

$$= f(x_1, \dots, x_N) = f(x_n).$$

For example, problems of linear optimization are separable. Given a separable problem with an optimal solution, we fix an optimal solution

$$x_{\min} = (x_1, \dots, x_N)_{\min}$$

with the minimum value $f(x_{\min})$. For this separable problem, we also consider an optimal solution $(x_{\min}, f(x_{\min}))$ to the "convexified problem", where convex hulls are taken of the graphs of the summand functions. Such an optimal solution is the limit of a sequence of points in the convexified problem

$$(x_j, f(x_j)) \rightarrow \text{Conv}(\text{Graph}(f_n)).$$

Of course, the given optimal point is a sum of points in the graphs of the original summands and of a small number of convexified summands, by the Shapley-Folkman lemma.

This analysis was published by Ivar Ekeland in 1974 to explain the apparent convexity of separable problems with many summands, despite the non-convexity of the summand problems. In 1973, the young mathematician Claude Lemaréchal was surprised by his success with convex minimization methods on problems that were known to be non-convex; for minimizing nonlinear problems, a solution of the dual problem need not provide useful information for solving the primal problem, unless the primal problem be convex and satisfy a constraint qualification. Lemaréchal's problem was additively separable, and each summand function was non-convex; nonetheless, a solution to the dual problem provided a close approximation to the primal problem's optimal value. Ekeland's analysis explained the success of methods of convex minimization on large and separable problems, despite the non-convexities of the summand functions. Ekeland and later authors argued that additive separability produced an approximately convex aggregate problem, even though the summand functions were non-convex. The crucial step in these publications is the use of the Shapley-Folkman lemma. The Shapley-Folkman lemma has encouraged the use of methods of convex minimization on other applications with sums of many functions.

== Probability and measure theory ==

Convex sets are often studied with probability theory. Each point in the convex hull of a (non-empty) subset Q of a finite-dimensional space is the expected value of a simple random vector that takes its values in Q , as a consequence of Carathéodory's lemma. Thus, for a non-empty set Q , the collection of the expected values of the simple, Q -valued random vectors equals Q 's convex hull; this equality implies that the Shapley-Folkman-Starr results are useful in probability theory. In the other direction, probability theory provides tools to examine convex sets generally and the Shapley-Folkman-Starr results specifically. The Shapley-Folkman-Starr results have been widely used in the probabilistic theory of random sets, for example, to prove a law of large numbers, a central limit theorem, and a large deviations principle. These proofs of probabilistic limit theorems used the Shapley-Folkman-Starr results to avoid the assumption that all the random sets be convex.

A probability measure is a finite measure, and the Shapley-Folkman lemma has applications in non-probabilistic measure theory, such as the theories of volume and of vector measures. The Shapley-Folkman lemma enables a refinement of the Brunn-Minkowski inequality, which bounds the volume of sums in terms of the volumes of their summand sets. The volume of a set is defined in terms of the Lebesgue measure, which is defined on subsets of Euclidean space. In advanced measure theory, the Shapley-Folkman lemma has been used to prove Lyapunov's theorem, which states that the range of a vector measure is convex. Here, the traditional term "range" (alternatively, "image") is the set of values produced by the function. A vector measure is a vector-valued generalization of a measure; for example, if p_1 and p_2 are probability measures defined on the same measurable space, then the product function $p_1 \otimes p_2$ is a vector measure, where $p_1 \otimes p_2$ is defined for every event A by

$$(p_1 \otimes p_2)(A) = (p_1(A), p_2(A)).$$

Lyapunov 's theorem has been used in economics , in (" bang @-@ bang ") control theory , and in statistical theory . Lyapunov 's theorem has been called a continuous counterpart of the Shapley ? Folkman lemma , which has itself been called a discrete analogue of Lyapunov 's theorem .