

8. Appendix

This appendix contains additional plots and proofs of the results from Section 2.

Lemma 6. *The divergence from $q(z)$ to $p(z)$ is*

$$KL(q(Z)\|p(Z)) = \underbrace{KL(q(Z|W)\|p(Z))}_{D_0} - I_q[W, Z], \quad (27)$$

where $D_0 = \mathbb{E}_{q(W,Z)} \log(q(Z|W)/p(Z))$ is conditional divergence and I_q denotes mutual information under q .

Proof. Define the joint distribution $p(w, z) = q(w)p(z)$. Then, the chain-rule of KL-divergence (Cover & Thomas, 2006, Thm. 2.5.3) states that

$$KL(q(Z, W)\|p(Z, W)) = KL(q(W|Z)\|p(W|Z)) + KL(q(Z)\|p(Z)). \quad (28)$$

The left-hand side simplifies into D_0 , and the first term on the right-hand side simplifies into $I_q[W, Z]$. \square

Theorem 7. *For fixed values of β and $p(w|z)$, the distribution $q(w)$ that minimizes D_β is*

$$\begin{aligned} q^*(w) &= \exp(s(w) - A) \\ A &= \log \int_w \exp s(w) \\ s(w) &= \log p(w) - KL(q(Z|w)\|p(Z|w)) \\ &\quad - (\beta^{-1} - 1) KL(q(Z|w)\|p(Z)). \end{aligned}$$

Moreover, at q^* , the objective value is $D_\beta^* = -\beta A$.

Proof. First, consider derivatives of D_0 and D_1 with respect to $q(w)$. The first can immediately be seen to be

$$\frac{dD_0}{dq(w)} = KL(q(Z|w)\|p(Z)).$$

For the second, we can derive

$$\begin{aligned} \frac{dD_1}{dq(w)} &= \frac{d}{dq(w)} \int_{w,z} q(w, z) \log \frac{q(z|w)}{p(w, z)} \\ &\quad + \frac{d}{dq(w)} \int_{w,z} q(w) \log q(w) \\ &= \int_z q(z|w) \log \frac{q(z|w)}{p(w, z)} + \log q(w) + 1 \\ &= KL(q(Z|w)\|p(Z|w)) - \log p(w) + \log q(w) + 1. \end{aligned}$$

If we create a Lagrangian for D_β with a Lagrange multiplier λ to enforce normalization of $q(w)$, we know that at

the optimal $q(w)$ its gradient will be zero. Using the above derivatives, we therefore have that

$$\begin{aligned} 0 &= (1 - \beta)KL(q(Z|w)\|p(Z)) + \beta KL(q(Z|w)\|p(Z|w)) \\ &\quad - \beta \log p(w) + \beta \log q(w) + \lambda, \end{aligned}$$

Which solved for $q(w)$, this gives

$$\begin{aligned} q(w) &\propto \exp(-(1 - \beta^{-1})KL(q(Z|w)\|p(Z)) \\ &\quad - KL(q(Z|w)\|p(Z|w)) + \log p(w)), \end{aligned}$$

which establishes the given form for $s(w)$ and A .

Now, to establish the value of D_β at the solution, expand the negative entropy of $q(w)$ to get

$$\begin{aligned} \beta \int_w q(w) \log q(w) \\ &= \beta \int_w q(w) \left(-(1 - \beta^{-1})KL(q(Z|w)\|p(Z)) \right. \\ &\quad \left. - KL(q(Z|w)\|p(Z|w)) + \log p(w) \right) - \beta A. \quad (29) \end{aligned}$$

Now, taking the left-hand side and terms in the bottom line, we can recognize that

$$\int_w q(w) \left(\log \frac{p(w)}{q(w)} - KL(q(Z|w)\|p(Z|w)) \right) = -D_1.$$

Further, if we take the terms from the middle line, we have that

$$-\beta \int_w q(w)(1 - \beta^{-1})KL(q(Z|w)\|p(Z)) = (\beta - 1)D_0.$$

Thus, we can re-write Eq. 29 as $-\beta A = (1 - \beta)D_0 + \beta D_1$, establishing the value of D_β^* . \square

