ParaGnosis Tool Demo

ParaGnosis is a C++ weighted model counting toolset for Linux. Its implementation is based on [1,2,3,4]. We have also added a significant number of Bayesian networks to play with (under *./data/net*). This demo will first introduce the user to the toolset and the input formats. Then we will demonstrate three ways to use the tool:

- Compile a Bayesian network to a knowledge base in different target languages.
- Compare the results of the compilation process for different target languages.
- Visualize the compilation result using dot
- Perform various inference queries on the compiled knowledge base:
  - marginalization,
  - conditional probabilities, and
  - posteriors.
- Compare marginalization results on different target languages.

The tool consists of the following command-line tools:

- `bn-to-cnf`: a c++ tool to create Conjunctive Normal Form (CNF) encodings from a Bayesian network.
- `bnc`: a c/c++ **B**ayesian **N**etwork **C**ompiler for multiple target representations.
- `bnmc`: a c++ **B**ayesian **N**etwork **M**odel **C**ounter.
- `pg`: a **Para****G**nosis user friendly interface to the tools above, written in Python.

The currently supported target languages are:

- Weighted Positive Binary Decision Diagrams (WPBDD)
- Weighted Positive Multi-Valued Decision Diagrams (WPMDD)
- Tree-driven Weighted Positive Multi-valued Decision Diagrams (TD-WPMDD)

The demo

The `pg` script is installed system wide, and directly available from the command-line by opening a terminal. A shortcut to open a terminal is `ctrl-alt-t`.

Encoding

Show a list of available Bayesian networks

The toolset comes with a comprehensive list of Bayesian networks to play with. To get a list of available networks, type:

```
> pg --list

    3nt
    4sp
    6hj
    6nt
    aggregate
    alarm
    ...
```

Any of the shown names can be used as input for the `pg` script. You can also provide a locally stored Bayesian network filename with `.net` extension (HUGIN format).

Show encoding statistics for the *asia* network

```
> pg encode asia

    ...

    Variables       : 8
    Probabilities   : 36
    Deterministic   : 8
    Unsatisfiable   : 4
    Literals        : 16
    Clauses         : 52
    Literal/clauses : 2.23
    Clause sizes    : 1-3
```

Compiling a network

Compile *asia* to a TD-WPMDD

```
> pg compile asia

    ...

    FINAL RESULT:

        Spanning tree     : 0.011ms
        Compilation       : 0.015ms
        Total Or #nodes   : 23
        Total And #nodes  : 6
        Total time        : 0.000s
        Total time        : 0.026ms

        Total #nodes      : 29
        Total #edges      : 58
        Total #operators  : 144
```

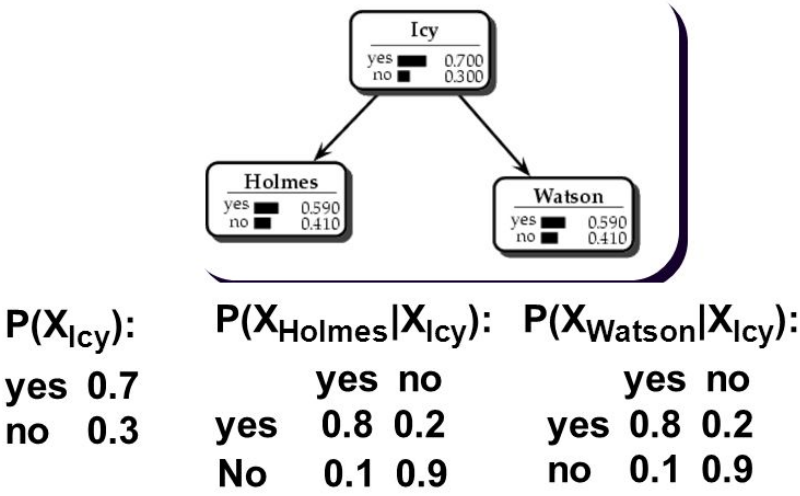
Compile *asia* to a WPBDD

```
> pg compile asia --method wpbdd

    ...

    FINAL RESULT:

        Compiled CPTs in  : 0.000s
        Conjoined CPTs in : 0.000s
        Total time        : 0.000s
        Total time        : 0.244ms

        Total #nodes      : 45
        Total #edges      : 90
        Total #operators  : 124
```

