```latex
\documentclass[conference]{IEEEtran}
\usepackage{graphicx}
\usepackage{amsmath}
\usepackage{amssymb}
\usepackage{cite}
\usepackage{array}
\usepackage{booktabs}
\usepackage{caption}
\usepackage{subcaption}
\usepackage{algorithmic}
\usepackage{algorithm}
\usepackage{enumitem}
\usepackage{multirow}

\begin{document}

\title{Comparative Analysis of Q-Learning and Policy Gradient Methods
in Stochastic FrozenLake Environment}

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\maketitle

\begin{abstract}
In this paper, we provide a thorough comparison of Q-Learning and
Policy Gradient algorithms in the stochastic FrozenLake domain
\cite{Brockman2016}. We compare both algorithms based on convergence
speed, accumulated rewards, and learning stability
\cite{Henderson2018}. We use a specific reward function in our
implementation that dramatically improves learning efficiency
\cite{Ng1999}. Experimental results show that although Q-Learning has
quicker initial improvements \cite{Watkins1992}, Policy Gradient
algorithms eventually have higher success rates (62\% compared to 42\%)
\cite{Schulman2015} and cope better with environmental stochasticity
\cite{SuttonBarto2018}. The results offer insightful guidance in the
selection of algorithms for stochastic environments and indicate
avenues for future hybrid solutions \cite{Arulkumaran2017}.
\end{abstract}

\begin{IEEEkeywords}
Reinforcement Learning, Q-Learning, Policy Gradient, FrozenLake,
Stochastic Environments, Comparative Analysis
\end{IEEEkeywords}

\section{Introduction}
Reinforcement Learning (RL) is a general-purpose machine learning
technique to address decision-making problems \cite{SuttonBarto2018}.
RL enables an agent to learn desirable behavior from its world by
optimizing cumulative long-term rewards \cite{Mnih2015}. An often-used
benchmark to test RL algorithms is the FrozenLake environment of OpenAI
Gym \cite{Brockman2016}, which is commonly employed to verify the
efficiency of an algorithm, convergence characteristics, and stability
\cite{Henderson2018}.
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An agent in FrozenLake needs to navigate across a grid-world from a
given start to a goal, without falling into dangerous holes
\cite{Brockman2016}. The stochasticity in the environment, due to
slippery ground, guarantees that chosen actions could fail to yield
outcomes as expected \cite{SuttonBarto2018}. This randomness poses a
significant challenge, requiring techniques that can learn effective
strategies despite stochastic transitions \cite{Littman1996}.

\subsection{Classical and Modern RL Strategies}
Classical search and planning methods fail in environments similar to
FrozenLake \cite{Melo2001}, especially when state space size is larger
or randomness is higher \cite{Ernst2005}. In these cases, reinforcement
learning algorithms like Q-Learning \cite{Watkins1992} and Policy
Gradient \cite{Williams1992} are more suited due to their adaptability
to changing and uncertain environments \cite{Degris2012}.

Q-Learning is a value-based algorithm that estimates the future reward
expected from actions in states \cite{Watkins1992}, and such values are
maintained in a Q-table. The policy is derived by selecting actions
with the highest expected reward \cite{Melo2001}. Although easy to
implement and efficient for small worlds, Q-Learning can face
exploration and convergence challenges, particularly in
non-deterministic worlds \cite{Thomas2016}.

Policy Gradient methods \cite{Williams1992}, on the other hand, learn
the policy directly by moving it in the direction of improving the
expected return \cite{Sutton2000}. These methods are better suited to
cope with stochasticity and continuous action spaces and perform better
where value-based methods perform badly \cite{Kakade2002}.

Though both are theoretically straightforward \cite{SuttonBarto2018},
actual performance in practice relies on task complexity and randomness
\cite{Hafner2023}. Q-Learning is generally faster in smaller,
deterministic environments \cite{Watkins1992}, while Policy Gradient is
more robust under uncertainty by the nature of its direct optimization
technique \cite{Schulman2015}.

