**Abstract**

In a real-time strategy (RTS) game, StarCraft II, players need to know the consequences before making a decision in combat. We propose a combat outcome predictor which utilizes terrain information as well as squad information. For training the model, we generated a StarCraft II combat dataset by simulating diverse and large-scale combat situations. The overall accuracy of our model was 89.7%. Our predictor can be integrated into the artificial intelligence agent for RTS games as a short-term decision-making module.

**Introduction**

Real-time strategy (RTS) games attract the attention of artificial intelligence (AI) researchers. StarCraft II is an RTS game where players destroy opponents’ bases to win, with elaborate tactics and orders. Combat decision-making is difficult because an agent must consider factors such as the unit-compositions, the fog of war, and where to fight. It is important to anticipate the result of a battle between a player’s units and opponent’s units on various battlefields.

Preceding StarCraft II combat prediction models include the clustering army analyzer (Synnaeve and Bessière 2012), the global state evaluator (Erickson and Buro 2014), and the neural-network machine (Sánchez-Ruiz 2015). There is a StarCraft combat simulator, SparCraft (Churchill and Buro 2013), which efficiently simulates combats by simplifying unit collisions. Nonetheless, it is hard to simulate the effects of terrains accurately because the fog of war and ramp visions are not implemented. Uriarte and Ontaño (2018) evaluated the performance of combat models such as lifetime damage (LTD) model (Churchill, Saffidine, and Buro 2012), decreasing/suspended damage per frame (DPF) model (Uriarte and Ontaño 2015). However, those combat models do not include factors of terrains.

Figure 1 shows the structure of our model, BattleNet, which has two submodels: SynergyNet (left) and TerrainNet (right). An input of SynergyNet is a squad combination, and an output is a squad synergy. Both input and output are a vector form. The input is represented as a squad vector that each element represents the type of units in a squad, and the value of each element represents the number of the given unit type. The output vector represents a synergy of the given squad. TerrainNet takes the terrain information and the synergies of each confronting squads and gives a prediction of the combat outcome. The terrain information is a one-hot encoded vector. Two synergy vectors are made from SynergyNet. Then TerrainNet gives a prediction of the combat outcome, based on the two synergy vectors and a terrain vector.

**Experiment**

For the experiment, we created a StarCraft II combat simulator which generates combat outcome dataset. The simulator generates two random squads, makes combat in a selected battlefield for five times, and records a winning rate of the combat. Equation (1) measures the winning rate. The number of the dataset is 15000 for each terrain. These datasets are separated into 60%, 20%, and 20% for the training set, validation set, and test set respectively.

\[
p_{\text{win}} = \frac{n_{\text{win}} + 0.5 \times n_{\text{draw}}}{n_{\text{win}} + n_{\text{draw}} + n_{\text{loss}}} \tag{1}
\]

Among the professional league maps of StarCraft II, we selected the categories of terrains that can represent most of the battlefields: plain, alley, narrow ramp, long alley, bush, two bushes, wide ramp, and foggy. A map can have several regions that fall into one of the categories. Plains have no special features such as obstacles, ramps, and alleys. Ramps have the high ground, the low ground, and a ramp that connects between them, while alleys have two grounds, and a
The accuracy of BattleNet was 89.7%. With the addition of terrain information, the overall accuracy of BattleNet was better than Baseline–’s. The overall accuracy of BattleNet was 9.2% higher than Baseline+. The accuracy of BattleNet was the highest regardless of battlefield, followed by Baseline+. Additional terrain information increased the accuracy regardless of battlefields, followed by Baseline+. The overall accuracy of BattleNet was 0.897.

