Probabilistic Programming in Birch

www.birch-lang.org

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SWEDISH FOUNDATION *for* STRATEGIC RESEARCH

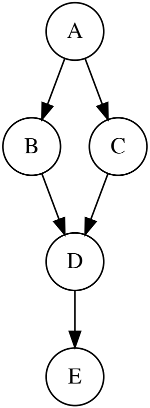
Outline

1. Graphical models $\longrightarrow$ probabilistic programs.
2. Birch: motivation and design.
3. Birch: language features.

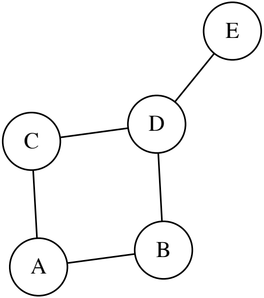
1 Graphical models $\longrightarrow$ probabilistic programs

Graphical models

(a) Directed

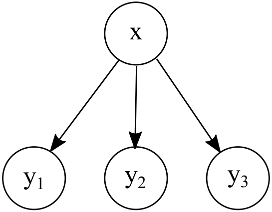


(b) Undirected

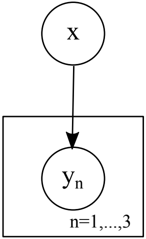


Graphical models

(a) Without plate notation



(b) With plate notation



Graphical models

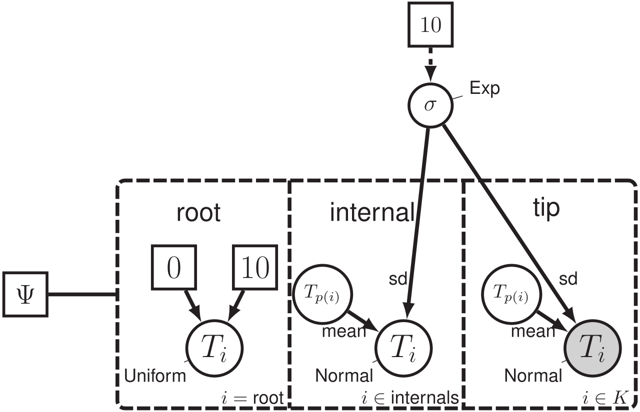


Figure: S. Höhna, M. J. Landis, T. A. Heath, B. Boussau, N. Lartillot, B. R. Moore, J. P.

Huelsenbeck, and F. Ronquist. Revbayes: Bayesian phylogenetic inference using graphical models and an interactive model-specification language. Systematic, 65(4):726–736, 2016.

doi: 10.1093/sysbio/syw021

Graphical models

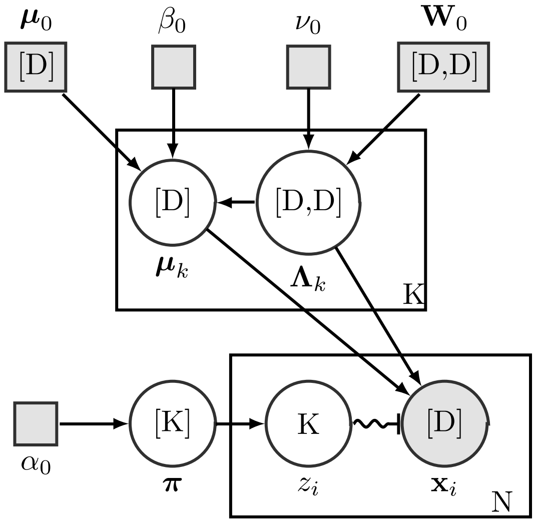


Figure: Benwing `https://commons.wikimedia.org/wiki/File:Bayesian-gaussian-mixture.svg`

Graphical models $\longrightarrow$ probabilistic programs

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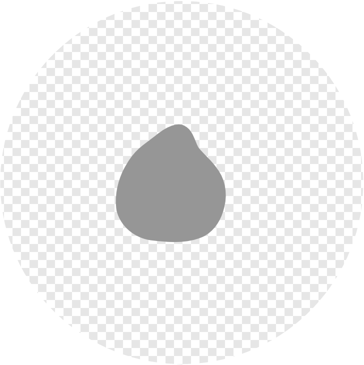

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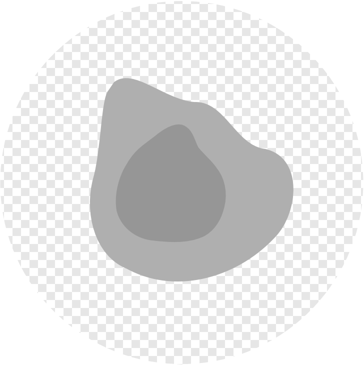

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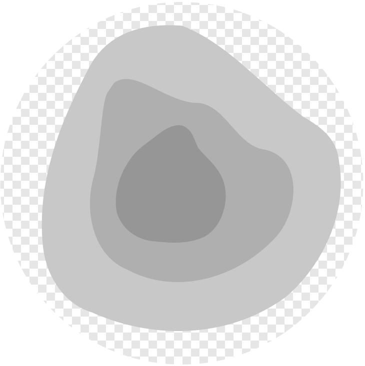


Graphical models $\longrightarrow$ probabilistic programs

The most expressive languages are known as **universal**

Also known as **Turing complete**.

Models written in such languages are **universal probabilistic programs**.

These are the most expressive languages for model specification, but also the most difficult for which to do inference.

Graphical models $\longrightarrow$ probabilistic programs

An alternative perspective on probabilistic programming is that it is a **programming paradigm** for probabilistic modelling and inference.

Graphical models $\longrightarrow$ probabilistic programs

An alternative perspective on probabilistic programming is that it is a **programming paradigm** for probabilistic modelling and inference.

- Other programming paradigms include object-oriented programming, generic programming, procedural programming, functional programming, etc.
- From this perspective, probabilistic programming languages merely emphasise this particular programming paradigm, providing ergonomic features for writing probabilistic models and probabilistic inference methods.

2 Birch: motivation and design

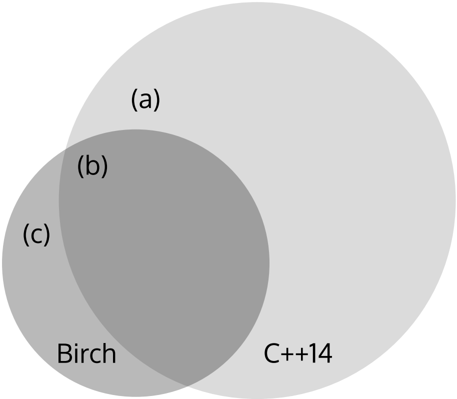
Birch

- Universal probabilistic programming language (PPL).
- Supports procedural, generic, object-oriented, and (of course) probabilistic programming paradigms.
- Both models and methods are written in the Birch language itself.
- Draws inspiration from many places, including existing PPLs such as LibBi (`www.libbi.org`), and modern object-oriented languages such as Swift.
- Free and open source, under the Apache 2.0 license.
- See `birch-lang.org`

Technical details

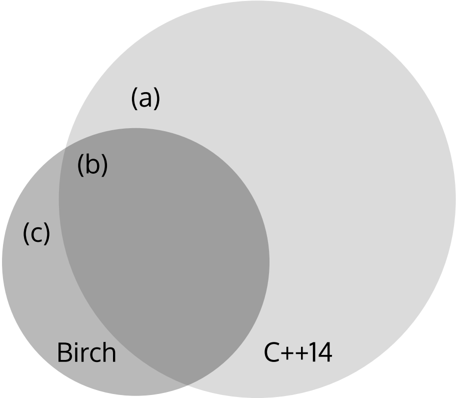
- Dynamic memory management with reference-counted garbage collection.
- Compiles to C++14 then native binaries.
- Uses standard C/C++ libraries for numerical computing, e.g. STL, Boost, Eigen.
- C/C++ code can be nested in Birch code to allow tight integration.

Birch $\longrightarrow$ C++14



Birch $\longrightarrow$ C++14

(a) C++14 provides a lot of things we would like to quarantine.



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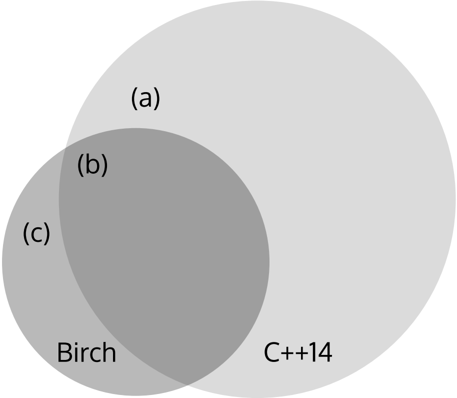
(b) Most Birch code translates directly to C++14
e.g. object model, higher-order functions, user-defined conversions

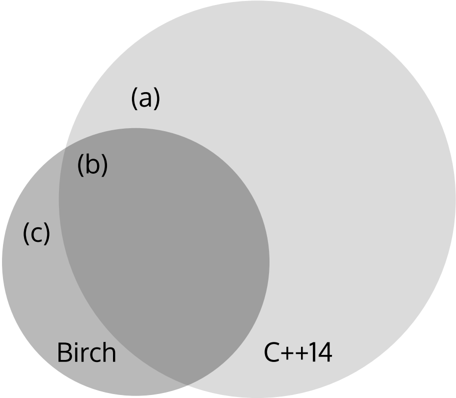


Birch $\longrightarrow$ C++14

(a) C++14 provides a lot of things we would like to quarantine.

(b) Most Birch code translates directly to C++14
e.g. object model, higher-order functions, user-defined conversions

(c) Some Birch code translates to verbose or intrusive C++14 that one would not want to code by hand
e.g. probabilistic operators, fibers, copy-on-write



Models in Birch

In Birch, a model is specified by writing a program that simulates from the **joint distribution**.

