pipeline: TODO

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ABSTRACT

TODO!!! The code is available online at http://mussles.github.io/pipeline/ under the GNU General Public License v3.

Subject headings: methods: statistical — methods: Markov chain Monte Carlo — TODO

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Note: If you want to get started immediately with the pipeline *package, start at Appendix A on page 4 or visit the online documentation at* https://mussles.github.io/pipeline*. If you are sampling with* pipeline *and having low-acceptance-rate or other issues, there is some advice in Section 3 starting on page 3.*

1. Introduction

Throughout previous years of development, Markov chain Monte Carlo (MCMC) has evolved from a foregone algorithm to a more general way to fit real-life data.

2. The Algorithm

One of the most commonly used MCMC algorithms is the Adaptive Metropolis-Hastings Algorithm (AM), first proposed by Haario, et al. in their *An Adaptive Metropolis Algorithm* Haario, et al. (2001). In their paper, they propose an algorithm that streamlines the task of setting the step-size, comparing to the arduous process outlined in the original algorithm. The original algorithm was introduced by Metropolis and Hastings, respectively, in their separate papers Metropolis, et al. (1953) and Hastings (1970).

Algorithm 1 The Metropolis-Hastings algorithm

Draw $X^0 \sim \mu$ where μ is the initial condition.
Set $t \leftarrow 0$.
repeat
    Draw $Y^t \sim q(y^t|x^t)$.
    Compute $\alpha = \min\left\{\frac{\pi(y^t)}{\pi(x^t)}\frac{q(x^t|y^t)}{q(y^t|x^t)}, 1\right\}$
    Draw $U \sim \mathcal{U}[0,1]$.
    if $U \leq \alpha$ **then**
        Set $X^{t+1} \leftarrow Y^t$.
    else
        Set $X^{t+1} \leftarrow X^t$.
    end if
    Set $t \leftarrow t + 1$.
until Sufficiently many samples have been produced.

Algorithm 2 Adaptive Metropolis-Hastings algorithm

Draw $X^0 \sim \mu$ where μ is the initial condition.
Set θ^0 to an arbitrary valid value.
Set $t \leftarrow 0$.
repeat
  Compute $\theta^t = \gamma^t(\theta^0, X^0, \ldots, X^{t-1})$ where γ^t is a transformation that update the parameters based on past samples.
  Draw X^{t+1} using the proposal $q(\cdot|x^t, \theta^t)$ with the Metropolis-Hastings rule.
  Set $t \leftarrow t + 1$.
until The accept rate of the last K iterations are close to 0.234.
Set $\theta \leftarrow \theta^t$.
Perform Algorithm 1 with proposal $q(\cdot|x) = q(\cdot|x, \theta)$.

3. Discussion & Tips

REFERENCES

Haario, H.; Saksman, E.; Tamminen, J. (2001). "An adaptive Metropolis algorithm." Bernoulli, 7(2): 223242.

Metropolis, N., Rosenbluth, A., Rosenbluth, M., Teller, A., and Teller, E. (1953). "Equations of state calculations by fast computing machines." J. Chem. Phys., 21(6): 10871092.

Hastings, W. (1970). "Monte Carlo sampling methods using Markov chains and their application." Biometrika, 57: 97109.

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A. Installation

B. Issues & Contributions

The development of pipeline is being coordinated on GitHub at http://github.com/mussles/pipeline and contributions are welcome. If you encounter any problems with the code, please report them at http://github.com/mussles/pipeline/issues and consider contributing a patch.

C. Online Documentation

To learn more about how to use pipeline in practice, it is best to check out the documentation on the website https://mussles.github.io/pipeline. This page includes the API documentation and many examples of possible work flows.