Remark 8. In the limit where $\beta \rightarrow 0$ the divergence bound becomes

$$\lim_{\beta \rightarrow 0} D_\beta^* = \inf_w KL(q(Z|w)\|p(Z)).$$

Proof. Use the representation that $\lim_{\beta \rightarrow 0} D_\beta^* = \lim_{\beta \rightarrow 0} -\beta A$ is equal to

$$\begin{aligned} \lim_{\beta \rightarrow 0} -\beta \log \int_w \exp \left(\log p(w) - KL(q(Z|w)\|p(Z|w)) \right. \\ \left. - (\beta^{-1} - 1) KL(q(Z|w)\|p(Z)) \right) \\ = \lim_{\beta \rightarrow 0} -\beta \log \int_w \exp \left(-\beta^{-1} KL(q(Z|w)\|p(Z)) \right). \end{aligned}$$

The form for D_β^* follows from the fact that $\lim_{\beta \rightarrow 0} \beta \log \int_w \exp(\beta^{-1} f(w)) = \sup_w f(w)$. \square

Lemma 9. If $p(w|z) = r(w)q(z|w)/r_z$ and r_z is a constant, then the solution in Thm. 3 holds with

$$s(w) = \log r(w) - \log r_z + \mathbb{E}_{q_w(Z)} [\beta^{-1} \log p(z) + (1 - \beta^{-1}) \log q(z|w)].$$

Proof. First, without using the particular form for $p(w|z)$, we can write $s(w)$ as

$$\begin{aligned} \log p(w) - \int_z q(z|w) \log \frac{q(z|w)}{p(z|w)} \\ - (\beta^{-1} - 1) \int_z q(z|w) \log \frac{q(z|w)}{p(z)} \end{aligned}$$

Cancelling terms involving $q(z|w)$ in the numerators, this is

$$\begin{aligned} \log p(w) - \int_z q(z|w) \log \frac{p(z)}{p(z|w)} \\ - \beta^{-1} \int_z q(z|w) \log \frac{q(z|w)}{p(z)} \end{aligned}$$

The $\log p(w)$ can be absorbed into the first term to give, after some cancellation that

$$s(w) = \int_z q(z|w) \log p(w|z) - \beta^{-1} KL(q(Z|w) \| p(Z)).$$

Now, using the assumed form for $p(w|z)$, we can immediately write that $s(w)$ is

$$\int_z q(z|w) \log \frac{r(w)q(z|w)}{r_z} - \beta^{-1} \int_z q(z|w) \log \frac{q(z|w)}{p(z)},$$