- In many other PPLs, there is a distinction between which variables are observed and which are latent **within the program**.
  - i.e. the program already factors the joint distribution into likelihood and prior.
- In Birch, the preference is to distinguish which variables are observed and which are latent **at runtime**.
  - i.e. at runtime, the user, or the inference method, chooses which conditionals or marginals of the joint distribution are of interest.

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  - i.e. at runtime, the user, or the inference method, chooses which conditionals or marginals of the joint distribution are of interest.
  - (Ideally, at least, as this is not always possible.)

Example: Bayesian linear regression model

```
class LinearRegressionModel < Model {
  X:Real[_,_];
  σ2:Random<Real>;
  β:Random<Real[_]>;
  y:Random<Real[_]>;

  fiber simulate() -> Real {
    N:Integer <- rows(X);
    P:Integer <- columns(X);
    if (N > 0 && P > 0) {
      σ2 ~ InverseGamma(3.0, 0.4);
      β ~ Gaussian(vector(0.0, P), identity(P)*σ2);
      y ~ Gaussian(X*β, σ2);
    }
  }
}
```

Example: linear-Gaussian state-space model

```
class LinearGaussianSSM = MarkovModel<LinearGaussianSSMState,
    LinearGaussianSSMParameter>;

class LinearGaussianSSMParameter < Parameter {
  a:Real <- 0.8;
  σ2_x:Real <- 1.0;
  σ2_y:Real <- 0.1;
}

class LinearGaussianSSMState < State {
  x:Random<Real>;
  y:Random<Real>;

  fiber initial(θ:LinearGaussianSSMParameter) -> Real {
    x ~ Gaussian(0.0, θ.σ2_x);
    y ~ Gaussian(x, θ.σ2_y);
  }
```

Example: linear-Gaussian state-space model

```
  fiber transition(z:LinearGaussianSSMState,
      θ:LinearGaussianSSMParameter) -> Real {
    x ~ Gaussian(θ.a*z.x, θ.σ2_x);
    y ~ Gaussian(x, θ.σ2_y);
  }
}
```

Example: nonlinear state-space model

```
class SIRModel = MarkovModel<SIRState,SIRParameter>;

class SIRParameter < Parameter {
  λ:Random<Real>;
  δ:Random<Real>;
  γ:Random<Real>;

  fiber parameter() -> Real {
    λ <- 10.0;
    δ ~ Beta(2.0, 2.0);
    γ ~ Beta(2.0, 2.0);
  }
}

class SIRState < State {
  τ:Random<Integer>;
  Δi:Random<Integer>;
  Δr:Random<Integer>;
```

Example: nonlinear state-space model

```
  s:Random<Integer>;
  i:Random<Integer>;
  r:Random<Integer>;

  fiber transition(x:SIRState, θ:SIRParameter) -> Real {
    τ ~ Binomial(x.s, 1.0 - exp(-θ.λ*x.i/(x.s + x.i + x.r)));
    Δi ~ Binomial(τ, θ.δ);
    Δr ~ Binomial(x.i, θ.γ);

    s ~ Delta(x.s - Δi);
    i ~ Delta(x.i + Δi - Δr);
    r ~ Delta(x.r + Δr);
  }
}
```

Models in Birch

- Knowing something about the structure of a model may help tailor the inference algorithm, so it will be useful if programs reveal something of this.
- One option is static analysis, but this is hard.
- The approach at this stage is for it to be the programmer's responsibility to reveal this by construction, e.g. using the `MarkovModel` class.
- Details are still developing.

Methods in Birch

Inference methods are also written in the Birch language.

- Currently available are:
  - Analytical solutions
  - Importance sampling
  - Bootstrap particle filter
  - Alive particle filter
  - Auxiliary particle filter (automated)
  - Rao–Blackwellized particle filter (automated)
- Not far off are:
  - Particle MCMC methods
  - Other MCMC methods.

3 Birch: language features

Optionals

Optionals allow variables to have a value of a particular type, or no value at all.

- They are used in other programming languages (e.g. Swift) to eliminate boilerplate that checks for `null` values, e.g. a function checking its arguments.
- In Birch, they are used for the same purpose, but also a second role: to represent **missing values**.

Randoms

Randoms are optionals to which a probability distribution can be attached.

- When they **don't have a value**, the probability distribution can be used to automatically **simulate a value**.

- Once a random has a value, that value is final, it cannot be overwritten.

Delayed sampling

- Randoms are essential for the **delayed sampling** mechanism within Birch.
- This is a heuristic algorithm for performing analytical optimizations at runtime.
- It automatically yields optimizations such as variable elimination/collapsing, Rao–Blackwellization and locally-optimal proposals.

See:

L. M. Murray, D. Lundén, J. Kudlicka, D. Broman, and T. B. Schön. Delayed sampling and automatic Rao–Blackwellization of probabilistic programs. Proceedings of the 21st International Conference on Artificial Intelligence and Statistics (AISTATS), 2018.

URL `https://arxiv.org/abs/1708.07787`

Delayed sampling example

Code	Checkpoint
`x ~ Gaussian(0.0, 1.0);`	
`for (n in 1..N) {`	
`  y[n] ~ Gaussian(x, 1.0);`	
`}`	
`stdout.print(x);`	

Delayed sampling example

Code	Checkpoint
`x ~ Gaussian(0.0, 1.0);`	**assume** x
`for (n in 1..N) {`	
`  y[n] ~ Gaussian(x, 1.0);`	
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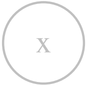

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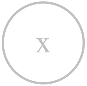

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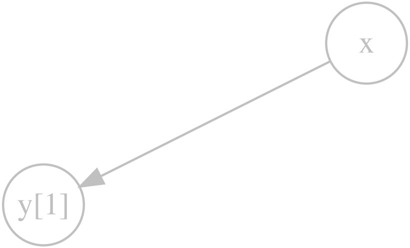

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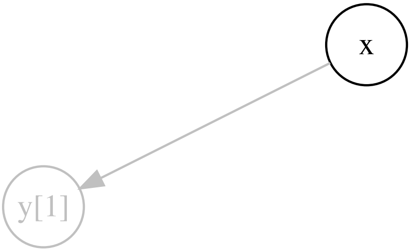

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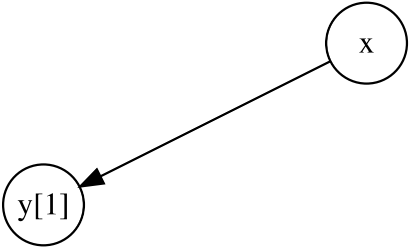

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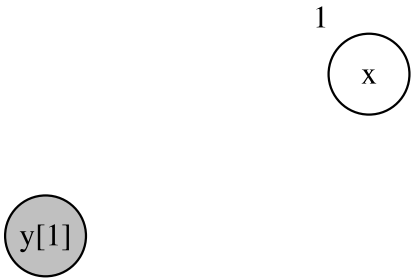

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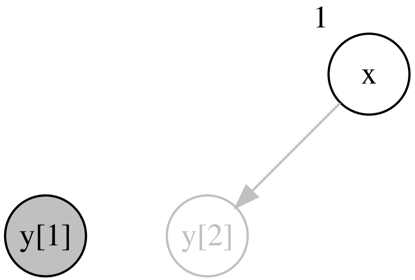

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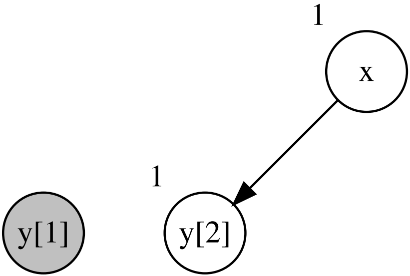

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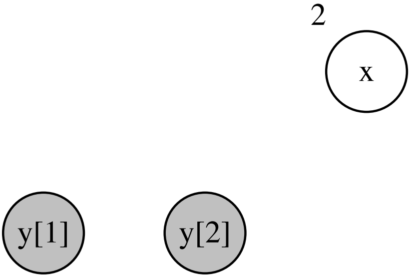

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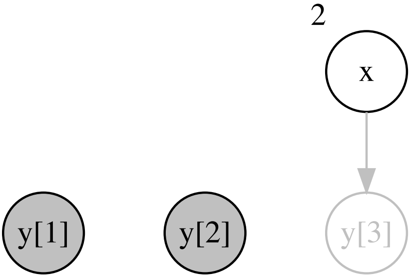

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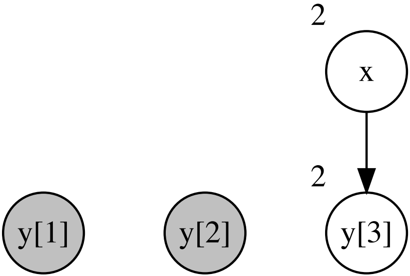

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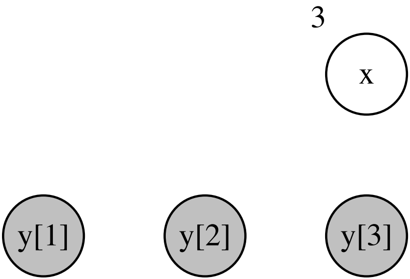

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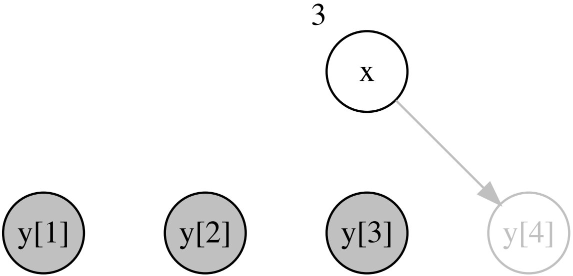

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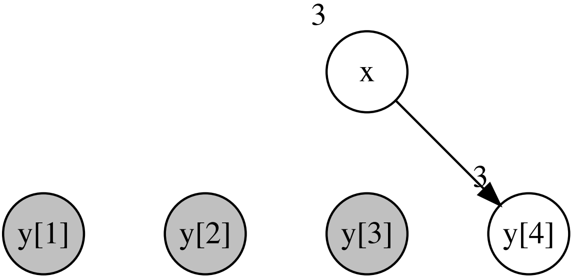

