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Intelligent wireless network selection

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ABSTRACT

WiFi network selection is typically based on the received signal strength of an access point (AP). However, the strongest signal does not necessarily lead to good user experience. For example, a strong signal or SSID may simultaneously attract many WiFi clients, causing congestion.

This disclosure utilizes machine learning models trained to intelligently select a wireless access point or an SSID based on multiple factors, e.g., neighboring APs, neighboring clients, historical service information, signal and interference levels, ping jitter, time-of-day, day-of-week, etc. Per the techniques, the selected AP is associated with a best overall score as determined by the machine learning model based on several factors. The selected AP therefore is not necessarily the AP with the strongest signal or geographically nearest to the client device making the selection. User experience is improved by selecting the AP in this manner.

KEYWORDS

- Access point
- SSID
- WLAN
- WiFi
- network selection
- machine learning
- signal strength
- RSSI

BACKGROUND

WiFi network selection by a client device is generally based on the received signal strength indicator (RSSI) of an access point (AP). Present techniques for WiFi selection are greedy, e.g., do not account for other clients that attempt to access the same network at the same time. The present greedy techniques sometimes lead to suboptimal user experience. For example, an AP with a strong signal may attract many WiFi clients simultaneously, causing greater per-user access-time and leading to lower per-user throughput. This phenomenon is known as the tragedy of the commons.

Since RSSI is a measure of signal strength, it may not necessarily capture the effects of interference due to neighboring networks or clients. A device that connects to an AP based on the RSSI therefore does not always obtain in a good signal-to-interference-plus-noise ratio (SINR).

Attempts have been made to broaden the basis for connecting a client to a given network. For example, factors other than RSSI such as load on AP, air time, interference level, user activity levels, etc. have been used as parameters to determine connection to a network. However, these techniques are ad hoc and use arbitrarily selected weights for the different factors. The optimum combination of factors in the evaluation is not known in these techniques.

DESCRIPTION

The techniques of this disclosure model a framework for a family of network selection algorithms that incorporate rich input and output sets, without a priori insight on which constituent factors are relatively more (or less) important. The resulting family of network selection algorithms has a multi-dimensional control variable rather than a single primary parameter such as RSSI. The framework uses machine learning models to determine an optimal combination of constituent factors, rather than using human-driven insight, setting, or tweaking of the relative importance of factors.