equivalent to the form stated. \square

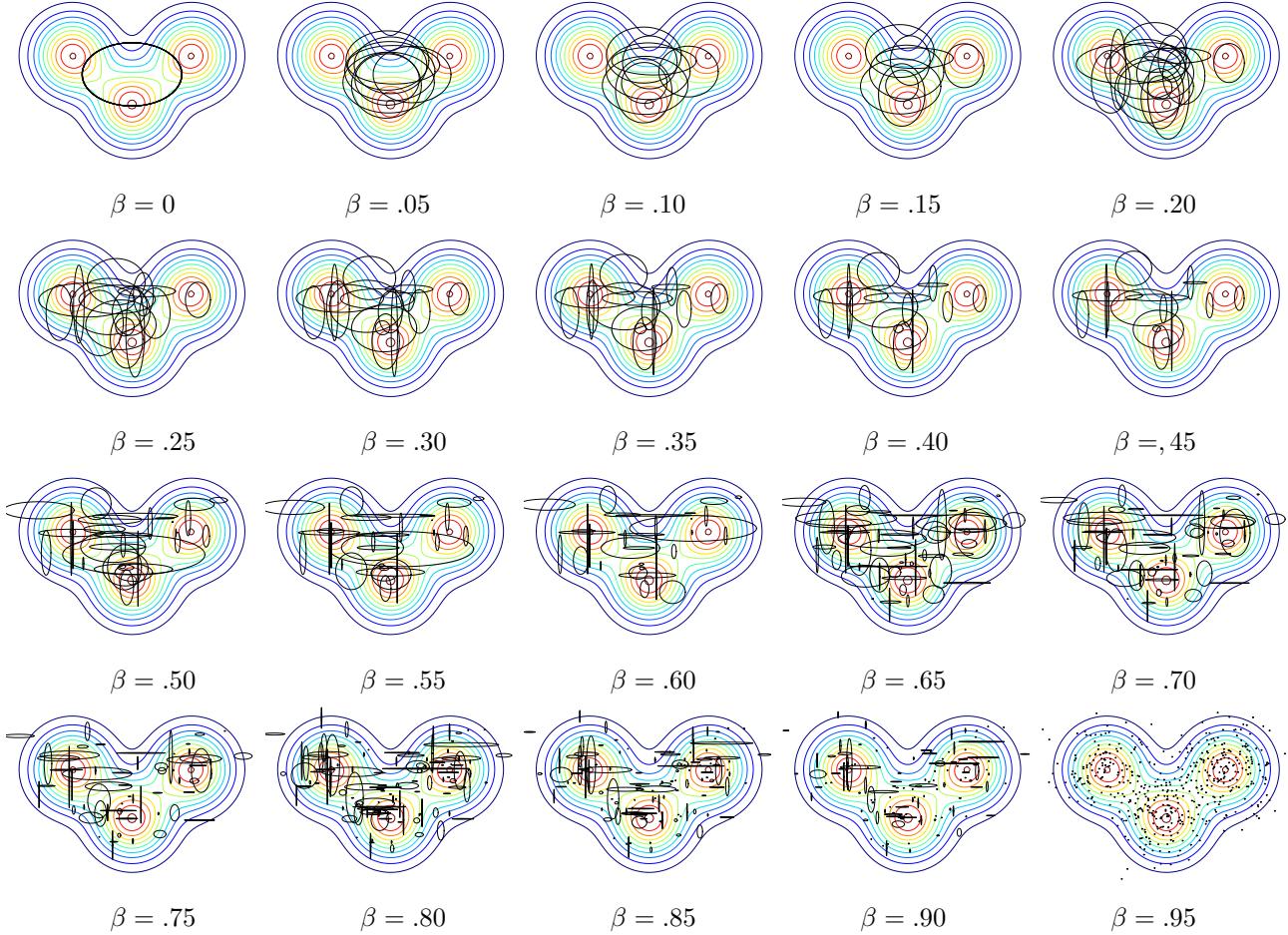


Figure 5. Examples sampling from a two-dimensional mixture of three gaussians after running inference for 5×10^5 iterations. The sampled weights w are pictured as ellipsoids at one standard deviation. Colored contours show the density $p(z)$. To avoid visual clutter, a smaller number (equally spaced) of samples are shown for smaller β .