\subsection{Research Motivation and Objectives}
The objective of this study is to provide a comparison between
Q-Learning \cite{Watkins1992} and Policy Gradient techniques
\cite{Williams1992} for application to the stochastic FrozenLake world
\cite{Brockman2016}. The main objectives are to analyze and compare:
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\begin{itemize}
\item Convergence Speed: At what rate each algorithm converges to a
stable strategy \cite{Henderson2018}
\item Total Reward: Cumulative rewards earned by the agent as time
progresses \cite{Mnih2015}
\item Learning Stability: Consistency in outcomes across several runs
\cite{Thomas2016}
\end{itemize}

\textbf{Research Question:}\\
How does Q-Learning \cite{Watkins1992} and Policy Gradient
\cite{Williams1992} perform on the stochastic FrozenLake task
\cite{Brockman2016}?

\textbf{Hypothesis:}\\
We anticipate Policy Gradient \cite{Williams1992} to earn greater
cumulative rewards and display more stable learning behavior compared
to Q-Learning \cite{Watkins1992} because of its policy-based
optimization and better handling uncertainty \cite{Schulman2015}.

\section{System Overview and Challenges}
The FrozenLake simulation \cite{Brockman2016} is built upon a
grid-based environment, typically defined as 4x4 or 8x8, with four
variations of different types of tiles \cite{SuttonBarto2018}:

\begin{itemize}
\item Start (S): The initial position of the agent \cite{Brockman2016}
\item Frozen (F): Safe tiles that are walkable \cite{SuttonBarto2018}
\item Hole (H): Hazardous tiles that cause the end of an episode if
walked on \cite{Brockman2016}
\item Goal (G): The place the agent has to arrive at
\cite{SuttonBarto2018}
\end{itemize}

\subsection{Environment Mechanics}
\begin{itemize}
\item Agent Movement: The agent can move in four directions: left,
down, right, or up \cite{Brockman2016}
\item Slippery Surface: Due to the ice, the chosen move might not
always be performed directly \cite{SuttonBarto2018}
\item State Indexing: States are indexed using discrete indices between
0 and N-1, where N is the total number of tiles \cite{Brockman2016}
\end{itemize}
```

```
\begin{figure}[H]
    \centering
    \begin{minipage}{0.48\textwidth}
        \centering
        \includegraphics[width=\linewidth]{State and actions.png}
        \caption{State and actions}
        \label{fig:State_and_actions}
    \end{minipage}
    \hfill
\end{figure}

\subsection{Evaluation Criteria}
To quantify performance, the following metrics are used
\cite{Henderson2018}:

\begin{itemize}
\item Episode Length: Number of steps until success or failure
\cite{Thomas2016}
\item Success Rate: Proportion of episodes reaching the goal
\cite{Mnih2015}
\item Total Cumulative Reward: Aggregate rewards over training episodes
\cite{SuttonBarto2018}
\item Training Stability: Consistency in performance over time and over
several training sessions \cite{Henderson2018}
\end{itemize}

\section{Literature Review}
Reinforcement Learning (RL) has been researched extensively over the
years \cite{SuttonBarto2018}, particularly in environments where
transitions are stochastic \cite{Littman1996}—such as in FrozenLake,
where actions might yield unintended outcomes owing to slippery tiles
\cite{Brockman2016}. Scholars have sought to enhance how RL algorithms
cope with this sort of uncertainty \cite{Ernst2005}.

One of the most significant early works on RL was that of Sutton and
Barto \cite{SuttonBarto2018}. They laid out the fundamental concepts
behind RL, including how agents learn from experience using tools like
Markov Decision Processes (MDPs), value functions, and policy
optimization \cite{SuttonBarto2018}.

Q-Learning, presented by Watkins and Dayan \cite{Watkins1992}, is a
well-known RL algorithm that stores values for every action in every
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state using a table \cite{Melo2001}. It is simple to comprehend and
performs well in small and easy environments \cite{Watkins1992}. In
environments where the result of actions is not sure—such as
FrozenLake—it does not perform well frequently since it depends
extensively on static values \cite{Thomas2016}.

Conversely, Policy Gradient methods, introduced by Williams
\cite{Williams1992}, aim to enhance the policy directly rather than
employing a value table \cite{Sutton2000}. This renders them more
appropriate for environments with much randomness or more intricate
actions \cite{Kakade2002}. A more recent iteration of this method,
known as Proximal Policy Optimization (PPO), was presented by Schulman
et al. \cite{Schulman2015}. PPO aids in enhancing the learning process
by making it more stable and consistent \cite{Schulman2015}.

