Overview of "GPS, A Program that Simulates Human Thought" by A. Newell and P. Simon

**Things I Like**

GPS lays the fundamental methodology for AI planning. It provides a framework that constitutes a truly universal strategy of means-ends analysis for solving a wide range of problems. The abstractions around problem-solving into operators, goals, and states are beautiful and, in fact, still pertinent today in most modern planners like STRIPS and SOAR. This was indeed a quantum leap in providing a generalizable framework for AI.

One of the salient features of the GPS framework is based on the simulation of human problemsolving strategies. The system thereby supplied knowledge not only for AI research but also for psychology to explore human thought. This relevance for psychology, as well as for AI, is impressive.

The application of the problem-specific operators within a general problem-solving method is an example of modular design. The option for flexibility and reuse when attacking all sorts of domains is a concept that remains significant in AI system architecture.

The GPS framework represents one of the first attempts to formalize the process of problem-solving in AI. It laid the basis for subsequent developments that have since shaped many of the major AI planning systems that integrated the core ideas into more advanced algorithms.

**Things I Did Not Like**

While GPS introduces a quite fascinating framework, it does rely on well-defined operators, states, and goals, which, in turn, assume some degree of formalization, normally out of reach in natural problems. Most realistic domains are far messier, and GPS can handle little ambiguity.

Even with means-ends analysis, the brute-force approach adopted by the system for finding solutions is computationally intractable. This brings us to another limitation: as the complexity of problems increases, without domain-specific optimizations, the scaling performance is unsatisfactory.

While being claimed as a "general" problem-solving algorithm, GPS essentially succeeds within the bounds of structured problem environments where the problem space is well defined. Anything unstructured or dynamic is out of its scope, hence extremely reducing its practical utility when juxtaposed with modern AI planners.

GPS deals with a fixed set of operators and does not adapt or learn from its experience. Much of modern AI emphasizes the ability of improvement through learning, something that was lacking in the GPS system. This rigidity diminishes its relevance when considering present-day AI applications.

In fact, it can also be considered a weakness in that, while trying to remain as close as possible to human reasoning, it misses opportunities for leveraging computation strategies that may be more efficient or robust but not as proximate to human-like processes.

**Conclusion**

The paper on GPS is a milestone in AI planning. It proposed a framework that is today as inspiring as it was then groundbreaking. The fact that it furthered systems like STRIPS and SOAR ensures its value for a long time to come. However, inefficiency of computation and inability to learn within this framework show that any improvement has to transcend its original formulation. All the same, GPS has been one of the building blocks in the history of AI, and its concepts still echo.