### Complex PRISM models for analyzing very large biological sequence data – plus a few notes on probabilistic abductive logic programming

### Henning Christiansen

Roskilde University, Denmark henning@ruc.dk, http://www.ruc.dk/~henning

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# This talk: Probabilistic tools which *may* be useful for systems biology

\* Experiences and adaptation of PRISM (Sato & al) for sequence data

- \* Developed in the LoSt project, funded by Danish Strategic Research Council
- Thanks especially to PhD students, Christian Theil Have, Ole Torp Lassen, postdoc Matthieu Petit; to the PRISM group, Taisuke Sato, Yoshitaka Kameya, Neng-Fa Zhou
- (Probabilistic) abductive logic programming developed with Constraint Handling Rules (here: only brief overview)

### PRISM (Sato & al) and the LoSt project

#### Chosen for the LoSt project because

- \* Declarative: Firm, theoretical basis
- Flexible: A full programming language
- Instrumented with powerful probabilistic inference methods
- LoSt project goal: investigate to which extent "such models" are useful for bio sequence analysis as compared with "traditional tools", e.g. HMM software written in C

#### Most of our effort

- Cope with inherently high complexity of PRISM models
- Increase scaleability
- \* (No revolutionary biological results yet)
- Learned quite a lot about writing different models in PRISM
  - \* E.g. (Christiansen, Have, Lassen, Petit. Taming the Zoo of discrete HMM subspecies & some of their relatives. In *Biology, Computation and Linguistics, New Interdisciplinary Paradigms,* volume 228 of Frontiers in Artificial Intelligence and Applications, IOS Press, 2011

# Sequence analysis with PRISM Example: HMM + study scaleability

### Hidden Markov Model

- \* Well-known probabilistic model for sequential phenomena, e.g., genomes
- Probabilistic, finite state machine with probabilistic emissions

### Viterbi path

- \* ≈ the most probable sequence of states for observed sequence
- aka explanation, description, annotation
- Linear time Viterbi algorithm dynamic programming (DP)
- PRISM has generalized Viterbi algorithm, DP effect obtained by B-Prolog's tabling

Our example: Simple 2-state HMM adapted from PRISM manual

```
Version 0
```

```
values(init,[s0,s1]).
values(out(_),[a,b]).
values(tr(_),[s0,s1]).
```

```
hmm(L):-
  msw(init,S0),
  hmm(S0,L).
```

```
hmm(_,[]).
```

```
hmm(S,[Ob|Obs]):-
  msw(out(S),Ob),
  msw(tr(S),Next),
  hmm(Next,Obs).
```

```
?- viterbif(hmm([b,a,a,b]))
```

```
hmm([a,a,b,b])
    <= hmm(s1,[a,a,b,b]) & msw(init,s1)
hmm(s1,[a,a,b,b])
    <= hmm(s1,[a,b,b]) & msw(out(s1),a)
        & msw(tr(s1),s1)
    hmm(s1,[a,b,b])
    <= hmm(s0,[b,b]) & msw(out(s1),a)
        & msw(tr(s1),s0)
hmm(s0,[b,b])
    <= hmm(s1,[b]) & msw(out(s0),b)
        & msw(tr(s0),s1)
hmm(s1,[b])
    <= hmm(s0,[]) & msw(out(s1),b)
        & msw(tr(s1),s0)
hmm(s0,[])</pre>
```

```
Viterbi_P = 0.008470728000000
```

### **Problem:**

- we want an explicit representation of the Viterbi path
- so let's add it ....

### Version 1: explicit annotation

```
values(init,[s0,s1]).
values(out(_),[a,b]).
values(tr(_),[s0,s1]).
```

```
hmm(L,Ss):-
  msw(init,S0),
  hmm(S0,L,Ss).
```

```
hmm(S,[],[S]).
```

```
hmm(S,[Ob|Obs],[S|Ss]):-
    msw(out(S),Ob),
    msw(tr(S),Next),
    hmm(Next,Obs,Ss).
```

