var(X) = $E(X - E(X))^2 = E\left(X^2\right) - E(X)^2$

$y = XB + \epsilon$
$var(y) = var(\epsilon) = \sigma^2$

$min\ ||y - XB||_2^2 = min\ sum\ of\ squared\ errors$
$\widehat{B} = \left(X^T X\right)^{-1} X^T y$
$=$
If X is not full rank - one eigenvalue of X is 0

https://math.stackexchange.com/questions/2131803/why-can-a-matrix-without-a-full-rank-not-be-invertible

If X is not full rank
Then there exists some non-zero c st X.c = 0 (from definition of linear dependence)
so 0 is an eigenvalue of X
but we also know X.0 = 0 $\Longrightarrow$ 0 = inv(X).0 $\neq$ c! so inv(x) cannot exist.
Also, X(B + c) = XB + 0 = XB
So there are infinitely many solutions B - i.e. there is more than one way to express the projection of y into the column space of X

Lasso
$min\ ||y - XB||_2^2 + \lambda||B||$