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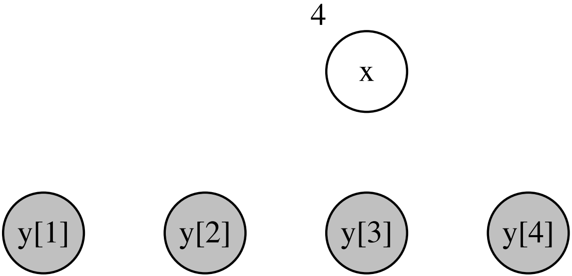

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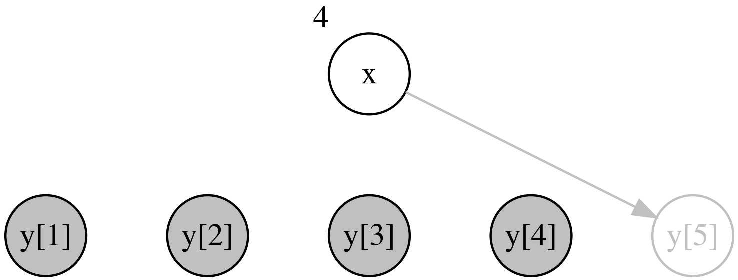

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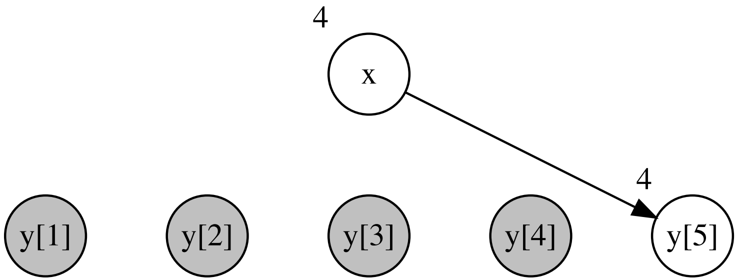

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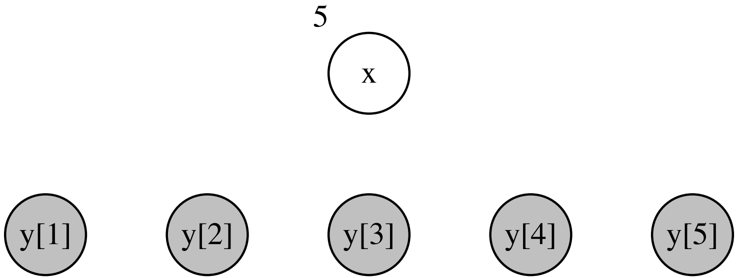

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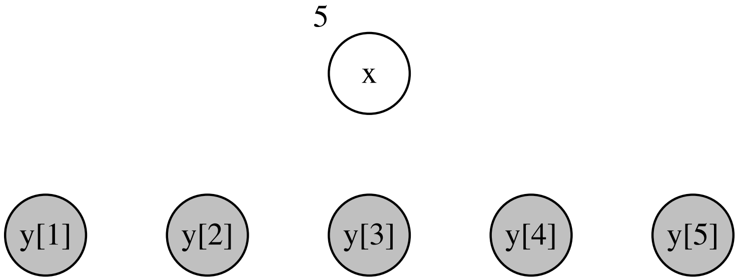
`for (n in 1..N) {`	
`  y[n] ~ Gaussian(x, 1.0);`	
`}`	
`stdout.print(x);`	**value** x



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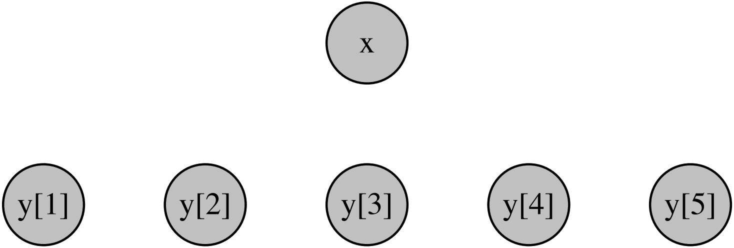

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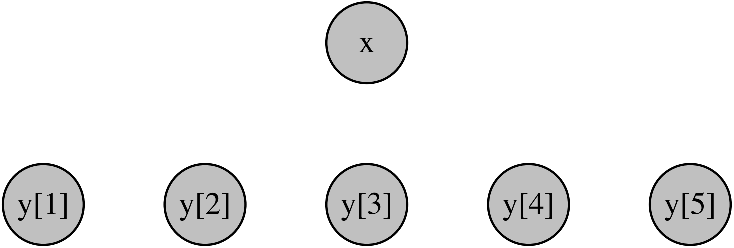


Delayed sampling

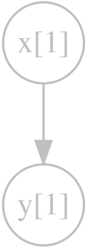
Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	

Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	**assume** x[1]
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	

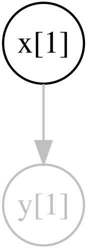
Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	**observe** y[1]
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	



Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	**observe** y[1]
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	



Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	**observe** y[1]
`for (t in 2..T) {`	
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`  y[t] ~ Gaussian(x[t], 1.0);`	
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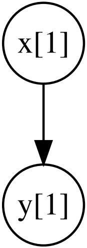
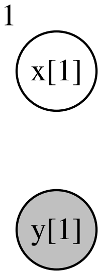


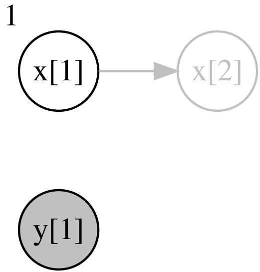
Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	**observe** y[1]
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	



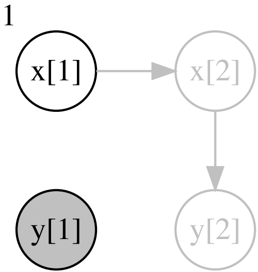
Delayed sampling

Code	**Checkpoint**
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	**assume** x[t]
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	



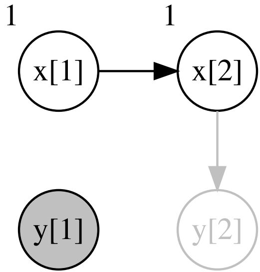
Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
`}`	
`stdout.print(x[1]);`	



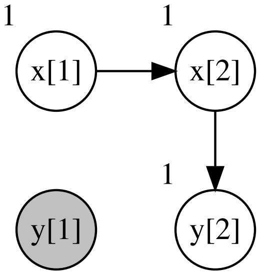
Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
`}`	
`stdout.print(x[1]);`	



Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
`}`	
`stdout.print(x[1]);`	



Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
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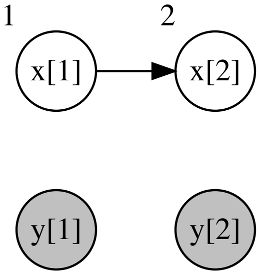
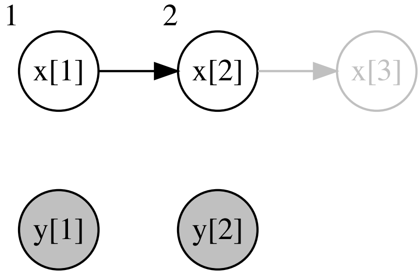


Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	**assume** x[t]
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	



Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
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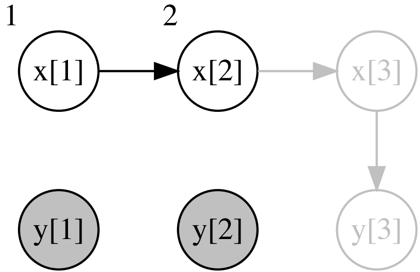

Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
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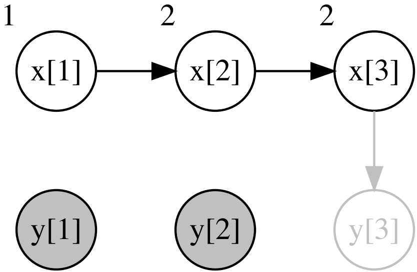

Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
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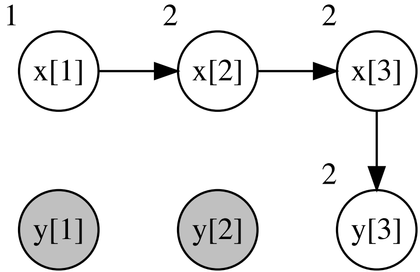
`stdout.print(x[1]);`	



Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
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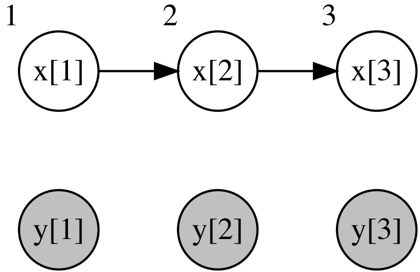
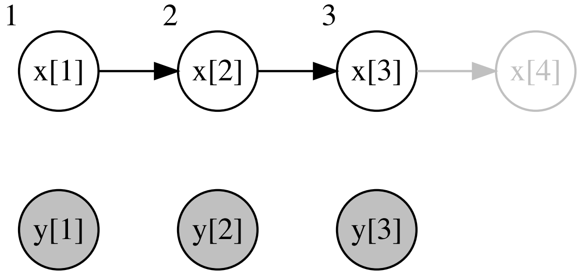
`stdout.print(x[1]);`	



Delayed sampling

Code	**Checkpoint**
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	**assume** x[t]
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	



Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
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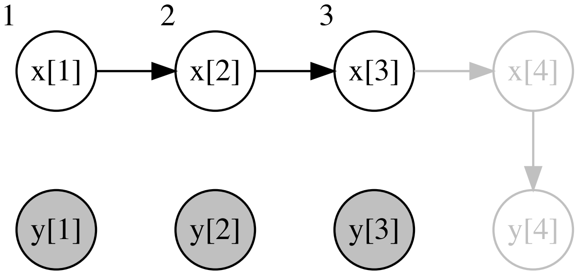

Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
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`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
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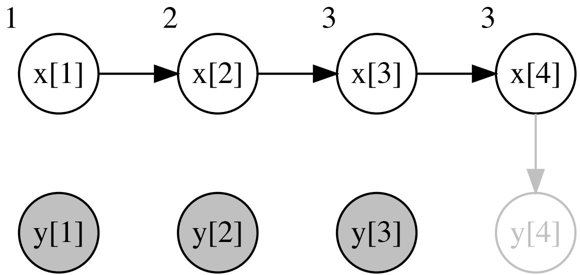

Delayed sampling

Code	**Checkpoint**
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
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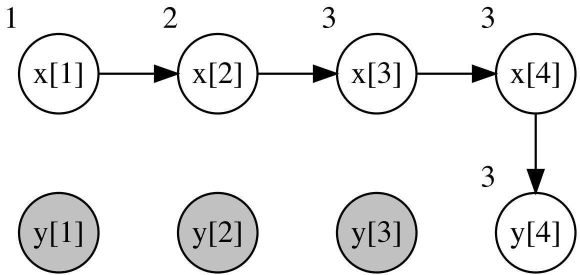

Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
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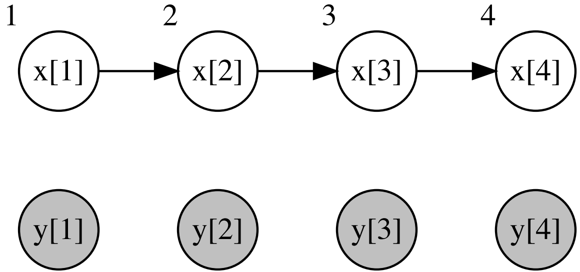
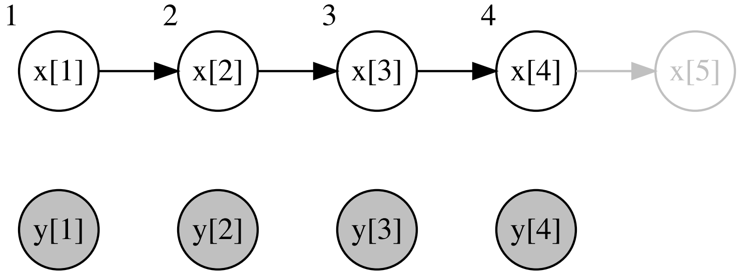
`stdout.print(x[1]);`	



Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	**assume** x[t]
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	



Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
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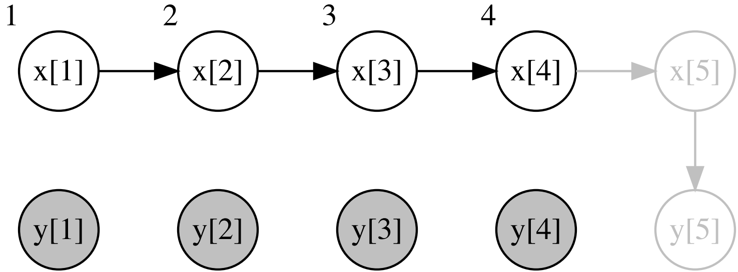

Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
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`}`	
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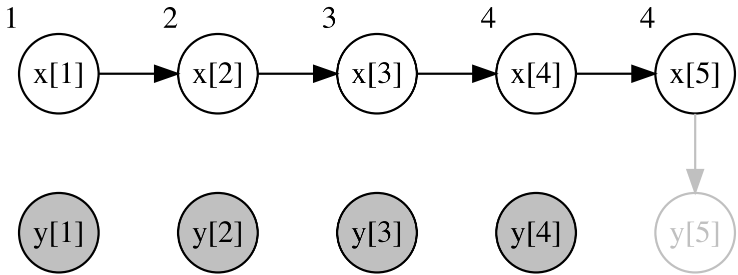

Delayed sampling

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
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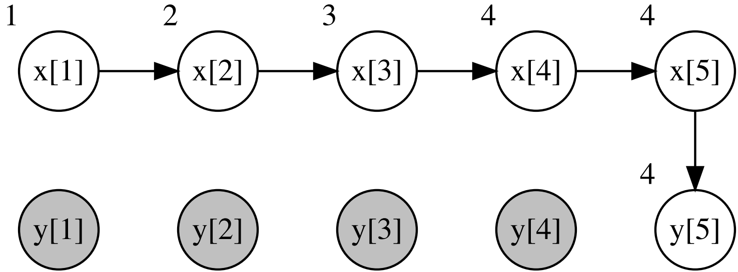
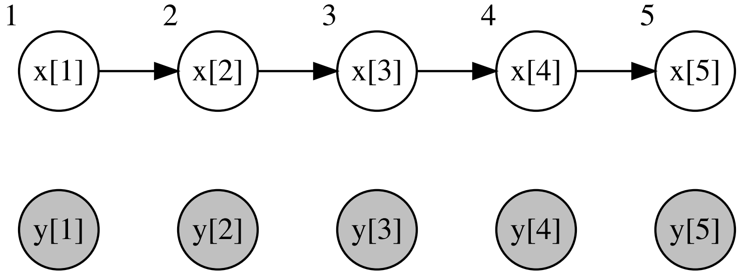
`stdout.print(x[1]);`	



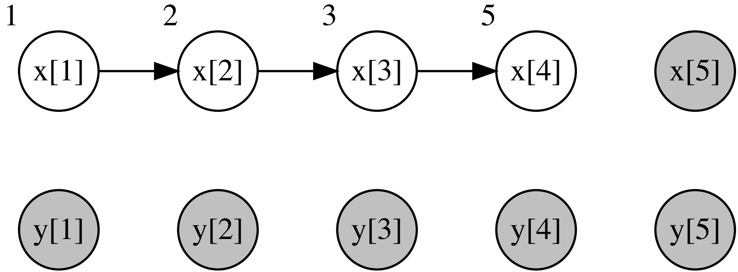
Delayed sampling: Kalman Filter

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	**observe** y[t]
`}`	
`stdout.print(x[1]);`	



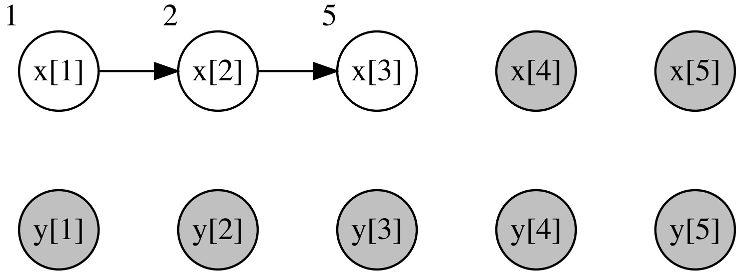
Delayed sampling: Kalman Filter

Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	**value** x[1]



Delayed sampling: Kalman Filter

Code	**Checkpoint**
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	**value** x[1]



Delayed sampling: Kalman Filter

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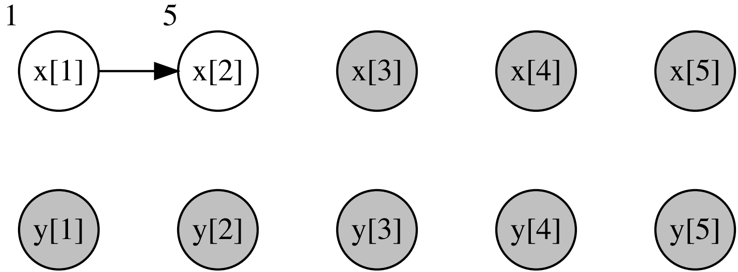
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	**value** x[1]



Delayed sampling: Kalman Filter

Code	**Checkpoint**
`x[1] ~ Gaussian(0.0, 1.0);`	
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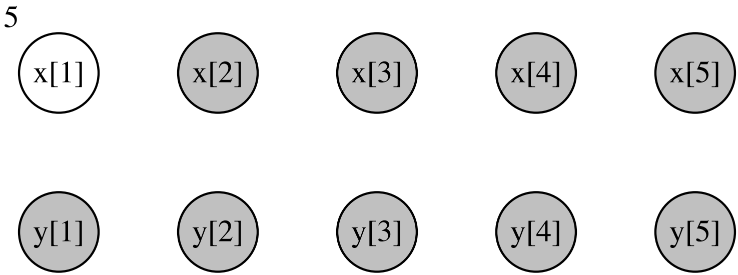
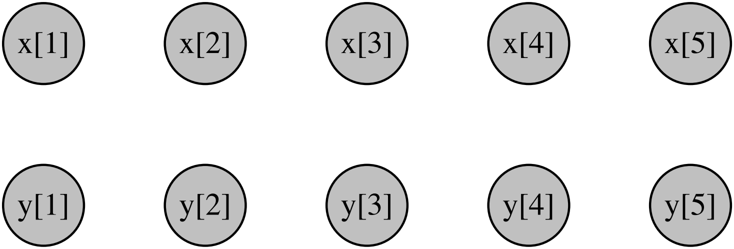
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	**value** x[1]



Delayed sampling: Kalman Filter

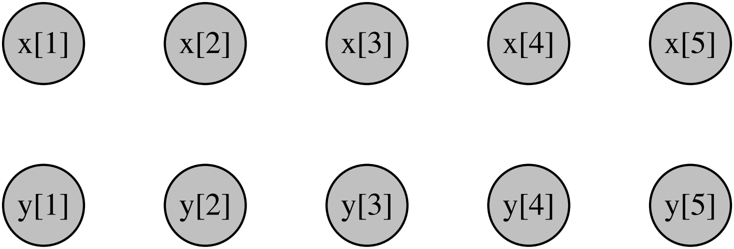
Code	Checkpoint
`x[1] ~ Gaussian(0.0, 1.0);`	
`y[1] ~ Gaussian(x[1], 1.0);`	
`for (t in 2..T) {`	
`  x[t] ~ Gaussian(a*x[t - 1], 1.0);`	
`  y[t] ~ Gaussian(x[t], 1.0);`	
`}`	
`stdout.print(x[1]);`	**value** x[1]



