Question 2

Let $Y_1, Y_2, ..., Y_n$ be n independent observations, but they're **not necessarily identically distributed**. This means it's possible some are from different distributions (normal, exponential, etc.) However, they do conveniently all have the same mean μ and finite variance σ^2 . The sample variance is defined as:

$$S^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (Y_{i} - \bar{Y})^{2}$$

(a) Prove
$$\mathbb{E}[S^2] = \sigma^2$$

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$$\mathbb{E}[S] \leq \sigma \rightarrow \text{requires Jensen's inequality.}$$

Suppose we learned that $Y_1, Y_2, ..., Y_n$ is identically distributed, and they are in fact observations from a **normal** distribution. How convenient! Find the constant a such that: $\mathbb{P}\left(\frac{3S^2}{\sigma^2} \geq a\right) = 0.9$

a)
$$\mathbb{E}[S^{2}] = \mathbb{E}[\frac{1}{N-1}\sum_{i=1}^{N}(Y_{i}-Y_{i})^{2}]$$

Note that $\sum_{i=1}^{N}(Y_{i}-Y_{i})^{2} = \sum_{i=1}^{N}(Y_{i}-2Y_{i}-2Y_{i}-Y_{i}+Y_{i})$
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and
$$E(y^2) = Var(y) + E(y^2)^2$$

 $= \sigma^2 N + \mu^2$
 $= \frac{1}{N-1} \sum_{i=1}^{N} (\sigma^2 + \mu^2) - \frac{N}{N-1} (\frac{\sigma^2}{N} + \mu^2)$
 $= \frac{N}{N-1} \left[\sigma^2 + \mu^2 - \frac{\sigma^2}{N} - \mu^2 \right]$

$$=\frac{n}{n-1}\left[\delta^2\left(\frac{n-1}{n}\right)\right]=\delta^2 \text{ as desired.}$$

b) Recall:
$$(n-1)s^2 \sim \chi^2_{(n-1)}$$
 thus

$$N-1=3$$
 thus from the table: $\chi^2_{0.9,df=3}$: 0.584375