?- viterbig(hmm([b,a,a,b],Path)).

```
Path = [s1, s0, s1, s0, s1]
```

#### **Problem:**

- PRISM not design with this in mind
- The history argument destroys tabling

Runtime more than exponential

Length	Runtime			
10	0.022 sec			
20	> 1 min			
21	???			
	6			

Version 2: Remove non-discriminating arguments (Christiansen, Gallagher, ICLP 2009)

```
values(init,[s0,s1]).
values(out(_),[a,b]).
values(tr(_),[s0,s1]).
```

```
hmm(L, --Ss):-
    msw(init, S0),
    hmm(S0, L, --Ss).
```

```
hmm(S,[],--[S]).
```

```
hmm(S,[Ob|Obs],--[S|Ss]):-
    msw(out(S),Ob),
    msw(tr(S),Next),
    hmm(Next,Obs,--Ss).
```

# Program transformation for PRISM programs:

- remove such arguments
- run viterbi on reduced program
- reconstruct arguments by deterministic run directed by proof tree.
- runtimes as Version 0 :)

```
?- prismAnnot(hmm2).
?- viterbiAnnot(hmm([b,a,a,b],Path),Prob)
Path = [s1,s0,s1,s0,s1]
Prob = 0.008470728 ?
```

# Runtimes still not good enough

Length	Version 1: With annot	Version 2+autoannot ≈ Version 0
10	0.022 sec	0
20	> 1 min	0
21	???	0
1,000	_	0.07 sec
5,000	_	1.6 sec
10,000	_	6 sec
20,000	_	25 sec
30,000	_	1 min

Tests made with PRISM 2.0 on iMac 2.8GHs Intel Core i5 with 12 GB ram

#### ≈ Quadratic time complexity :(

- \* B-Prolog's tabling copies and compares structure
- No optimization for ground structures where in principle storing and comparing pointers would do

Version 3: As Version 2 but now simulating pointers (Have, Christiansen, PADL 2011)

```
hmmTop(L, --S):-
store_list(L, Index),
hmm(Index, --S).
```

```
hmm(S,[],--[S]):-!.
```

```
hmm(S,ObY,--[S|Ss]):-
    retrieve_list(ObY,Ob,Y),
    msw(out(S),Ob),
    msw(tr(S),Next),
    hmm(Next,Y,--Ss).
    ?
```

```
Program trans. for PRISM:– translate structured args. into
```

pointer representation

:- store\_list([b,a,a,b],Idx).

May result in

```
retrieve_list(1, b, 2).
retrieve_list(2, a, 3).
retrieve_list(3, a, 4).
retrieve_list(4, b, 5).
retrieve_list(5, _, []).
```

```
?- prismAnnot(hmm3).
?- viterbiAnnot(hmmTop([b,a,a,b],Path),Prob)
Path = [s1,s0,s1,s0,s1]
Prob = 0.008470728 ?
```

# Runtimes, finally

Length	V. 1: With annot	V. 2 = V.1 + autoannot	V. 3 = V. 2 + pointers
10	0.022 sec	0	
20	>1 min	0	
21	???	0	
•••			
1,000	_	0.07 sec	0.016 sec
5,000	_	1.6 sec	0.052 sec
10,000	_	6 sec	0.11 sec
20,000	_	25 sec	0.24 sec
30,000	_	1 min	0.4 sec
100,000	_	_	2.9 sec

Linear time complexity :)

- \* ... crashes around length = 150,000 :/
- \* independently of memory settings, 32 vs. 64 bit machine with extreme amount of RAM

# Runtimes, finally

Length	V. 1: With annot	V. 2 = V.1 + autoannot	V. 3 = V. 2 + pointers	$V. 4 = V3 + log_scale$
10	0.022 sec	0		
20	>1 min	0		
21	???	0		
1,000	_	0.07 sec	0.016 sec	0.018 sec
5,000	_	1.6 sec	0.052 sec	0.08 sec
10,000	_	6 sec	0.11 sec	0.19 sec
20,000	_	25 sec	0.24 sec	0.44 sec
30,000	—	1 min	0.4 sec	0.66 sec
100,000	_	_	2.9 sec	3.8 sec

Linear time complexity :)

- \* ... crashes around length = 150,000 :/
- \* independently of memory settings, 32 vs. 64 bit machine with extreme amount of RAM

### Our approach to complex models: **Bayesian Annotation Networks** (Christiansen, Have, Lassen, Petit, ICLP 2011)

Divide complex model into sub-models (= separate PRISM models) organized in a Bayesian network

each model possibly parameterized by outcome of other models

```
m_i (+Sequence, -Annot, +Annot<sub>1</sub>, +Annot<sub>2</sub>, ... ) :-
```

••••

msw(xxx(part-Annot1, part-Annot2), part-Annot)

A distinguished top-model

.... .