Delayed sampling: Kalman Filter

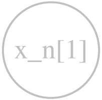
Code **Checkpoint**

```
x[1] ~ Gaussian(0.0, 1.0);
y[1] ~ Gaussian(x[1], 1.0);
for (t in 2..T) {
  x[t] ~ Gaussian(a*x[t - 1], 1.0);
  y[t] ~ Gaussian(x[t], 1.0);
}
stdout.print(x[1]);
```

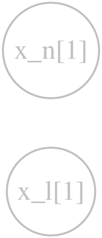


Delayed sampling

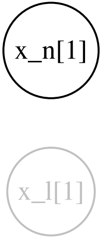
Delayed sampling



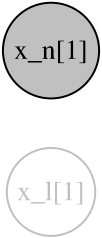
Delayed sampling



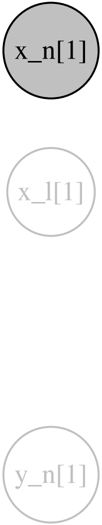
Delayed sampling



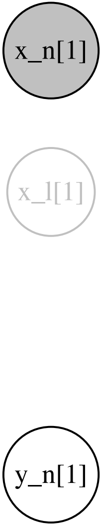
Delayed sampling



Delayed sampling

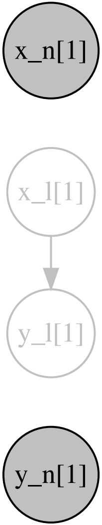


Delayed sampling

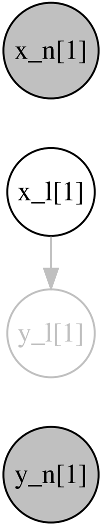


Delayed sampling

Delayed sampling



Delayed sampling



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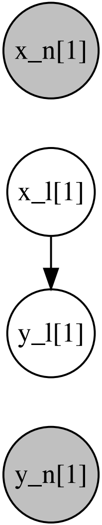

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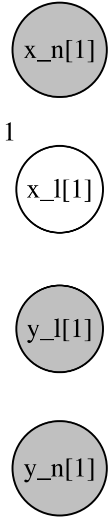

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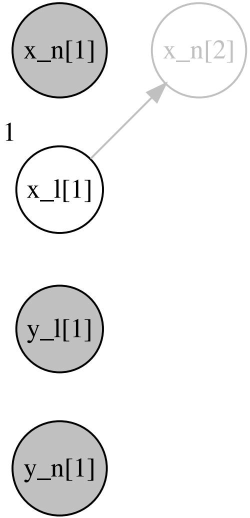

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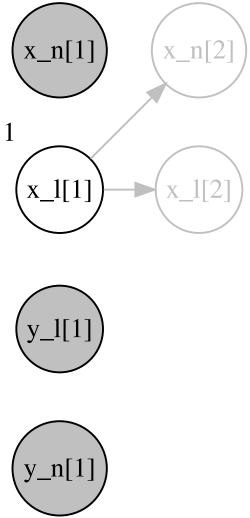

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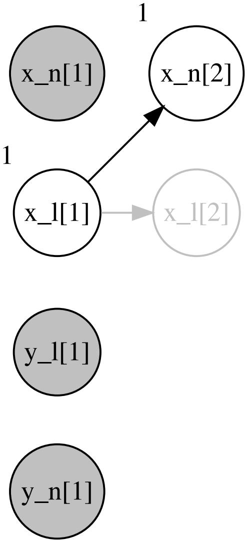

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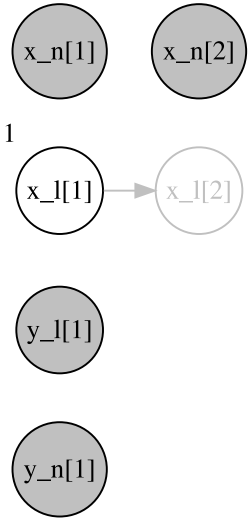

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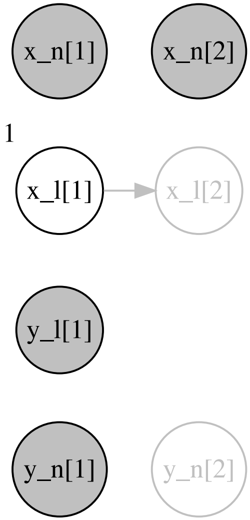

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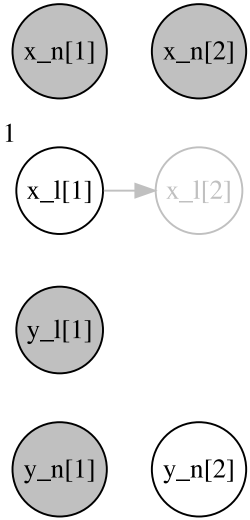

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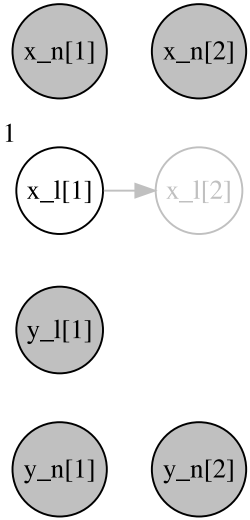

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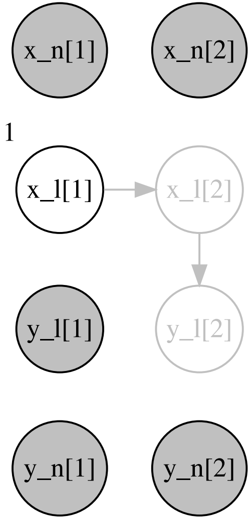

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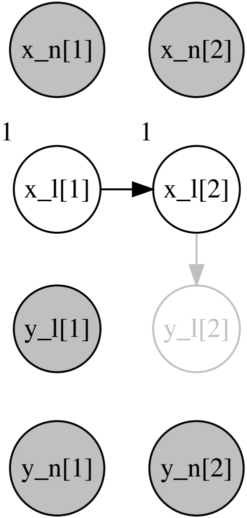

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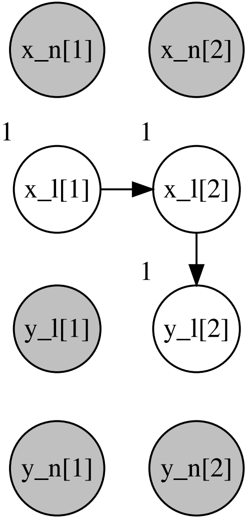

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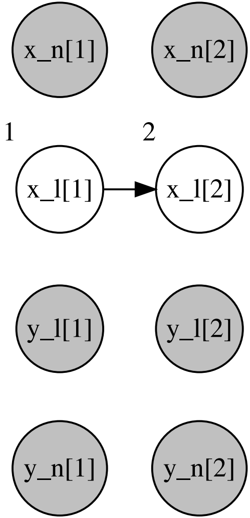

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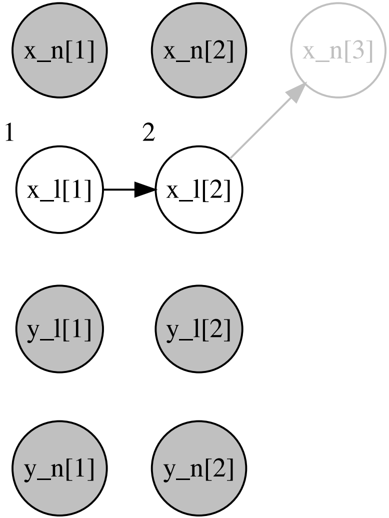

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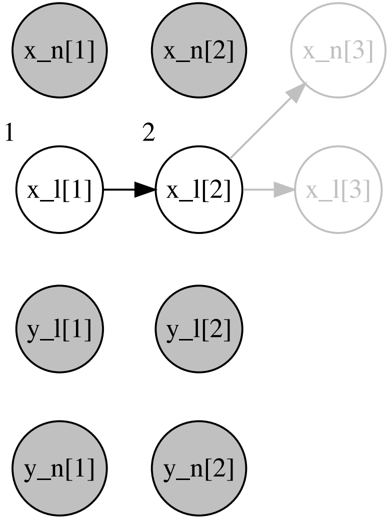

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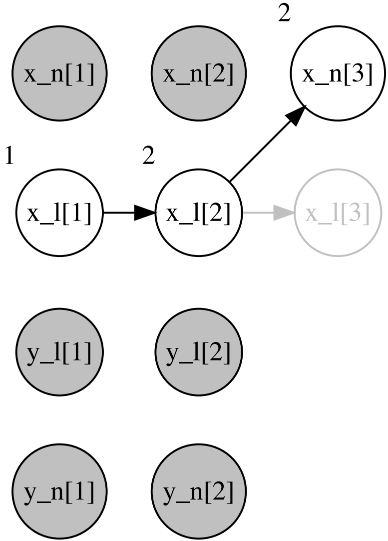

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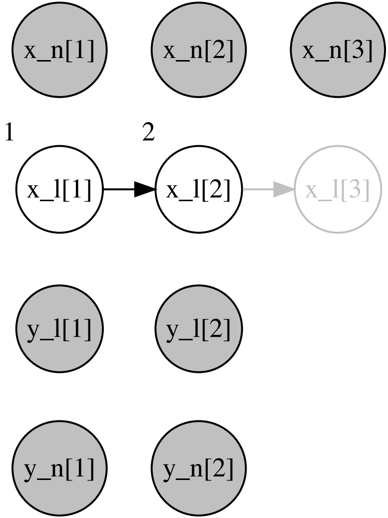