---

**Table 1: Hyperparameters.** $n_U$, $n_S$, $n_T$, and $n_F(1,2)$ are the number of features in one squad vector, one synergy vector, one terrain vector, and one fully-connected layer, respectively. $n_{L(1,2)}$ is the number of fully-connected layers.

| Squad ($n_U$) | Baseline– | Baseline+ | BattleNet |
|---------------|-----------|-----------|-----------|
| 29            | 29        | 29        |

| Synergy ($n_S$) | -         | -         | 32        |
| Terrain ($n_T$) | 0         | 8         | 8         |
| FC ($n_F(1,2)$) | 512       | 512       | 256 / 512 |
| #Layers ($n_{L(1,2)}$) | 10        | 10        | 5 / 5     |

**Table 2: The average accuracy of models.**

| Battlefields | Baseline– | Baseline+ | BattleNet |
|--------------|-----------|-----------|-----------|
| Plain        | 0.831     | 0.880     | 0.901     |
| Alley        | 0.748     | 0.890     | 0.914     |
| Narrow ramp  | 0.785     | 0.891     | 0.917     |
| Long alley   | 0.758     | 0.879     | 0.905     |
| Bush         | 0.782     | 0.870     | 0.890     |
| Two bushes   | 0.789     | 0.820     | 0.830     |
| Wide ramp    | 0.841     | 0.892     | 0.902     |
| Foggy        | 0.778     | 0.894     | 0.918     |
| Overall      | 0.789     | 0.877     | 0.897     |

---

**Results and Conclusion**

The aforementioned experiment attributes were applied to three outcome prediction models (Baseline–, Baseline+, and BattleNet), which were trained and tested with the generated combat dataset for ten times. Baseline+ is a deep neural network (DNN) with squad and terrain information given, while Baseline– has squad information only. Hyperparameters are in Table 1. In 200 epoch of training, we used Adam optimizer and Binary Cross-Entropy loss with a learning rate = 1e-4 and a batch size = 1000. After 10 trainings and tests, the average accuracy of predicting combat outcomes on eight terrains is shown in Table 2. BattleNet showed the best accuracy regardless of battlefields, followed by Baseline+ and Baseline–. Additional terrain information increased the accuracy, considering Baseline+’s 9.2% better overall accuracy than Baseline–’s. The overall accuracy of BattleNet is 89.7%, which is 2.0% better than the Baseline+.

We presented a new combat outcome predictor module for StarCraft II. We generated StarCraft II combat dataset and proposed a model, BattleNet, which utilizes the battlefield information. On the dataset of large-scale combat simulation, the accuracy of BattleNet was 89.7%. With the terrain analysis tool, our combat outcome predictor can be implemented as a module of the StarCraft II artificial intelligence agent, with additional decision-making modules for long-term problems such as operation and build order.

---

**References**

Churchill, D., and Buro, M. 2013. Portfolio greedy search and simulation for large-scale combat in StarCraft. In 2013 IEEE Conference on Computational Intelligence in Games (CIG), 1–8.

Churchill, D.; Saffidine, A.; and Buro, M. 2012. Fast heuristic search for RTS game combat scenarios. In Proceedings of the Eighth AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, 112–117.

Erickson, G., and Buro, M. 2014. Global state evaluation in StarCraft. In Proceedings of the Tenth Annual AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE 2014), 112–118.

Sánchez-Ruiz, A. A. 2015. Predicting the outcome of small battles in StarCraft. In Proceedings of the ICCBR 2015 Workshops., 33–42.

Stanescu, M.; Barriga, N.; and Buro, M. 2015. Using lanchester attrition laws for combat prediction in StarCraft. In Proceedings of the Eleventh AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE-15), 86–92.

Synnaeve, G., and Bessière, P. 2012. A dataset for StarCraft AI and an example of armies clustering. In Proceedings of the Eighth AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, 25–30.

Uriarte, A., and Ontaño, S. 2015. Automatic learning of combat models for RTS games. In Proceedings of the Eleventh AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE-15), 212–218.

Uriarte, A., and Ontaño, S. 2018. Combat models for RTS games. IEEE Transactions on Games 10(1):29–41.