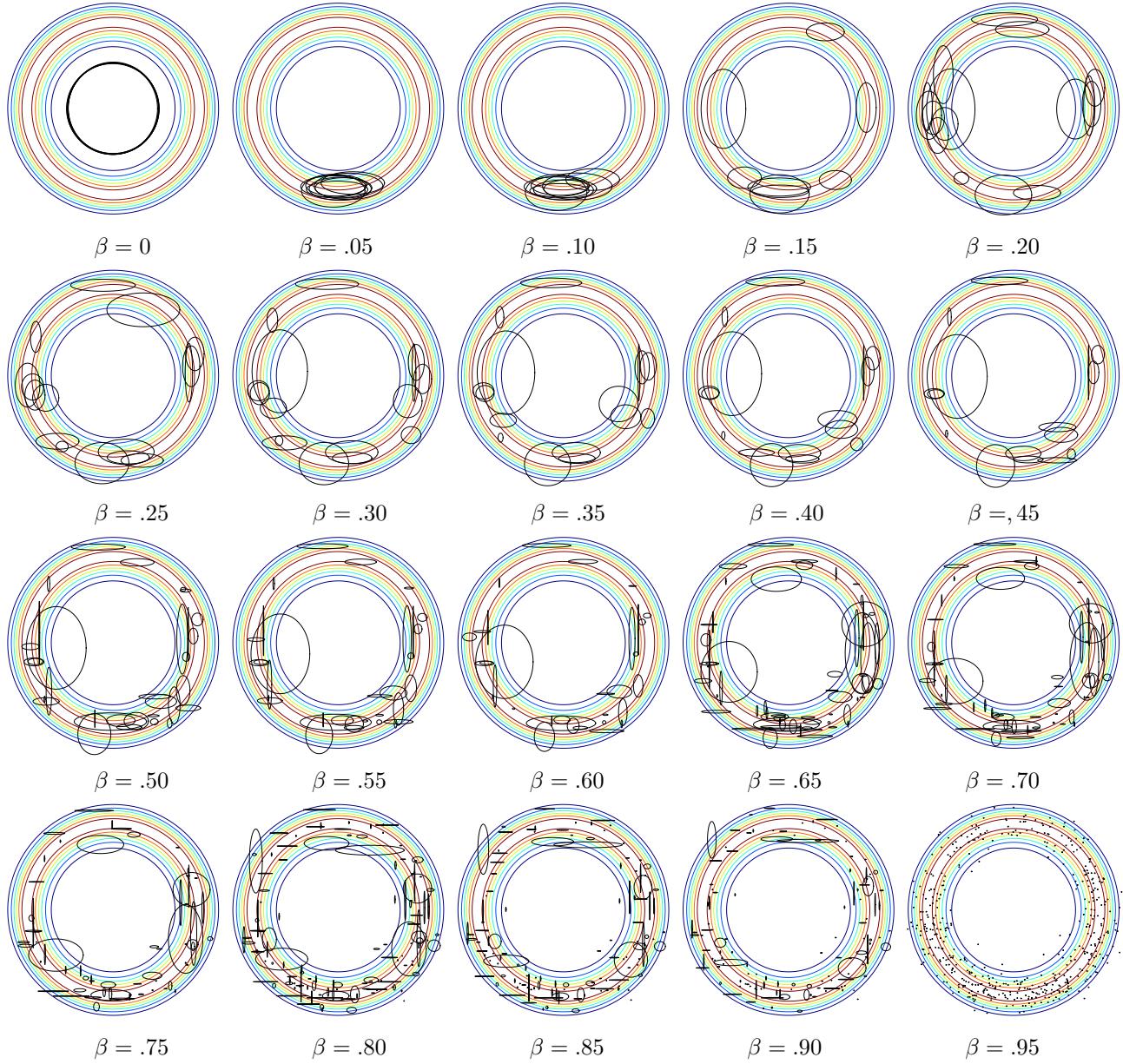


Figure 6. Examples sampling from a two-dimensional “donut” distribution after running inference for 5×10^5 iterations. The sampled weights w are pictured as ellipsoids at one standard deviation. Colored contours show the density $p(z)$. To avoid visual clutter, a smaller number (equally spaced) of samples are shown for smaller β .