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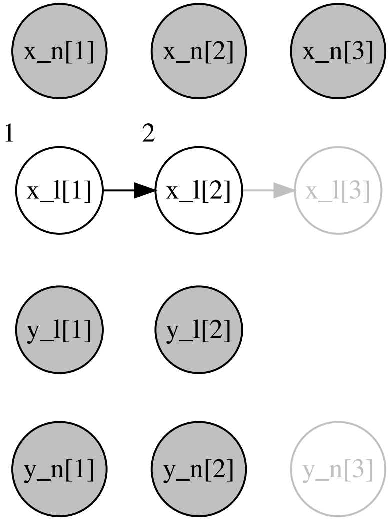

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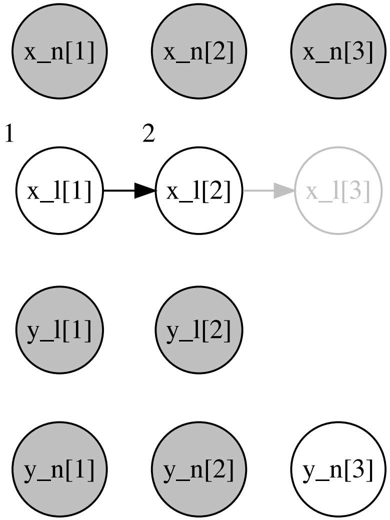

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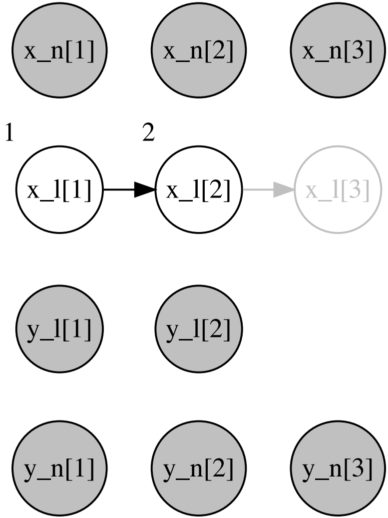

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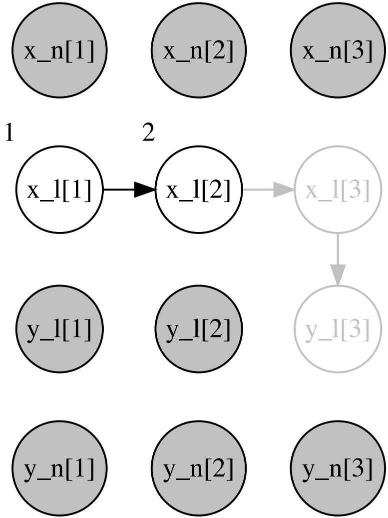

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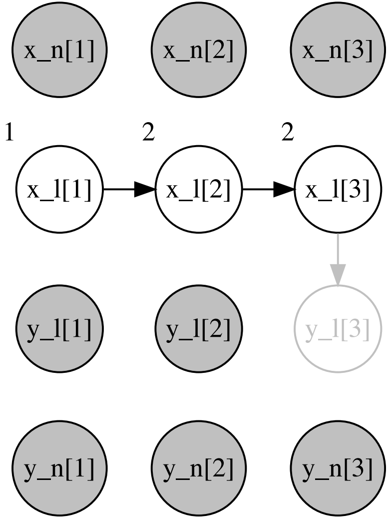

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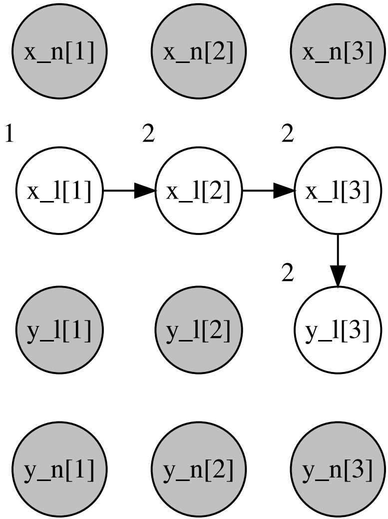

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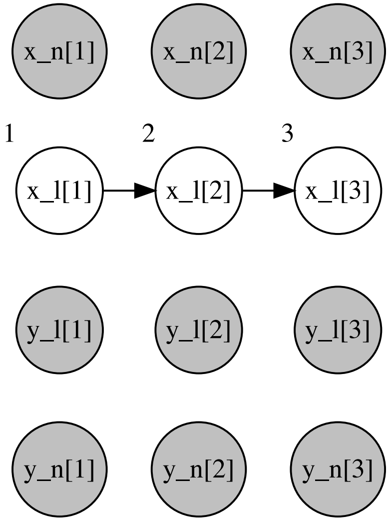

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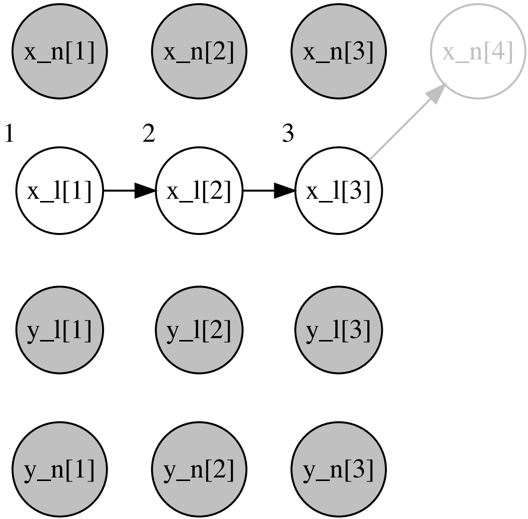

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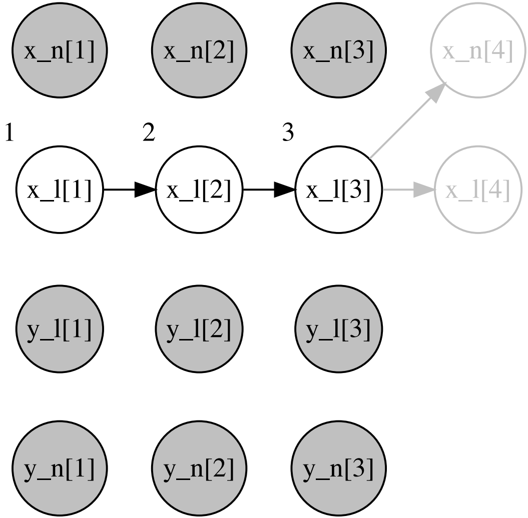

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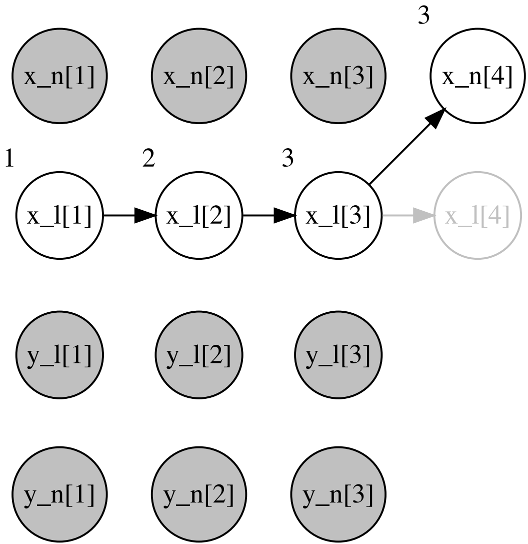

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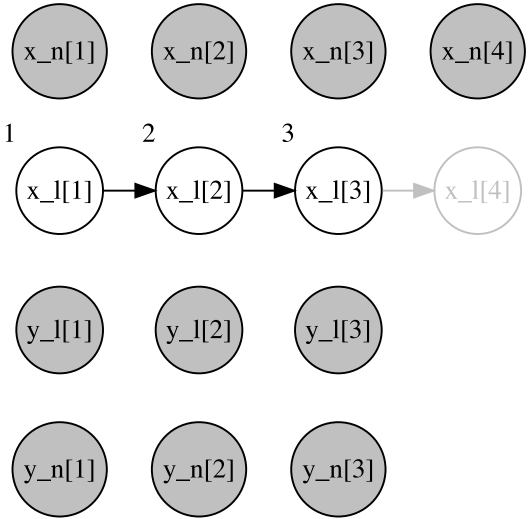

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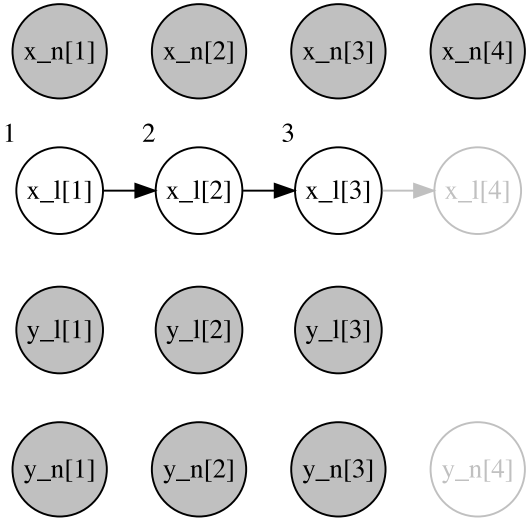

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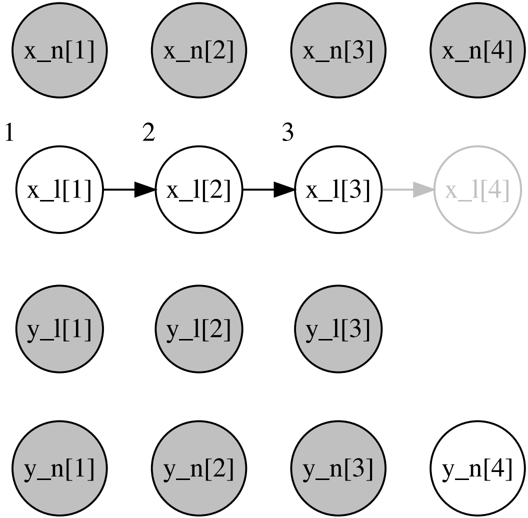

