Graph embedding is a mapping from vertices of a graph into real vector space. A good embedding should capture the graph topology, vertex-to-vertex relationship, and other relevant information about the graph, its subgraphs, and vertices. If these objectives are achieved, an embedding is a meaningful, understandable, and provides a compressed representation of a network. Moreover, vector operations are usually simpler and faster than comparable operations on graphs. Unfortunately, selecting the best embedding is a challenging task and very often requires domain experts. We propose a divergence score that can be assigned to embeddings to help distinguish good ones from bad ones. This general framework provides a tool for an unsupervised graph embedding comparison. In order to achieve it, we needed to generalize the well-known Chung-Lu model to incorporate geometry which is an interesting result in its own right. This framework has quadratic complexity in the number of vertices, so it is only suitable for small networks. We also present a landmark-based version of our framework which allows for much greater scalability. Detailed quality and speed benchmarks are provided. (Received September 11, 2020)