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Network Latency Classification for Computer Games

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Abstract—WTFast’s Gamers Private Network (GPN) technology improves and stabilizes network latency of communication between players and servers in online video games, especially when players are distributed worldwide. Latency is known to be the most critical factor in gaming quality of experience. We investigate the classification of game sessions based on their features to five “playability” levels of latency using a large data set collected from the GPN network in 2019–2020. Various machine learning models were developed using this data set and evaluated using conventional and new performance metrics. The results confirm that such a classifier could be developed with reasonable average accuracy. The correct classification and hence “playability” of a game session based on its environmental, sizing, game type, and physical features is important for the operation and continuous management of a game-focused network such as the GPN. The use of an effective machine learning classifier will pave the way for building an effective and productive pipeline for game traffic routing and dynamic network reconfiguration. While the proposed measure of classifier performance shows promise, more research work would be required to understand its mathematical and statistical properties and its relationships to existing metrics: (a) because it’s a very specific type of application area (gaming+networking) for which there is relatively little ML research; (b) what very-high quality classifiers could mean for a real-time GPN management system that would provide QoE feedback to the GPN routing heuristics.

Index Terms—online video games, network, latency, big data, machine learning, deep learning applications

I. INTRODUCTION

The “Gamer’s Private Network” or WTFast’s GPN improves normal internet connections between video game servers and players that are distributed worldwide

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and require stable, low latencies. We have real-time GPN networking data in laboratory and using massive datasets [1]–[9]. We investigated every gamer-server connections including games genres, IP, geolocation of hosts and gamers, trace-routes, time, latency, etc. In papers [1], [2], [4]–[6] preliminary research results were discussed. We demonstrated, that GPN reduces latency and improves overall gaming experience for gamers.

In this paper, we summarize the analysis of a large real-time data set of game sessions with latency (ping value), environment (underlying internet network variables), sizing (bytes transmitted), game types, and physical (duration and distance to game server) variables. The objective is to use machine learning models to classify game sessions into various classes of latency as a presentation of “playability” from the gamer perspective.

Within the context of the tested machine learning (ML) models, we have identified the best ones to classify game sessions into ping classes using two conventional measures of accuracy for classification. A weighted accuracy measure is also proposed to further differentiate the ML classifiers taking into consideration the fact that the ping classes are ordered. Incorrectly classifying a “very fast” game session into an “ineffective” class should have a different connotation than incorrectly classifying it into a “fast” class.

Our focus is on the “performance and user satisfaction of the GPN.” “Removing latency in a way that is meaningful for users is the core challenge for WTFast, and the implementation of genre analysis is a useful step forward in that task” [9]. We used the following primary genres in our analysis [6], [10]:

- First Person Shooter (FPS)

- Massively Multiplayer Online Role-Playing Games (MMORPG)
- Real-Time Strategy (RTS)
- Multiplayer Online Battle Arena (MOBA)
- Sports Games

In this paper we will show the possibility of reliable automatic classification of GPN traffic according to its effect on video game playability, and measured its average accuracy to about 90%.

II. EXISTING WORKS

Latency is a key factor of online games. This dimension has been studied for many years [11] and in their recent paper [12], “Saldana and Suznjevic confirm the necessity of low latency, even above that of bandwidth throughput, for player engagement in almost every kind of online game.” The main genres/types for online video games according to [13] are: “First Person shooters (FPS), Massively Multiplayer Online Role Playing Games (MMORPG), Real Time Strategy (RTS), Multiplayer Online Battle Arena (MOBA) and Sports games that simulate team sports such as racing.”

In research publications [6], [12] we found that “FPS games requires a one-way delay of 80ms.” MMORPG gamers indicate game quality below “excellent” with latency above 120 ms [6]. Authors in [14] reported that “Predictable and sub-second response time has long been a key concern for interactive computer systems”, what is obvious conclusion for most of video games.

Sitrick in [15] defined *video game network* in a patent dated 1986 as “a distributed set of apparatus which are capable of exhibiting an interactive single identity game”. On the other hand, “the on-line service’s computers themselves introduce latencies, typically increasing as the number of active users increases” [16].

In [17], [18] the “peer-to-peer architectures for multiplayer online video games with a goal to improve the quality of the gamers’ experience” reducing bandwidth were discussed.

Pellegrino et al. in [19] discussed “a hybrid architecture called P2P with central arbiter”, with the lower requirements. In [20] authors studied performance problems of mobile gamers. Internet delays investigated by authors in [21]. They made a conclusion, that “Internet delay is important for FPS games because it can determine who wins or loses a game.”