- Viterbi computations done one submodel at a time in topological order, thus reducing degrees of freedom (≈no of states) in each step
- \* Training done in a similar way
- Implemented as "The LoSt Framework" with its own script language for dependencies
- \* To be released spring 2012, integrated with the previous PRISM optimizations

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Our approach to complex models: Bayesian Annotation Networks

(Christiansen, H

Divide complex model into s Bayesian network

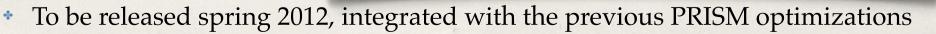
each model possibly paramet

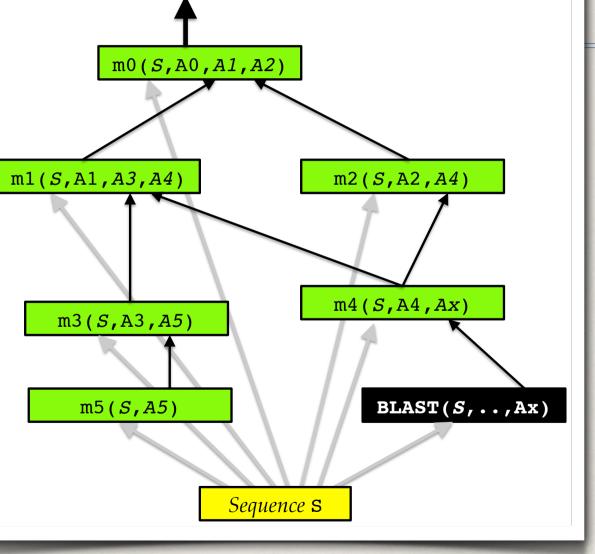
m<sub>i</sub> (+Sequence, -Annot, + .... msw ( xxx ( part-Annot<sub>1</sub>

A distinguished top-mode

.... .

- Viterbi computations done reducing degrees of freedc
- Training done in a similar
- Implemented as "The LoS<sup>1</sup> dependencies





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### Overview of probabilistic abduction, inspired by PRISM and Constraint Handling Rules

State of the art Probabilistic Abductive Logic Programming:

(Christiansen, 2008, in "Constraint Handling Rules, Current Research Topics", LNCS 5388)

- An LP language with possibly non-ground abducibles and integrity constraints
- A nice semantics (possible worlds; assumed independent abducibles)
- Prototype implementations in CHR, including with best-first search

Probabilistic Abductive Logic Programming with *dependencies* in simult. probability distr. over abducibles specified using CHRiSM (Sneyers,...).

(Christiansen, Saleh, CHR-Workshop, 2011)

- Nice semantics (possible worlds)
- Slow prototype implementation in CHR+CHRISM

Efficient implementation of non-prob. abduction, with powerful ICs (Christiansen. Executable specifications for hypothesis-based reasoning with Prolog and Constraint Handling Rules, Journal of Applied Logic, vol 7, 2009) SEE EXAMPLE IN SEPARATE FILE 14

### Conclusions

#### (Probabilistic) Logic programming technology apply to biological sequence analysis

- \* Clean semantics: (Probabilistic) Herbrand models, ...
- Transparency, modifiability, easy experiments, high expr. power
- Flexibility of a full programming language (incl. dirty tricks)

#### It does scale

- \* Our program transformation based optimizations obvious to implement at low level
- If you want n>100.000 in LoSt Framework, use a chunker as submodel ;-)

Newer logic programming paradigms add forward chaining rules, (state --> state)

CHR, CHRiSM (= CHR\*PRISM)

(P)LP technology demonstrated here for sequence analysis, so obvious in the toolbox for systems biology