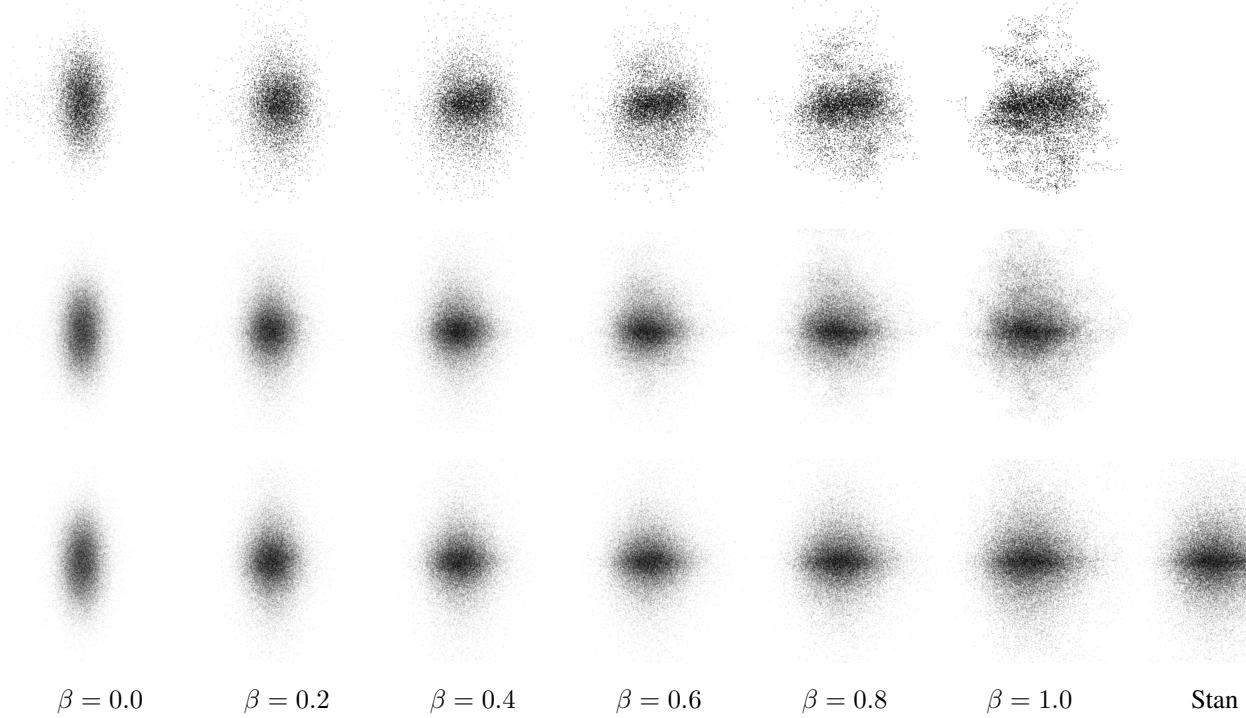


Figure 7. Inference for various values of β on ionosphere after 10^4 (top row) 10^5 (middle row) or 10^6 (bottom row) iterations. After each iteration, one sample is drawn from $q_w(Z)$, and plots show the first two principal components (computed on samples from Stan). Each plot shows samples resulting from the (constant) step-size ϵ that resulted in the minimum MMD for that β and number of iterations. The same sequence of random numbers is for all inference methods. (More results are in the appendix.)

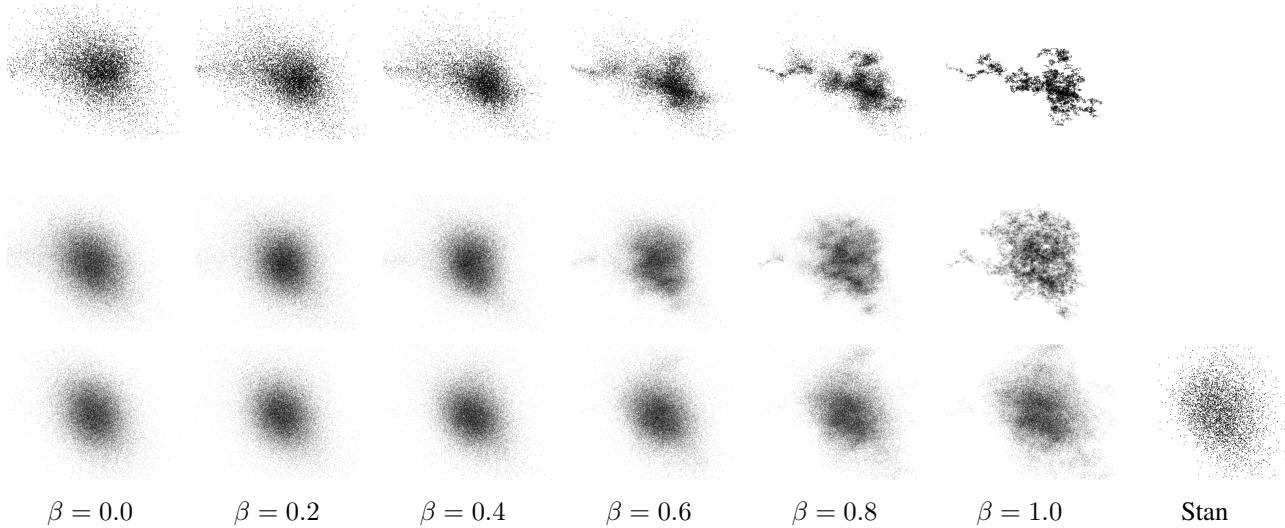


Figure 8. Inference for various values of β on a1a after 10^4 (top row) 10^5 (middle row) or 10^6 (bottom row) iterations. In some of these plots, a “tail” is visible, reflecting the path into the high-density region from where $w = 0$ where inference was initialized.