Claypool et al. in [22] made a conclusion, that “Internet latency’s effect is strongest for games with a first-person perspective and a changing model.” They investigated Minecraft strategy game.

The first-person shooter games investigated in [23], [24] using eight different games. Wu, Huang and Zhang in [25] demonstrated “that the server-generated traffic has a tight relationship with specific game design”.

Moreover, Hariri et al. in [26] designed “a model of the player’s activity to extract traffic patterns”.

Faerber in [27] conducted “a study of different first-person games and demonstrated that the client traffic is characterized by an almost constant packet and data rate” and “the average interpacket time for client to server traffic to be 51ms for the game being studied”. In our research work [2] we investigated Minecraft game using custom developed bot sending “action packets at 50ms intervals.”

Authors in [28] demonstrated that “the bottleneck in the server is both game-related as well as network-related processing (about 50%-50%)”.

Several researchers in [23], [21], [24] investigated “interactive online games” and network traffic related to FPS, and network impact on games. Hariri et al. in [26] demonstrated that “online games become major contributors to Internet traffic” and “latency is the another challenge for online games” [22], [19], [11] and “it’s an important factor of an online gaming experience.” Jardine and Zappal in [18] deeply investigated “massively multiplayer online games with a client-server architectures and peer-to-peer game architectures”. Iimura [17] suggested “to implement a zoned federation model for the multi-player online games trying to reduce workloads of the centralized authoritative game servers.”

IBM in [14] “demonstrated that rapid system response time, ultimately reaching subsecond values and implemented with adequate system support, offers the promise of substantial improvements in user productivity” and they considered to “implement subsecond system response for their own online systems”.

In conclusion we want to mention Ghosh et al., who in [20] investigated “online multiplayer gaming issues in wireless networks, which is an additional problem related to the game players experience on the Internet.” Wu et al. in [25] “investigated a multiplayer on-line game traffic including modelling traffic in mobile networks.”

III. DATA PREPROCESSING AND FEATURE ENGINEERING

The data set used in our experiments was collected by WtFast in July 2020. It contains data on network latency, game environment, sizing, and the name of game sessions that were routed through the company’s GPN. In addition to these variables, we created other features which are related to networking performance, such as physical distance between gamers, nodes and game servers [6], whether the game sessions were played on the weekend (Friday to Sunday), and the type of game played (e.g., Action, Sports, etc.) [13]. Together, thirty nine features, fifteen of them numerical and rest of them binary categorical, were processed for the modelling exercise.

In this research, our interest is the network latency, measured by the ping value, associated with game sessions routed by the WTFast’s GPN. For the classification exercise, the ping value was classified into five classes based on following criteria (see Table I).

Sixty percent of the game sessions in the data set were used for the development of the ML classifiers. The remaining forty percent of the data set were used as the testing data set to evaluate their performance.

1) *Scaling Techniques:* Because a significant portion of the game sessions has very long duration that was confirmed to be legitimate and therefore should not be removed, the distribution of all numerical features is skewed to the right, that is, have very large values. Accordingly, “a square-root transformation was applied to all numerical features” [29] to make the distribution closer to a normal distribution.

From a ML perspective, the unit of all numerical features should be the same. As usual, a min-max normalization technique (Equation 1) was applied to the square-rooted transformed features:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

In addition to a square-root transformation and the min-max normalization techniques, a binning method of categorizing a numerical feature into a small number of categories (bins) to some of the numerical features (selective binning) to alleviate the impact of “skewness” to the modelling results was applied. Table II shows our approach to binning to these features.

Two sets of numerical features were selected for binning in selected machine learning models that we ran. The first set has only the “volume” features (TCP and UDP bytes uploaded) whereas the second set includes also the “physical” features like “Ping value if session is routed the Internet” and “Calculated distance between gamer and game server”.

IV. PERFORMANCE METRICS AND LATENCY CLASSIFICATION

The performance of ML classifiers was evaluated using two conventional performance metrics: overall accuracy and average accuracy. A third metric, called “weighted error rate”, is proposed to further differentiate these classifiers.

The overall accuracy rate focuses only on the proportion of true positive. It tends to underestimate the classification accuracy of a model. To deal with this issue, we considered also the average accuracy rate (the average of each class’ accuracy rate). The accuracy rate of each class is the ratio of the sum of true positive and false negative divided by the total number of predictions.

