THM：For any probability density function and any real number $k>0$

$$
P(|X-\mu| \geq k \sigma) \leq \frac{1}{k^{2}} \text { or } P(|X-\mu| \leq k \sigma) \geq \frac{1}{k^{2}}
$$

Note：This theorem gives an upper bound on how much of the probability density can lie farther than $k \sigma$ from the mean value．Thus，the probability density is constrained in how far its tails can lie from the mean value on a scale measured by standard deviations．

Note：This theorem is only useful for values of $k>1$ ，since probability is always less than or equal to unity，and the theorem is most useful for larger values of $k$ ．For example，all but one－ninth of the probability lies within three standard deviations of the mean，regardless of what the probability density function happens to be．

Proof：We start with the definition of standard deviation：

$$
\sigma^{2}=\int_{-\infty}^{\infty}(x-\mu)^{2} f(x) d x
$$

The figure below shows a generic probability density function，$f(x)$ ．


For the calculation of $\sigma^{2}$ ，we will multiply $f(x)$ by the quadratic function $(x-\mu)^{2}$ added to the graph below．


The product $(x-\mu)^{2} f(x)$ is shown below，and the area under this curve， （i．e．，the integral of $\left.(x-\mu)^{2} f(x)\right)$ ，shown in brown，is the value of $\sigma^{2}$ ．


We split the integral for $\sigma^{2}$ into regions within $k \sigma$ of the mean（center region）and without $k \sigma$ of the mean（gray regions）giving us the following result．
$\sigma^{2}=\int_{-\infty}^{\mu-k \sigma}(x-\mu)^{2} f(x) d x+\int_{\mu-k \sigma}^{\mu+k \sigma}(x-\mu)^{2} f(x) d x+\int_{\mu+k \sigma}^{\infty}(x-\mu)^{2} f(x) d x$.

Since the quantities being integrated are all non-negative, if we were to delete the middle integral (i.e., the integral for values within $k \sigma$ of the mean) we would have the following result:

$$
\sigma^{2} \geq \int_{-\infty}^{\mu-k \sigma}(x-\mu)^{2} f(x) d x+\int_{\mu+k \sigma}^{\infty}(x-\mu)^{2} f(x) d x
$$

In other words, the areas under the side portions are less than the entire area. We obtain an even smaller area on the sides if we replace $(x-\mu)^{2}$ with a smaller multiplier, namely $k^{2} \sigma^{2}$. That is, for the integrals in the above equation we have $(x-\mu)^{2} \geq k^{2} \sigma^{2}$, so we can write the following inequality:

$$
\sigma^{2} \geq \int_{-\infty}^{-k \sigma} k^{2} \sigma^{2} f(x) d x+\int_{k \sigma}^{\infty} k^{2} \sigma^{2} f(x) d x
$$

The figure below shows the right-hand side of this equation as red areas that are clearly smaller than the original side areas.


At this point, we factor out the $k^{2} \sigma^{2}$ from the integrals to obtain

$$
\sigma^{2} \geq k^{2} \sigma^{2}\left(\int_{-\infty}^{-k \sigma} f(x) d x+\int_{k \sigma}^{\infty} f(x) d x\right)
$$

or, if we divide both sides by $\sigma$,

$$
1 \geq k^{2}\left(\int_{-\infty}^{-k \sigma} f(x) d x+\int_{k \sigma}^{\infty} f(x) d x\right)
$$

The value in parentheses is now a probability, and we have

$$
1 \geq k^{2} P(|X-\mu| \geq k \sigma)
$$

or, if we divide both sides by $k^{2}$,

$$
\frac{1}{k^{2}} \geq P(|X-\mu| \geq k \sigma)
$$

This result is equivalent to the theorem statement, and our proof is finished.

One might wonder the bound is achievable, and the answer for $k>1$ is yes. The distribution shown below achieves the bound by putting as much of the probability as possible (i.e., $1 / 2 k^{2}$ ) at points masses located at distance $k \sigma$ from $\mu$. Thus, we have a discrete distribution:

We verify that the calculated variance is indeed $\sigma^{2}$ :

$$
\sigma^{2}=\sum_{x_{i}}\left(x_{i}-\mu\right)^{2} P\left(x_{i}\right)=(-k \sigma)^{2} \frac{1}{2 k^{2}}+0 \cdot\left(1-\frac{1}{k^{2}}\right)+(k \sigma)^{2} \frac{1}{2 k^{2}},
$$

which simplifies to $\sigma^{2}=\sigma^{2}$, as required.
Ref: Ronald E. Walpole, Raymond H. Myers, Sharon L. Myers, and Keying Ye, Probability and Statistics for Engineers and Scientists, 8th Ed., Upper Saddle River, NJ: Prentice Hall, 2007.