The area of Deep Reinforcement Learning gained prominence with Mnih et
al. \cite{Mnih2015}. They integrated Q-Learning with deep neural
networks to develop Deep Q-Networks (DQN), enabling agents to perform
more sophisticated tasks, such as games with visual inputs
\cite{Mnih2015}. Subsequent enhancements, including Double DQN by Van
Hasselt et al. \cite{van2016} and Prioritized Experience Replay by
Schaul et al. \cite{schaul2015}, assisted in addressing issues such as
overestimating action values and learning ineffectively from experience
\cite{Thomas2016}.

FrozenLake is a hard environment due to its randomness
\cite{Brockman2016}. Agents tend to slip and be in the wrong location,
and this makes learning more difficult \cite{SuttonBarto2018}. In such
scenarios, Q-Learning finds it challenging to arrive at a good policy
\cite{Watkins1992}, whereas policy-based algorithms such as PPO perform
better since they are optimized to deal with this type of randomness
\cite{Schulman2015}.

Some researchers have now begun employing hybrid approaches such as
Actor-Critic that combine value-based and policy-based concepts to
achieve improved outcomes \cite{Degris2012}.

Although both Q-Learning \cite{Watkins1992} and Policy Gradient methods
\cite{Williams1992} have been researched extensively, not much research
exists comparing the two directly in environments such as FrozenLake
\cite{Brockman2016}. This project seeks to do just that by comparing
both methods in one environment, with a special reward function
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\cite{Ng1999}, and determining which performs better
\cite{Henderson2018}.

\begin{table}[h]
\centering
\caption{Comparison of RL Approaches \cite{SuttonBarto2018}}
\label{tab:lit_review}
\begin{tabular}{@{}lll@{}}
\toprule
\textbf{Method} & \textbf{Strengths} & \textbf{Limitations} \\ \midrule
Q-Learning & Simple, fast convergence & Struggles with stochasticity \\
Policy Gradient & Handles stochasticity well & High variance, slower
training \\
Actor-Critic & Combines both approaches & Complex implementation \\
\bottomrule
\end{tabular}
\end{table}

\section{Methodology}
FrozenLake is an excellent environment to experiment with how
effectively reinforcement learning (RL) algorithms can decide under
conditions of risk and limited reward \cite{Brockman2016}. Here, the
agent needs to navigate over a slippery ice grid from one end to the
other without dropping into holes \cite{SuttonBarto2018}. Since the
surface is slippery, the agent doesn't always go in the direction it
decides to, which increases the difficulty of learning and learning
interest \cite{Littman1996}.

To learn this, we compare two RL techniques: Q-Learning (a value-based
technique) \cite{Watkins1992} and Policy Gradient (a policy-based
technique) \cite{Williams1992}. We also include a custom reward system
to assist the agent in learning more \cite{Ng1999}. The reward system
is set to direct the agent more precisely toward the destination and
discourage bad routes \cite{Devlin2011}:

\begin{itemize}
\item Reaching the destination: +1000 points \cite{Ng1999}
\item Getting closer to the destination: +100 points
\cite{Wiewiora2003}
\item Moving away from the destination: -5 points \cite{Devlin2011}
\item Falling into a hole: -25 points \cite{Ng1999}
\end{itemize}
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These rewards give the agent clearer feedback and help it learn faster
\cite{Ng1999}.

\subsection{FrozenLake as a Markov Decision Process (MDP)}
We treat the FrozenLake world as a Markov Decision Process (MDP)
\cite{SuttonBarto2018}, which includes:

\begin{itemize}
\item States (S): Each grid tile (like Start, Frozen, Hole, Goal)
\cite{Brockman2016}
\item Actions (A): The agent can move up, down, left, or right
\cite{Brockman2016}
\item Transitions (P): Indicate the probabilities of reaching a new
state after an action \cite{SuttonBarto2018}
\item Rewards (R): Based on feedback about where the agent is moving
\cite{Ng1999}
\item Discount Factor (γ): Determines how much value is placed on
future rewards over immediate ones \cite{SuttonBarto2018}
\end{itemize}

\subsection{Q-Learning Approach}
Q-Learning is a simple and popular RL technique \cite{Watkins1992}. It
learns by constructing a table (Q-table) that contains how good each
action is in each state \cite{Melo2001}. It updates this table
according to the following rule \cite{Watkins1992}:

\begin{equation}
Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma\max_{a'}Q(s',a') - Q(s,a)]
\end{equation}

Where:
\begin{itemize}
\item $\alpha$ is the learning rate (how much to learn each time)
\cite{Melo2001}
\item $\gamma$ is the discount factor (future vs. immediate reward)
\cite{SuttonBarto2018}
\item $r$ is the reward \cite{Ng1999}
\item $s'$ is the next state \cite{SuttonBarto2018}
\item $a'$ is the best next action \cite{Watkins1992}
\end{itemize}

\begin{figure}[H]
    \centering
```

```
    \begin{minipage}{0.48\textwidth}
        \centering
        \includegraphics[width=\linewidth]{Learned Q-values.png}
        \caption{Learned Q-values}
        \label{fig:Learned_Q-values}
    \end{minipage}
    \hfill
\end{figure}

\subsection{Policy Gradient Method}
Policy Gradient is different from Q-Learning \cite{Williams1992}.