In addition to overall and average accuracy rates, a third metric, called Weighted Accuracy Rate, is proposed

to further differentiate these classifiers. For this research, the elements of a weight matrix W are defined as follow:

$$W_{ij} = \begin{cases} 0 & \text{if } i = j \\ |i - j| & \text{otherwise} \end{cases} \quad (2)$$

The weighted accuracy rate is then calculated as 1 minus the sum of the elements of the Hadamard product of W and the confusion matrix divided by the number of predictions. It can also be expressed as the following formula:

$$1 - \frac{\sum_{i,j=1}^5 W_{ij} e_{ij}}{\sum_{i,j=1}^5 e_{ij}} \quad (3)$$

For a given classification problem, the weights in Equation 2 could be defined differently to reflect on the varying impact of misclassifying the different classes. Note that the overall accuracy rate is a special case where the weights used are 1 except at the diagonal elements where they are 0.

We implemented three types of ML algorithms: random forest (RF), multiple layer perceptron (MLP), and support vector machine (SVM). Our previous study on the same data set from a different perspective has indicated that the MLP algorithm may not effective [29]. Therefore, besides using a single-input MLP algorithm, we have also experimented with one using multiple input layers: one input layer for numerical features and another one for categorical features. Figure 1 shows the structure of this MLP model.

V. RESULTS

Over eighty ML models with different combinations of hyperparameters and feature engineering techniques mentioned in the previous section were implemented and compared using the performance metrics described above. Table III shows the best four models, in terms of average accuracy rate of each ML algorithm.

Based on the results shown in Table III, the best model is based on a RF algorithm (number of trees = 175, maximum depth = 30). It has a 90.94% average accuracy and 77.36% overall accuracy rate. As we can see from the table, comparison of the models using the weighted accuracy rate is consistent with those using the average accuracy rate but indeed further differentiates the models with larger differences among them. The results also showed that the use of two input layers do not improve the accuracy of the MLP classifiers (7 layers in a two input layer model is not better than 3 layers within a single input layer model) which are in general slightly inferior to those using the RF algorithm. The binning techniques do not improve the performance of the classifiers. It seems that the square-root transformation is adequate in dealing with the skewness issues (length of Bin 3 is much longer than Bin 1 and 2 in Table 2.)

TABLE I
CATEGORIZED WTFast PING EXPLANATION AND RANGE

Class Label	Ping Value Range	Class Description
1	[0, 20)	The network speed is very fast
2	[20, 60)	The network speed is fast
3	[60, 100)	The network speed is medium
4	[100, 180)	The network speed is slow
5	[180, 250]	The network speed is ineffective for gaming

TABLE II
BINNING CRITERIA FOR ALL NUMERICAL FEATURES

Numerical Features	Bin 1	Bin 2	Bin 3
INTERNET_PING	[0, 117]	(117, 211]	(211, 500]
INTERNET_FLUX	[0, 9]	(9, 16]	(16, 368]
INTERNET_LOSS	[0, 19]	(19, 62]	(62, 25770]
INTERNET_SPKE	[0, 30]	(30, 72.6]	(72.6, 13217]
BYTES_UP_TCP	[0, 2.47]	(2.47, 4.98]	(4.98, 564.01]
BYTES_UP_UDP	=0	(0, 27.22]	(27.22, 32226.17]
BYTES_DOWN_TCP	[0, 36.87]	(36.87, 77.02]	(77.02, 63300.35]
BYTES_DOWN_UDP	[0, 37.14]	(37.14, 95.79]	(95.79, 30650.83]
SOCKET_COUNT_TCP	[0, 23]	(23, 50]	(50, 25405]
SOCKET_COUNT_UDP	[0, 12]	(12, 38]	(38, 8449]
CLIENT_IP_COUNT	1	(1, 17]	NA
GAME_IP_COUNT	[1, 11]	(11, 24]	(24, 2835]
BYTES_PER_SECOND	[0, 9.48]	(9.48, 22.59]	(22.59, 11316.87]
CALCULATED_DISTANCE	[0, 7.24]	(7.24, 12.15]	(12.15, 35.47866]
DURATION	[1, 6945]	(6945, 20060.2]	(20060.2, 662624]

