To show $W^*_{MLE} = \arg\max LL(W) = \arg\min SAE(W)$.

Given, $SAE(W) = \sum_{i=1}^{n} |y_i - W^T x_i|$

Now, we could write the log-likelihood as:

$$LL(W) = \sum_{i=1}^{n} \log p(y_i | x_i, W) = n \log \frac{1}{2b} + \frac{-1}{b \sum_{i=1}^{n} |y_i - W^T x_i|}$$

Note, the likelihood is proportional to $\sum_{i=1}^{n} |y_i - W^T x_i|$

if b is a fixed positive term when it is ~~maximized~~ minimized.

we can write. MLE of W = minimized $\left(\sum_{i=1}^{n} |y_i - W^T x_i| \right)$

$= SAE(W)$

y	0	0	0	1	0	0	1	0	0	1	1	0	1	1	1	1
p(y|x)	0.1	0.1	0.25	0.25	0.3	0.33	0.4	0.52	0.55	0.7	0.8	0.85	0.9	0.9	0.95	1.0
t=0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
t=0.2	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
t=0.4	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
t=0.6	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
t=0.8	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
t=1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Let #TP be true positive, FN be False Negative, FP be False Positi

t	TP	FP	FN	recall	precision
0	8	8	0	1	$\frac{1}{2}$
0.2	8	6	0	1	$\frac{8}{14}$
0.4	6	3	2	$\frac{6}{8}$	$\frac{6}{9}$
0.6	6	1	2	$\frac{6}{8}$	$\frac{6}{7}$
0.8	4	1	4	$\frac{4}{8}$	$\frac{4}{5}$
1	0	0	8	0	0