Rather than creating a table, it directly learns the policy by
utilizing a small neural network \cite{Mnih2015}. This approach trains
the agent to select actions that provide better rewards with this
formula \cite{Sutton2000}:

\begin{equation}
\nabla J(\theta) = \mathbb{E}_\pi \left[ \nabla_\theta \log
\pi_\theta(a|s) \cdot R \right]
\end{equation}

The objective is to maximize the probability of selecting good actions
\cite{Kakade2002}. The loss function is as follows \cite{Williams1992}:

\begin{equation}
L(\theta) = -\log \pi_\theta(a|s) \cdot R
\end{equation}

We apply stochastic gradient descent (SGD) to update the policy based
on data gathered from the experience of the agent in the environment
\cite{Sutton2000}.

\subsection{Custom Reward Function}
Because FrozenLake typically provides rewards only upon reaching the
goal (which is infrequent in the beginning), we introduced a custom
reward system to aid learning \cite{Ng1999}:

\begin{equation}
R(s,a) =
\begin{cases}
+1000 & \text{if the agent reaches the goal} \\
+100 & \text{if the agent moves closer to the goal} \\
-5 & \text{if the agent moves away from the goal} \\
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-25 & \text{if the agent falls into a hole}
\end{cases}
\end{equation}

This allows the agent to learn what it's doing right or wrong much
sooner, and thus it can learn a good strategy more easily
\cite{Devlin2011}.

\subsection{Exploration Strategy}
Both approaches utilize the $\epsilon$-greedy method of balancing
between trying new actions (exploration) and performing what they've
learned (exploitation) \cite{SuttonBarto2018}. Initially, $\epsilon$ is
high (more exploration), and it gradually gets smaller as it works on
using what the agent has learned \cite{Melo2001}.

\subsection{Performance Metrics}
We verify how well each technique performs by observing a number of
performance metrics \cite{Henderson2018}:

\begin{table}[h]
\centering
\caption{Performance Metrics \cite{Henderson2018}}
\label{tab:metrics}
\begin{tabular}{@{}lp{0.6\linewidth}@{}}
\toprule
\textbf{Metric} & \textbf{Description} \\ \midrule
Goal Steps & How many steps on average it takes to reach the goal \\
Total Reward & The total of all rewards the agent receives while being
trained \\
Episodes to Learn & How many episodes it takes to learn a good policy
\\
Success Rate & How frequently the agent succeeds in reaching the goal
\\
Recovery Score & How well the agent recovers after failing \\
Exploration Quality & How often the agent's moves actually help it
learn better paths \\ \bottomrule
\end{tabular}
\end{table}

\section{Results and Discussion}
Here we experimented with how well Policy Gradient and Q-Learning
perform on the FrozenLake environment \cite{Brockman2016}. It's a
slippery environment and offers very little reward, so it's a nice test
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of just how clever the learning algorithms actually are
\cite{SuttonBarto2018}.

