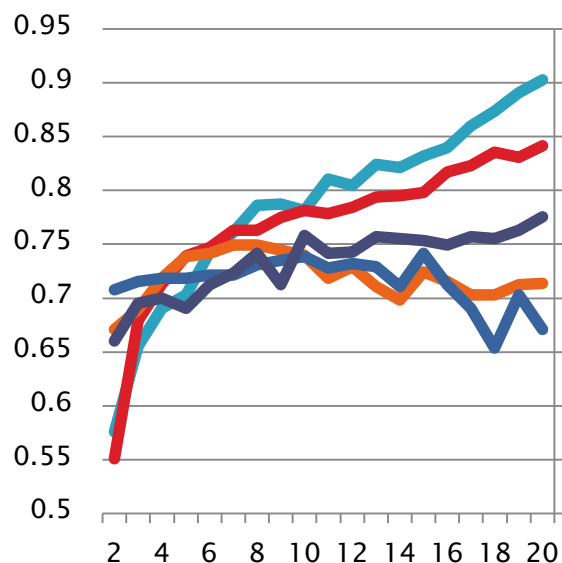
- ▶ Five plans (intentions) detected by clustering
 - Clustering access log data from the Internet Traffic Archive (NASA, ClarkNet, U of S) by a mixture of PCFGs (CFG rules common, parameters different) yields five clusters
- ▶ We write 102 CFG rules (32 NTs)
 - $S \rightarrow \text{Survey} [0.2], S \rightarrow \text{News} [0.4], \dots$
 - $\text{UpDown} \rightarrow \text{Up, Down} [0.3]$
 - $\text{UpDown} \rightarrow \text{Up, SameLayer, Down} [0.6]$
 - $\text{Up} \rightarrow \text{Up, up} [0.2], \dots$
- ▶ We determine the gold standard
 - Access log data paired with a category inferred by the Viterbi algorithm using a mixture of PCFGs (parameters are estimated from access log data as sentences)

Classification accuracy

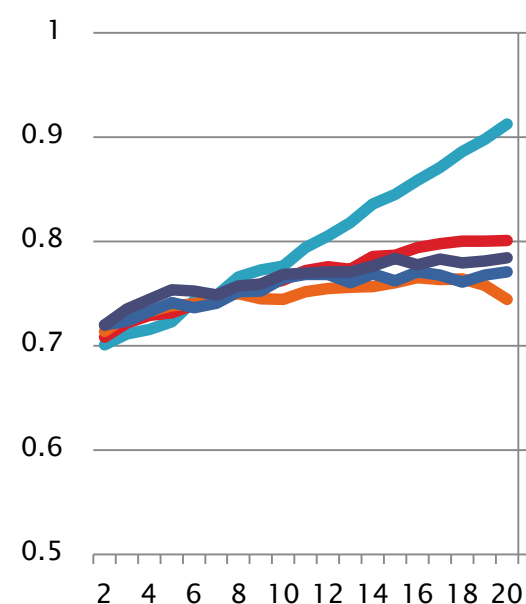
U of S



ClarkNet



NASA



entropy



5.12×10^4

Prefix length

2.77×10^5

3.14×10^6

- prefix
- HMM
- LR
- SVM
- SVM(BOW)

(PCFG's entropy: $-\sum_t p(t) \log p(t)$ of PCFG[Chi+99])

The prefix method performs better when the prefix is long

Conclusion and announcement

- ▶ PRISM2.2 allows cyclic explanation graphs and can compute probabilities of PCFGs' prefixes by solving a set of probability equations.
- ▶ We applied prefix probability computation to plan recognition from access log data in web sites.
- ▶ The prefix method outperformed HMM, LR, (two types of) SVMs when prefix length is long.
- ▶ The pre-release of PRISM2.2 is available from <http://sato-www.cs.titech.ac.jp/prism/>