TABLE III
THE BEST FOUR MODELS BASED ON AVERAGE ACCURACY RATE

ML Algorithms	Average Accuracy	Overall Accuracy	Weighted Accuracy
Random Forest (Trees: 175, Max. depth: 30)	90.94%	77.36%	73.40%
Random Forest (Trees: 200, Max. depth: 30)	90.94%	77.34%	73.36%
Multiple Layer Perceptron (Two Inputs Model) Refer to Figure 1	90.12%	74.01%	69.57%
Support Vector Machine (Gamma: Scale, C: 5)	87.93%	69.83%	64.95%

VI. CONCLUSION

The correct classification and hence “playability” of a game session based on its environmental, sizing, game type, and physical features is important for the operation and continuous management of a game focused network such as the GPN. The use of an effective machine learning classifier will pave the way for building an effective and productive pipeline for game traffic routing and dynamic network re-configuration. Some non-trivial fraction of the sessions do not need GPN improvement and so those customers could save money; a smaller fraction of sessions need GPN improvement but don’t get it so finer techniques could improve on the service to those high-end customers.

In this paper we have shown the possibility of reliable automatic classification of GPN traffic according to its effect on video game playability, and measured its average accuracy to about 90%. While the proposed measure of classifier performance shows promise, more research work would be required to understand its mathematical and statistical properties and its relationships to

existing metrics: (a) because it’s a very specific type of application area (gaming+networking) for which there is relatively little ML research; and (b) what very-high quality classifiers could mean for a real-time GPN management system that would provide QoE feedback to the GPN routing heuristics.

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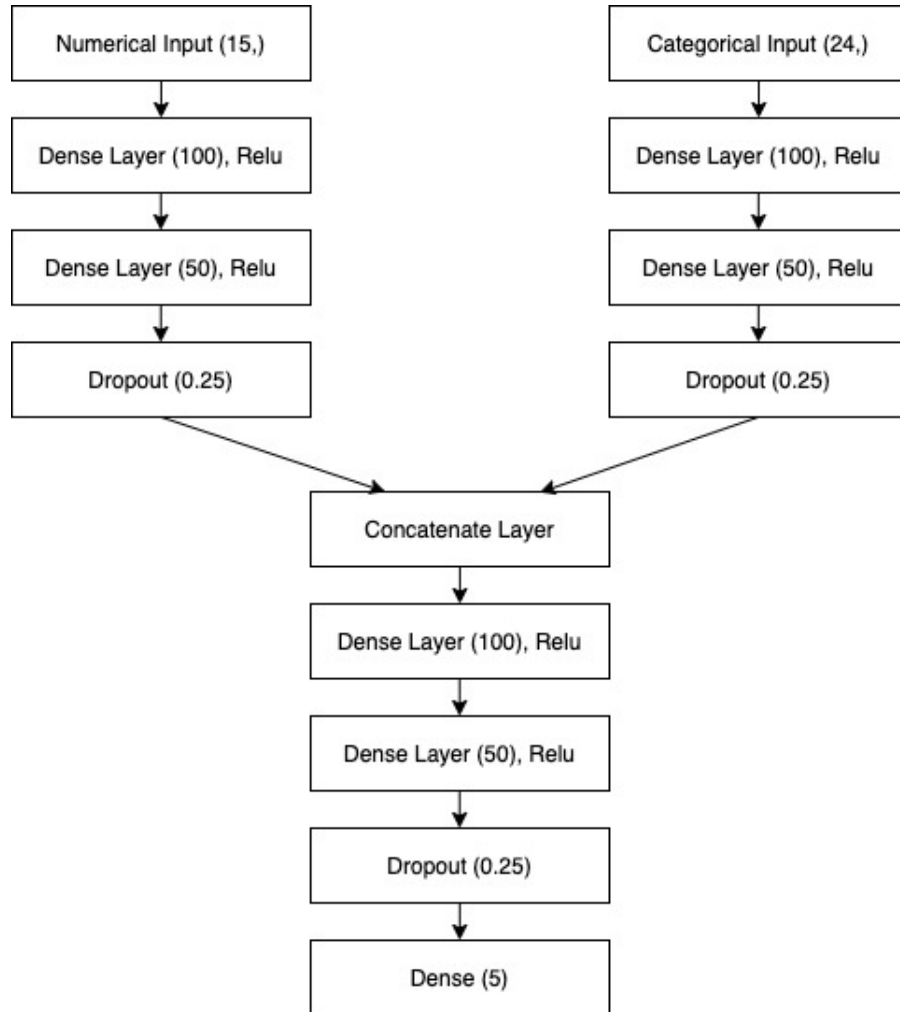


Fig. 1. The Structure of a MLP model with Two Input Layers

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