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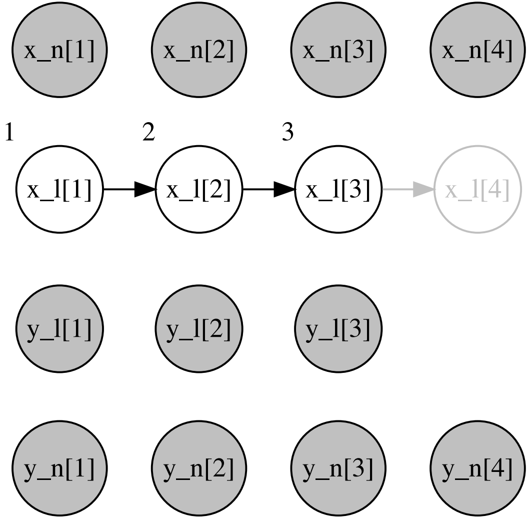

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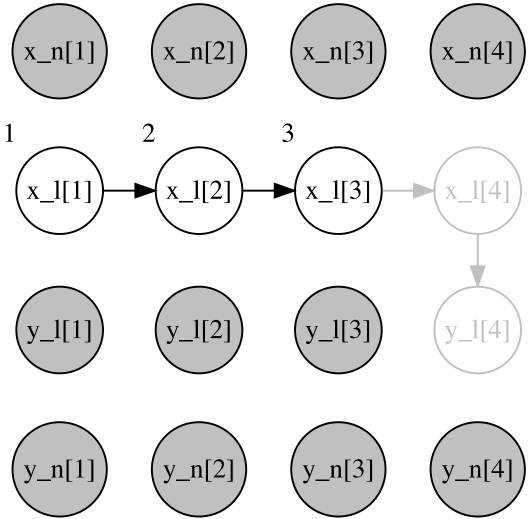

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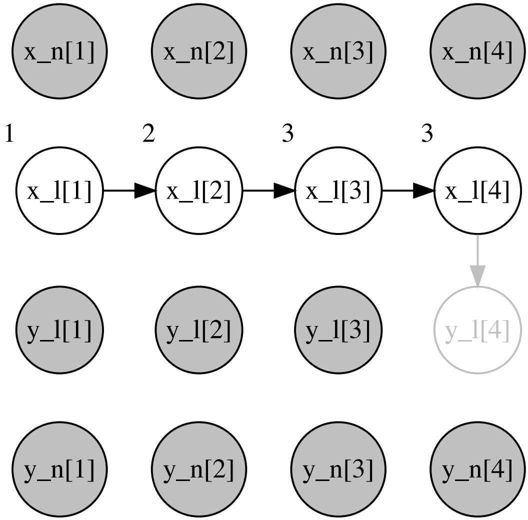

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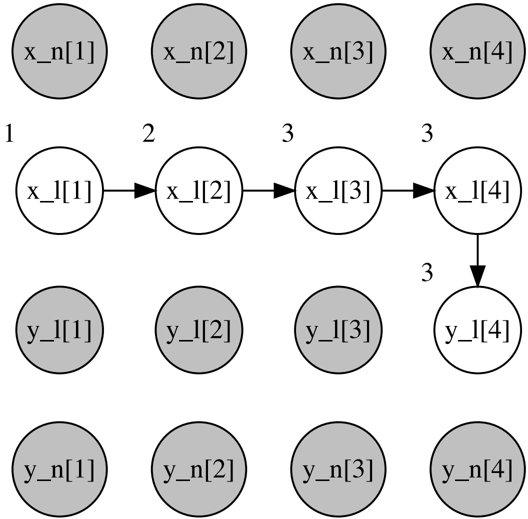

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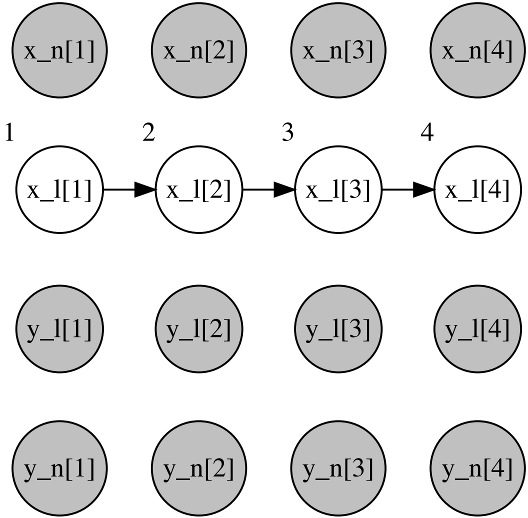

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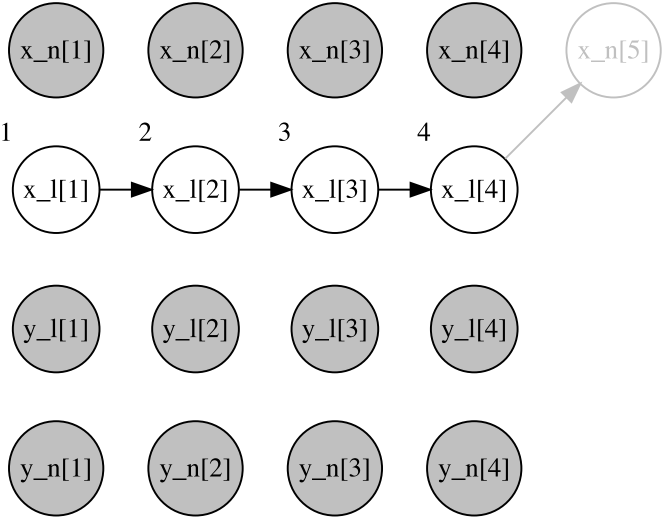

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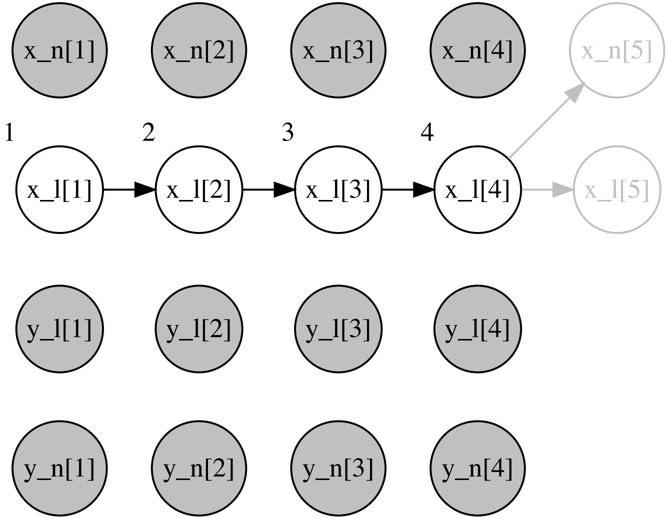

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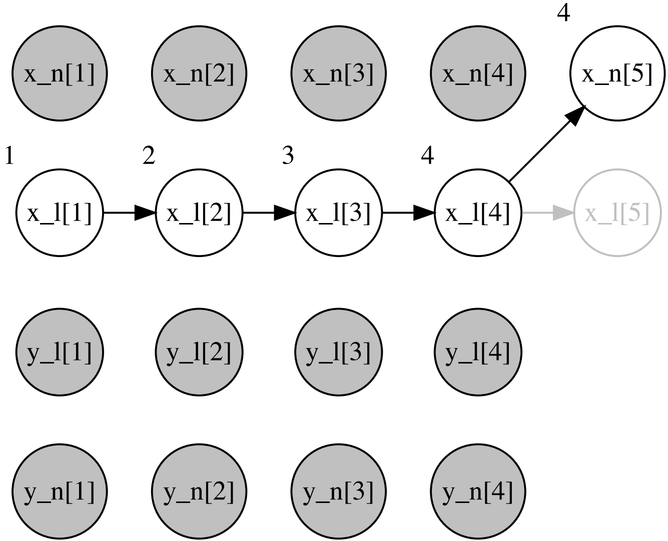

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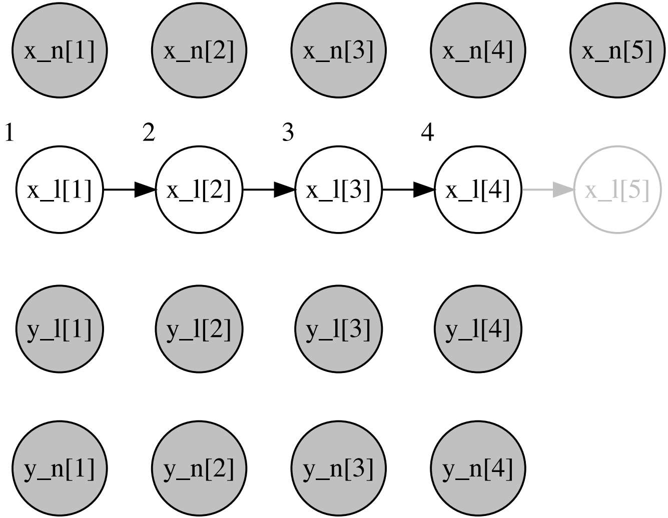

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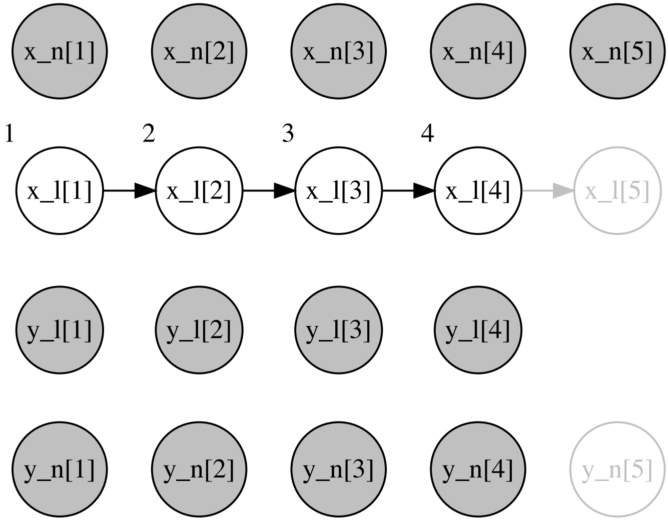