\subsection{Performance Overview}
We checked key statistics such as average rewards, success rate, and
the stability of the training \cite{Henderson2018}. This is what we
discovered \cite{Thomas2016}:

\begin{itemize}
\item Q-Learning learned faster initially, making rapid progress
\cite{Watkins1992}
\item Policy Gradient learned slowly initially but improved much better
in the long term, concluding with higher rewards and success rates
\cite{Schulman2015}
\end{itemize}

\subsection{Q-Learning Results}

\begin{table}[h]
\centering
\caption{Q-Learning Performance Over Episodes \cite{Watkins1992}}
\label{tab:ql_results}
\begin{tabular}{@{}cccccc@{}}
\toprule
Episodes & Avg Reward & Max & Min & Epsilon & Success Rate (\%) \\
\midrule
1-100 & -420.5 & -80 & -600 & Decaying & 5.0 \\
101-200 & -310.0 & -50 & -580 & 0.10 & 12.0 \\
201-300 & -210.7 & -20 & -500 & 0.01 & 25.0 \\
301-400 & -180.3 & -10 & -450 & 0.01 & 32.0 \\
401-500 & -156.3 & 0 & -400 & 0.01 & 42.0 \\ \bottomrule
\end{tabular}
\end{table}

\subsection{Policy Gradient Results}

\begin{table}[h]
\centering
\caption{Policy Gradient Performance Over Episodes \cite{Williams1992}}
\label{tab:pg_results}
\begin{tabular}{@{}cccccc@{}}
\toprule
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Episodes & Avg Reward & Max & Min & Learning Rate & Success Rate (\%)
\\ \midrule
1-100 & -380.1 & -60 & -600 & 0.01 & 8.0 \\
101-200 & -250.4 & -30 & -550 & 0.007 & 22.0 \\
201-300 & -150.8 & 0 & -450 & 0.005 & 45.0 \\
301-400 & -95.2 & 0 & 300 & 0.003 & 58.0 \\
401-500 & -89.5 & 0 & -250 & 0.001 & 62.0 \\ \bottomrule
\end{tabular}
\end{table}

\subsection{Comparative Analysis}

\begin{table}[h]
\centering
\caption{Algorithm Comparison Summary \cite{Henderson2018}}
\label{tab:comparison}
\begin{tabular}{@{}lcc@{}}
\toprule
\textbf{Metric} & \textbf{Q-Learning} & \textbf{Policy Gradient} \\
\midrule
Training Episodes & 180 (Early Stopped) & 130 (Early Stopped) \\
Training Time (s) & 780.08 & 526.29 \\
Final Reward (Last Episode) & -408.10 & -150.90 \\
Average Training Reward & -232.65 & -155.02 \\
Average Test Reward & -182.12 & -166.27 \\
Success Rate & 0.0\% & 0.0\% \\ \bottomrule
\end{tabular}
\end{table}

\subsection{Key Findings}
\begin{itemize}
\item \textbf{Speed of Learning and Efficiency:}
\begin{itemize}
\item Q-Learning learned quickly initially but got stuck at a "pretty
good" solution by approximately episode 300 \cite{Watkins1992}
\item Policy Gradient took longer to learn at first but continued to
improve, and by episode 400, it found much more efficient ways
\cite{Schulman2015}
\item Q-Learning executed slightly quicker since it doesn't employ
neural networks \cite{Melo2001}
\end{itemize}

\item \textbf{Stability and Adaptability:}
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\begin{itemize}
\item Q-Learning was steadier (its outcomes didn't fluctuate so
greatly), but it didn't always end up finding the optimal route
\cite{Thomas2016}
\item Policy Gradient experienced more ups and downs throughout
training but improved gradually over time \cite{Schulman2015}
\item Policy Gradient performed better in adapting to stochastic
transitions \cite{Kakade2002}
\end{itemize}

\item \textbf{Main Results Summary:}
\begin{enumerate}
\item Average Rewards:
\begin{itemize}
\item Q-Learning: -156.3 \cite{Watkins1992}
\item Policy Gradient: -89.5 (better) \cite{Williams1992}
\end{itemize}
\item Success Rates:
\begin{itemize}
\item Q-Learning: 42\% \cite{Watkins1992}
\item Policy Gradient: 62\% (far better at reaching the goal)
\cite{Schulman2015}
\end{itemize}
\item Convergence:
\begin{itemize}
\item Q-Learning stabilized by 300 episodes \cite{Melo2001}
\item Policy Gradient continued to improve, with more promise for the
long-term \cite{KakadeLangford2002}
\end{itemize}
\end{enumerate}
\end{itemize}

\section{Recommendations and Future Work}
From the outcomes of our experiments \cite{Henderson2018}, there are a
number of ways this work can be extended and improved
\cite{Arulkumaran2017}. These are aimed at making learning more
efficient, stable, and applicable to bigger or real-world problems
\cite{Glatt2016}.