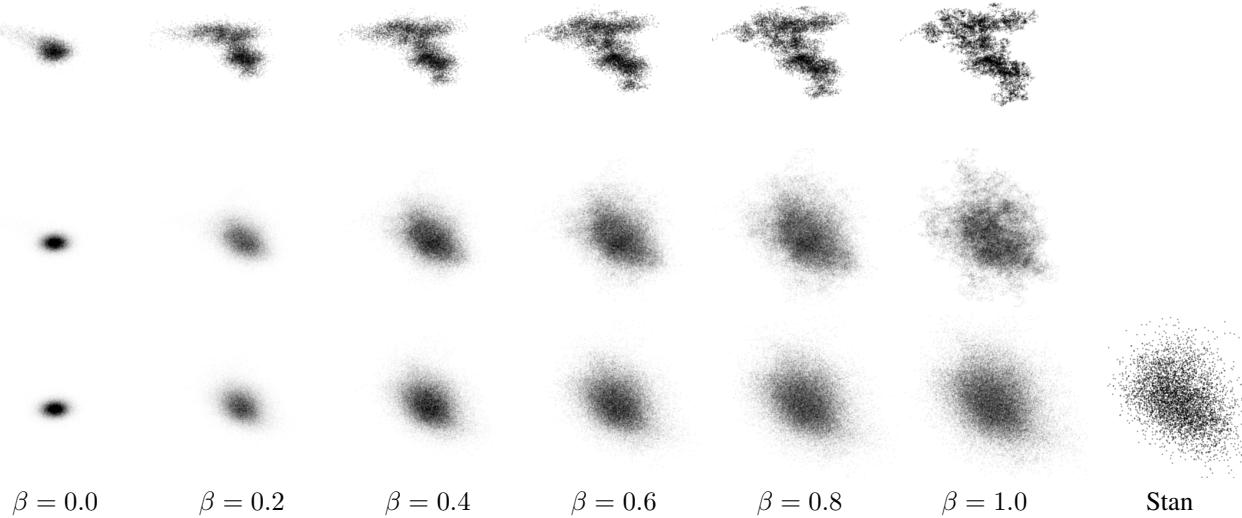


Figure 9. Inference for various values of β on australian after 10^4 (top row) 10^5 (middle row) or 10^6 (bottom row) iterations.

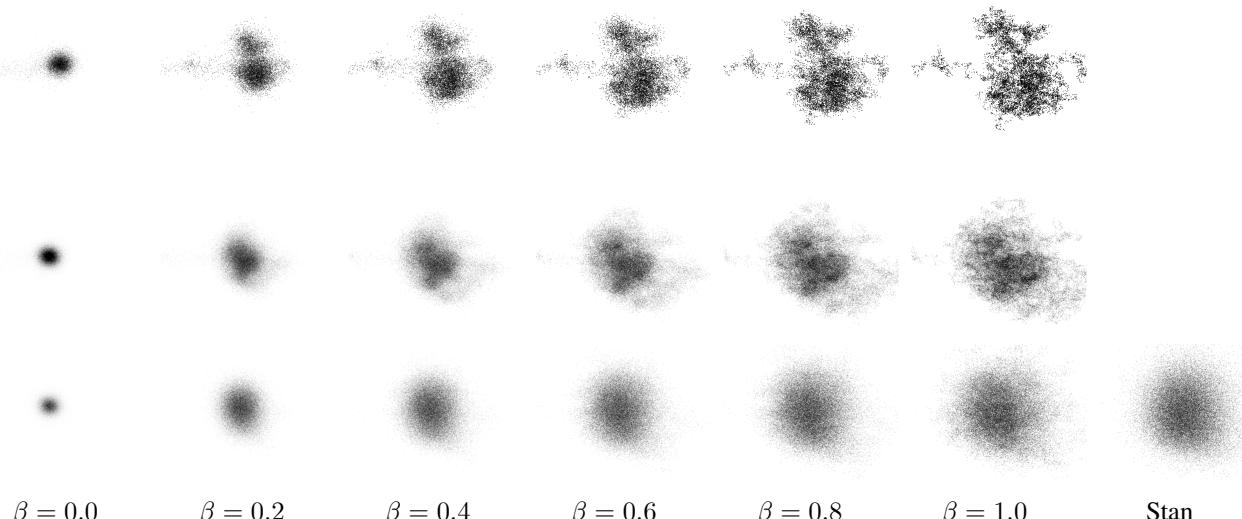


Figure 10. Inference for various values of β on sonar after 10^4 (top row) 10^5 (middle row) or 10^6 (bottom row) iterations.