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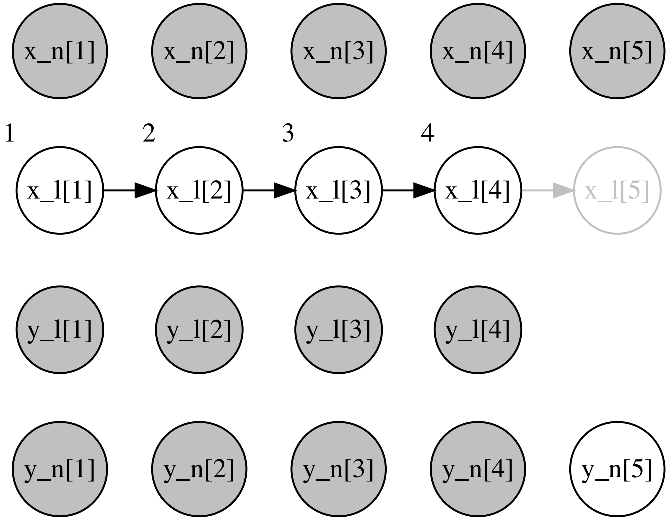

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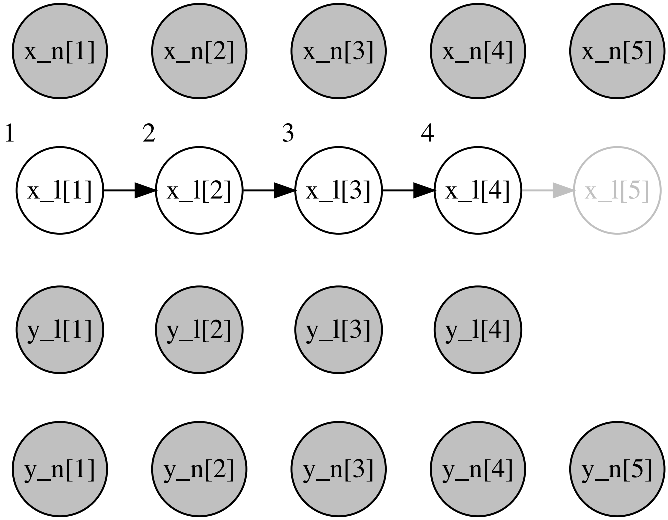

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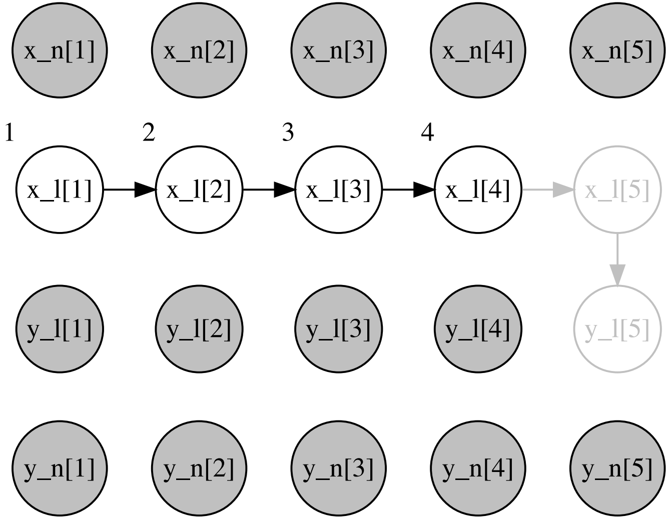

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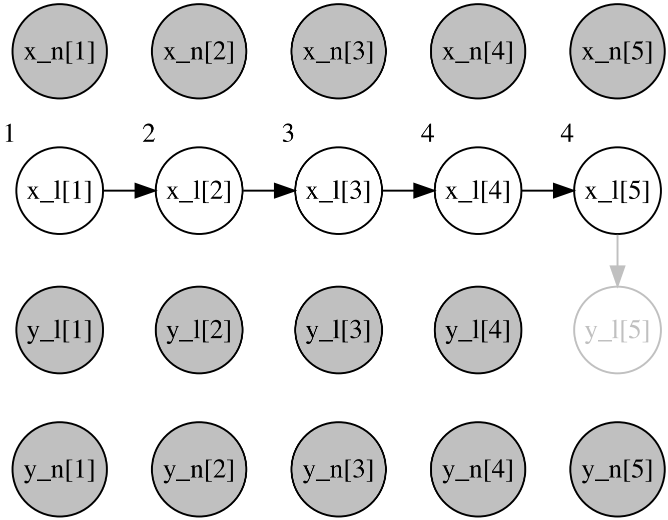

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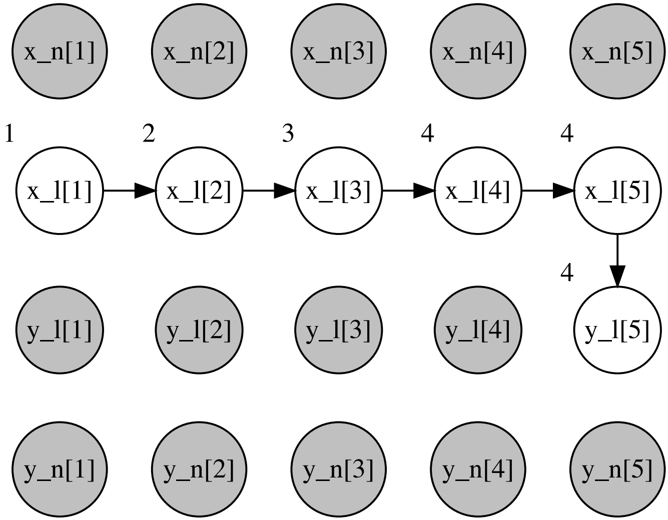

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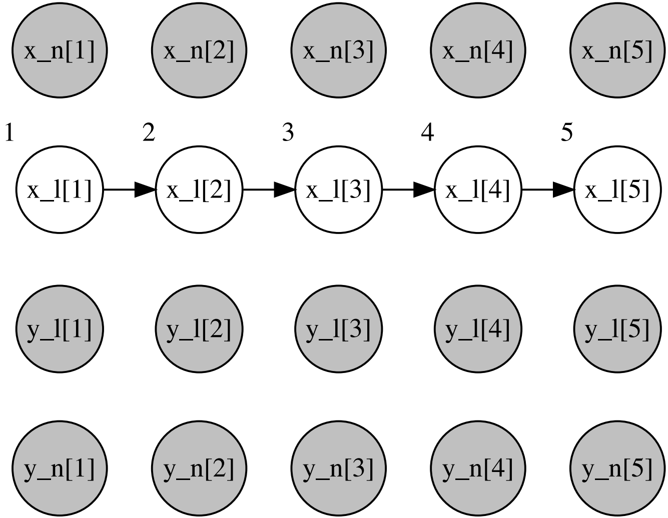
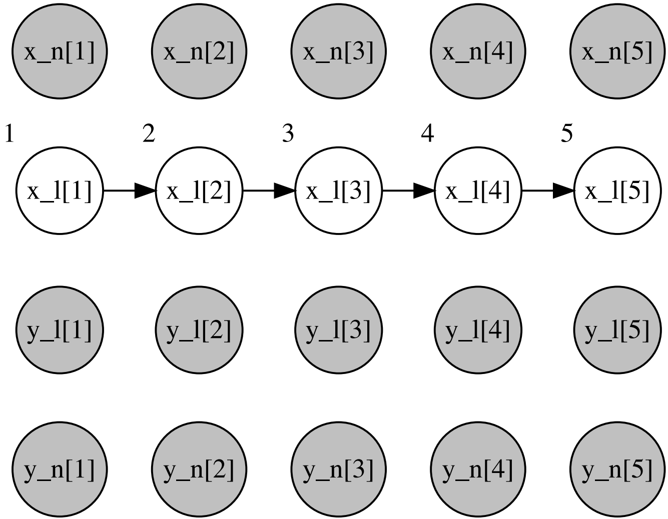


Delayed sampling: Rao–Blackwellized Particle Filter



Fibers

Fibers (also known as **coroutines** elsewhere) are like functions, but their execution can be paused and resumed.

- A function, when called, executes to completion and **returns** a value to the caller.
- A fiber, when called, executes to its first pause point and **yields** a value to the caller. The caller can then proceed with some other computation. Later, the caller may resume the fiber; it will execute to its next pause point and yield another value to the caller, and so on.

Fibers

- In Birch, fibers are used to simulate a probabilistic model. Each time an observation is encountered, the fiber pauses and **yields a weight**.
- This is a key ingredient for many inference methods (e.g. Sequential Monte Carlo).
- Fibers can be replicated. When resumed, replicated fibers proceed independently.
- A copy-on-write mechanism is used to minimise copying when replicating fibers.
- Can also be useful for **prospective computation**, e.g. anything with an accept/reject step.

Probabilistic operators

Optionals, randoms and fibers come together in the probabilistic operators of Birch. These are:

`a <~ b` **simulate** the distribution `b` and assign the value to `a`,

`a ~> b` **observe** the value `a` with distribution `b` and yield its log-likelihood from the current fiber,

`a ~ b` if `a` has a value then **observe** it, otherwise **simulate** it (perhaps lazily).

Looking ahead

- **Current focus** is pilot applications.
- **Near ahead** is adding new inference methods.
- **Further ahead** is performance tuning and parallelism.

Getting started guide and tutorial available on the website: `birch-lang.org`.