Compare compilation between WPBDD, a WPMDD, and a TD-WPMDD

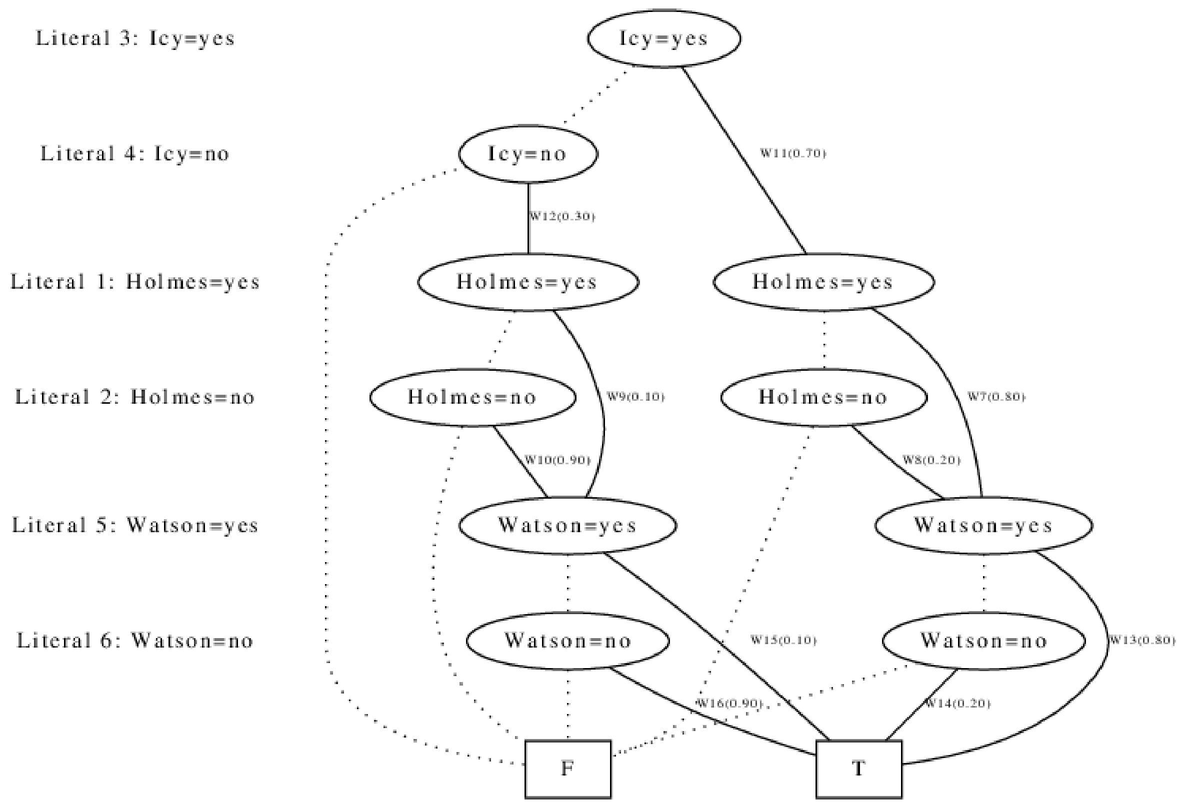
```
> pg compile asia --method wpbdd mg tdmg

    ...

     nr  | type    |  seconds | milliseconds |   speed-down |    operators |   nodes |   edges
     ----|--------|----------|--------------|--------------|--------------|---------|---------
       0 | TDMG   |    0.000 |        0.031 |        1.000 |          144 |      29 |     58
       1 | MG     |    0.000 |        0.089 |        2.871 |          132 |      22 |     44
       2 | WPBDD  |    0.000 |        0.155 |        5.000 |          124 |      45 |     90
```

