Abstract: Wang et al. (2020, JASA) studied the high-dimensional sparse penalized rank regression and established its nice theoretical properties. Compared with the least squares, rank regression can have a substantial gain in estimation efficiency while maintaining a minimal relative efficiency of 86.4%. However, the computation of penalized rank regression can be very challenging for high-dimensional data, due to the highly non-smooth rank regression loss. In this work we view the rank regression loss as a non-smooth empirical counterpart of a population level quantity, and a smooth empirical counterpart is derived by substituting a kernel density estimator for the true distribution in the expectation calculation. This view leads to the convoluted rank regression loss and consequently the sparse penalized convoluted rank regression (CRR) for high-dimensional data. Under the same key assumptions for sparse rank regression, we establish the rate of convergence of the L1-penalized CRR for a tuning free penalization parameter and prove the strong oracle property of the folded concave penalized CRR. We further propose a high-dimensional Bayesian information criterion for selecting the penalization parameter in folded concave penalized CRR and prove its selection consistency. We derive an efficient algorithm for solving sparse convoluted rank regression that scales well with high dimensions. Numerical examples demonstrate the promising performance of the sparse convoluted rank regression over the sparse rank regression. Our theoretical and numerical results suggest that sparse convoluted rank regression enjoys the best of both sparse least squares regression and sparse rank regression.