The first prompt I chose to analyze was understanding the differences between AlphaGo Zero and its predecessors and the resulting improvements in performance. The most notable difference between AlphaGo Zero and its predecessors is the way the programs learned. Previous iterations utilized vast amounts of man-made data, such as viewing amateur or professional player games. Alternatively, AlphaGo Zero learned simply by playing against itself, starting with random play and incrementally increasing exploitation (Silver & Hassabis, 2017). This modification significantly improves the performance of AlphaGo Zero, as it allows the program to learn twice as fast by evaluating both perspectives. Subsequently, the program progressively and rapidly learns effective trends, tactical moves, innovations, and strategies faster than previous iterations could. This trend also allows the program to rapidly learn by experiencing and exploring the game itself rather than strictly relying on expert data sets, which can contain inaccuracies, biases, or are simply unreliable. Additionally, AlphaGo Zero combined the two neural networks used in previous iterations to select future moves and predict the game winner. In doing so, the program can be trained and evaluated more efficiently by simultaneously performing both operations (Silver & Hassabis, 2017). By combining these networks, the program can evaluate positions better based on the output of the neural network rather than relying on stored experiences. With these changes, AlphaGo Zero saw such an increase in performance that it became the best player in just over a month.

The second prompt I chose to analyze was understanding the implications of AlphaGo Zero's performance on future AI developments. One of the key aspects of the implications for future AI developments is the vast amount of information and quantity of experiences that can be performed in such a short time. For instance, the AlphaGo Zero program was able to uncover thousands of years of experience in Go strictly by playing against itself in a few days (Silver et

al., 2017). This can be incredibly useful in developing a program to produce highly accurate medical diagnoses that can be considered alongside an expert opinion. By slicing medical slides into segments and feeding them into a similar program, a highly accurate medical diagnosis can be reached. The benefits of combining AI with expert opinions are described as "the predictions of the algorithms with those of humans led to an 85% decrease in human error in detecting metastatic breast cancer in lymph nodes" (Granter et al., 2017). Additionally, AlphaGo Zero highlighted how powerful AI programs can be without requiring expert training data. This is especially important for innovative or underdeveloped fields that do not have the ability to provide exceptional datasets or where data may be unreliable. In doing so, the program can learn from its own experiences to identify patterns and provide precise determinations that can aid in human learning and technological advancements. By untying machine learning from human knowledge and inherent biases, future AI developments may surpass human capabilities by solving extremely complex problems and providing new schools of thought, elevating our own endeavors.

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