The following is the *icy roads* Bayesian network that we want to compile



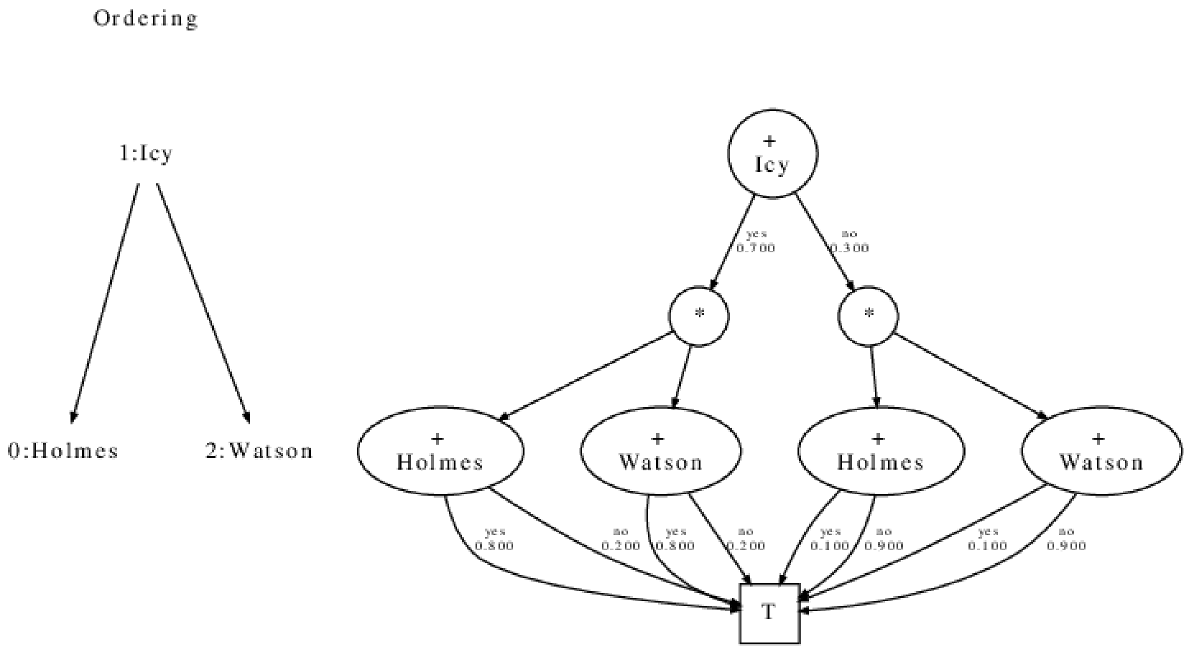
Directly visualize the WPBDD for the *icy_roads* network

```
> pg compile icy_roads --method wpbdd --dot
```



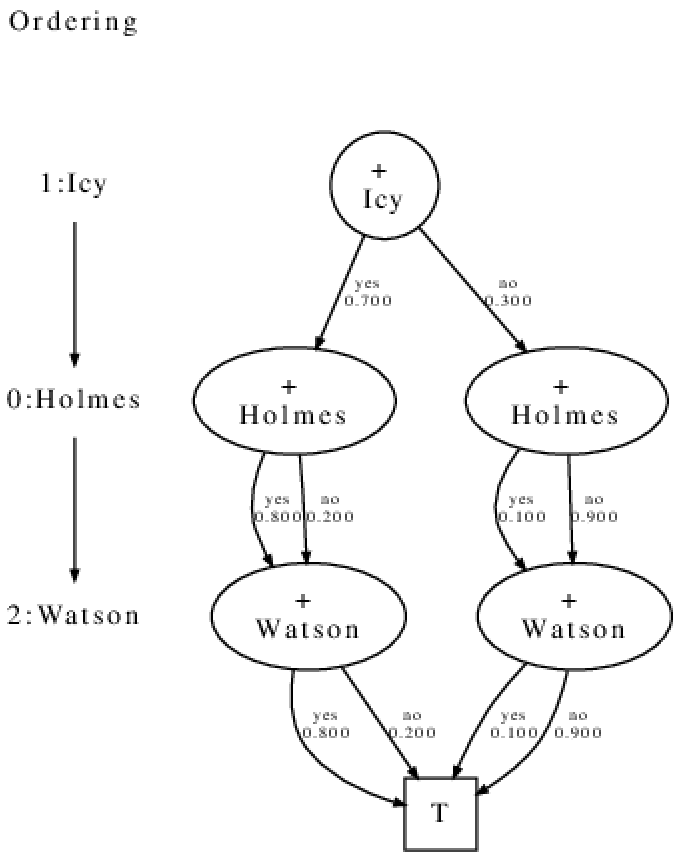
Directly visualize the TD-WPMDD

```
> pg compile icy_roads --method tdmg --dot
```