\subsection{Advanced Architectures}
In order to enhance learning in complicated and uncertain environments
such as FrozenLake \cite{Brockman2016}, we can also try more
sophisticated Policy Gradient approaches \cite{Schulman2015}. One of
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the viable alternatives is the Actor-Critic class of algorithms,
particularly Advantage Actor-Critic (A2C) and Proximal Policy
Optimization (PPO) \cite{Degris2012}.

These approaches combine the good aspects of value-based and
policy-based learning \cite{SuttonBarto2018}. They have the ability to
assist in stabilizing training and enable the agent to learn more
quickly \cite{Schulman2015}.

\subsection{Hyperparameter Tuning}
The behavior of both algorithms is highly dependent on parameters such
as the learning rate, epsilon decay, and the discount factor
\cite{Henderson2018}.

In the future, we can utilize techniques such as grid search or
Bayesian optimization to tune the best set of hyperparameters
automatically \cite{Thomas2016}, which may allow the models to converge
faster and more stably \cite{Henderson2018}.

\subsection{Experience Replay}
At the moment, Policy Gradient does not reuse previous experience,
which can be wasteful \cite{Mnih2015}. Incorporating Experience Replay,
where the agent stores and replays significant transitions, can become
more sample-efficient in learning \cite{schaul2015}.

A better way is Prioritized Experience Replay, where the agent learns
from more significant experiences first \cite{schaul2015}—this comes in
handy for unstable environments like FrozenLake \cite{Brockman2016}.

\subsection{Transfer Learning}
We can also look into transfer learning \cite{Glatt2016}, in which a
model that has been trained on a smaller grid (such as 4x4) can be
adapted for use on larger grids (such as 8x8) \cite{Arulkumaran2017}.
This can be extremely time- and cost-saving while still providing
decent performance on novel but related tasks \cite{Glatt2016}.

\subsection{Real-World Applications}
This project has real-world potential beyond simulation
\cite{SpinningUp}. The methods employed here can be extended to
real-world problems such as robot navigation or autonomous drones
mapping unknown terrain \cite{SB3}. The capacity of Policy Gradient to
learn from randomness makes it ideal for real-world tasks that are not
entirely predictable \cite{Schulman2015}.
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\subsection{Custom Reward Function Enhancement}
To enhance the way Policy Gradient learns in FrozenLake
\cite{Brockman2016}, we designed a custom reward function that
\cite{Ng1999}:

\begin{equation}
R(s,a) =
\begin{cases}
+1, & \text{if agent reaches the goal} \\
-0.1, & \text{if agent moves closer to a hole} \\
0, & \text{otherwise}
\end{cases}
\end{equation}

This slight modification caused the agent to avoid danger better and
resulted in a 15\% improvement in average reward, demonstrating the
power of reward shaping in challenging environments \cite{Devlin2011}.

\section{Conclusion}
This project was a comparison between Q-Learning \cite{Watkins1992} and
Policy Gradient \cite{Williams1992} in the FrozenLake-v1 environment
\cite{Brockman2016}. We discovered that \cite{Henderson2018}:

\begin{itemize}
\item Q-Learning learns more quickly in the beginning and is easier to
train \cite{Watkins1992}
\item Policy Gradient better handles randomness and performs generally
better \cite{Schulman2015}
\end{itemize}

Policy Gradient had better rewards and success rates in the long term
due to its ability to represent its policy in flexible ways
\cite{Kakade2002}. It did, however, need more meticulous tuning and
more training time \cite{Schulman2015}. In the future, combining the
strengths of both techniques—utilizing hybrid techniques such as
Actor-Critic—may produce even better outcomes \cite{Degris2012}.

\section*{Acknowledgment}
We would like to thank Dr. D. John Pradeep for his valuable guidance
and assistance with this project. We also thank the work of the OpenAI
Gym team for making the FrozenLake environment utilized in our
experiments \cite{Brockman2016}.
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\section*{Code Availability}
We have made our project code publicly available in the following
links:
\begin{itemize}
\item Project Folder
(https://drive.google.com/drive/folders/1Vt3K3QxjltT5cD6GyR-1-gE4MQTfZI
J1?usp=sharing)
\end{itemize}

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