Directly visualize the TD-WPMDD

```
> pg compile icy_roads --method tdmg --dot
```

Perform Inference

Verify *icy roads* posteriors, previously shown

```
> pg inference --posteriors="" icy_roads

...

Holmes=yes: 0.590000
Holmes=no: 0.410000
Icy=yes: 0.700000
Icy=no: 0.300000
Watson=yes: 0.590000
Watson=no: 0.410000
```

Run every possible marginalization on a network using TD-WPMDD (press ctrl-c to stop)

```
> pg inference asia

    ...

     nr |         type |  cores |      queries | milliseconds |         ms/q
    ----|--------------|--------|--------------|--------------|--------------
      0 | TDMULTIGRAPH |      1 |        18360 |       8.7516 |       0.0005
```

Compare WPBDD inference speed with TD-WPBDD

```
> pg inference asia --method wpbdd tdmg --compare

    ...

     nr |         type |  cores |      queries | milliseconds |         ms/q |   speed-down
    ----|--------------|--------|--------------|--------------|--------------|--------------
      0 | WPBDD        |      1 |        18360 |       5.7327 |       0.0003 |         1.00
      1 | TDMULTIGRAPH |      1 |        18360 |      10.5697 |       0.0006 |         1.84
```

Compute conditional probability P(tub | bronc = yes, smoke = yes) for the *asia* netwrok

```
> pg inference asia --evidence='bronc=yes,smoke=yes' --posteriors='tub'

    ...

    tub=yes: 0.010400
    tub=no: 0.989600
```

Compute posteriors of `lung` and `xray` for evidence `bronc = yes`, and `smoke = yes`

```
> pg inference asia --evidence='bronc=yes,smoke=yes' --posteriors='lung,xray'

    ...

    lung=yes: 0.100000
    lung=no: 0.900000
    xray=yes: 0.151705
    xray=no: 0.848295
```

Compute posteriors all non-observed variables, for evidence `bronc = yes`, and `smoke = yes`.

```
> pg inference asia --evidence='bronc=yes,smoke=yes'

    ...

    asia=yes: 0.010000
    asia=no: 0.990000
    dysp=yes: 0.810936
    dysp=no: 0.189064
    either=yes: 0.109360
    either=no: 0.890640
    lung=yes: 0.100000
    lung=no: 0.900000
    tub=yes: 0.010400
    tub=no: 0.989600
    xray=yes: 0.151705
    xray=no: 0.848295
```

References

[1] G.H. Dal, A.W. Laarman, A. Hommerso and P.J.F. Lucas, "*A Compositional Approach to Probabilistic Knowledge Compilation*", in International Journal of Approximate Reasoning, vol 138:38-66, 2021.

[2] G.H. Dal, A.W. Laarman and P.J.F. Lucas, "*Parallel Probabilistic Inference by Weighted Model Counting*", in Proceeding of the International Conference on Probabilistic Graphical Models, PMLR, vol 72:97-108, 2018.

[3] G.H. Dal, S. Michels and P.J.F. Lucas, "*Reducing the Cost of Probabilistic Knowledge Compilation*", in Proceedings of Machine Learning Research, volume 73, pages 41-152, 2017.

[4] G.H. Dal and P.J.F. Lucas, "*Weighted Positive Binary Decision Diagrams for Exact Probabilistic Inference*", in Journal of Approximate Reasoning, volume 90, pages 411-432, 2017.