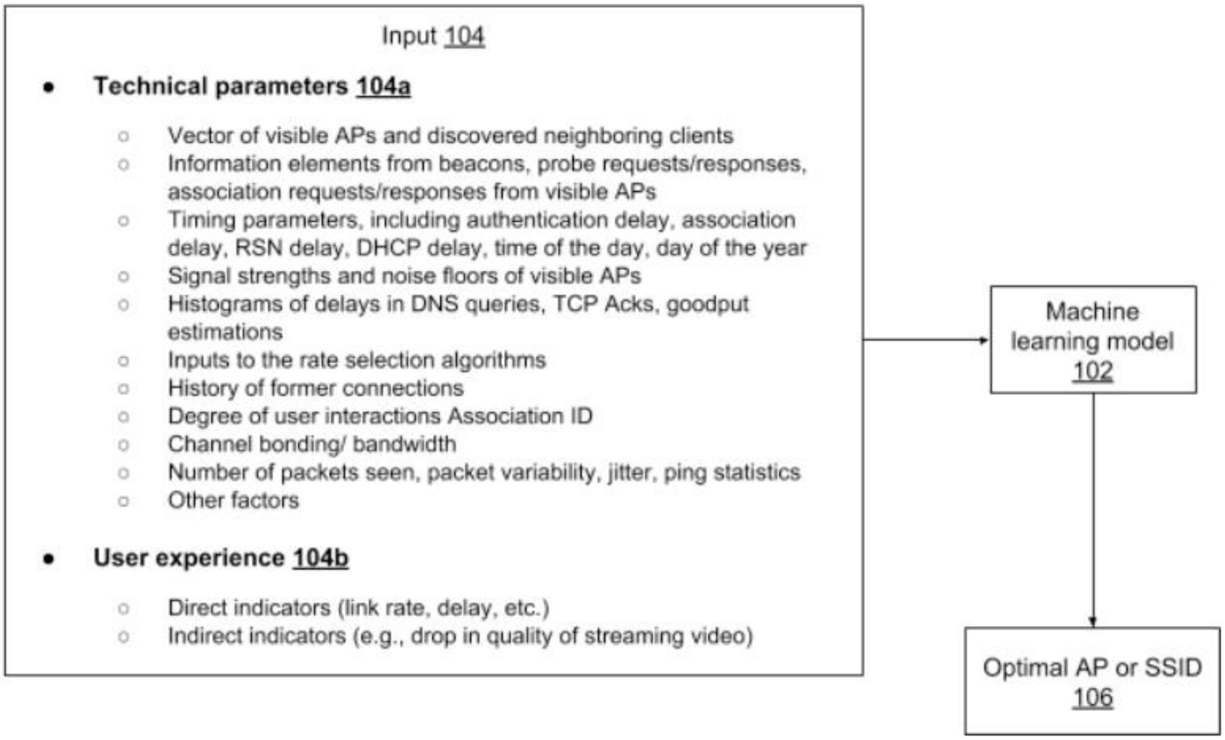

Fig. 1: Determination of optimal WLAN AP or SSID using trained ML model

Fig. 1 illustrates an example from the family of network selection algorithms, per the techniques of this disclosure. A trained machine learning model (102) accepts as input a number of factors (104) in order to determine an optimal access point or network (SSID) (106). Among the factors utilized are one or more available technical parameters (104a), such as

- a vector of visible APs, e.g., APs neighboring the client, and discovered neighboring clients;
- information elements from beacons, probe requests/responses, association requests/responses from visible APs;
- timing parameters, including authentication delay, association delay, RSN delay, DHCP

delay, ARP delay, time of the day, day of week, day of the year;

- signal strengths and noise floors of visible APs;
- histograms of delays in DNS queries, TCP acks, goodput estimations;
- inputs to the rate selection algorithms;
- performance history of former connections;
- degree of user interactions, e.g., is the connection made manually or automatically;
- association ID, which is an indicator of the number of active associations of an AP;
- channel bonding and bandwidth of visible APs, which can be a proxy for the traffic load on the APs;
- number of packets seen, their variability, jitters and delay statistics of pings; etc.

In addition, other factors, e.g., combinations drawn from connection-related parameters, negotiation details, chipset capabilities, timings, etc. as described in IEEE protocols, can be added as necessary. Some technical parameters can be actively measured by the client device, e.g., by sending out a ping to measure delays, jitters and losses within the network, or by downloading a small file from the internet to obtain performance statistics. The client measures technical parameters non-invasively and with minimal or zero extra traffic, e.g., by carrying out measurements on on-going user-driven traffic. The client can also advantageously carry out measurements in the background, e.g., when the user is not actively using the device.

When users permit use of user experience based factors (104b), such factors are also provided as input to the machine learning model. User experience can be measured directly or indirectly. Direct measures of user experience include, e.g., link rate, supported modulation and code rate, number of spatial streams, packet latency, packet jitter, etc. Indirect measures of user experience include, e.g., quality of audio or video, etc. For example, a drop in the resolution of streaming video is an indirect indicator of lowered user experience.

The machine learning model can use unsupervised learning, e.g., clustering, to correlate technical parameters with user experience. Based on the input factors, the ML model outputs selection of an optimal AP or SSID. The selection can be performed in a continuously adaptive manner cognizant of changing conditions. The machine learning model can be, e.g., a generative machine learning model, a regression learning model, a neural network, etc. Example types of neural networks that can be used include long short-term memory (LSTM) neural networks, recurrent neural networks, convolutional neural networks, etc. Other models, e.g., support vector machines, random forests, boosted decision trees, etc., can also be used. Techniques such as Hidden Markov Models (HMM), conditional random field (CRF) can also be used. If users permit, multiple client devices can mutually share respective machine learning models (e.g., weights of various nodes of a neural network) to facilitate federated learning.

Per the described techniques, the connection of a client to an AP or SSID is not wholly or necessarily driven by the geographical proximity or the signal strength of the AP or SSID. Rather, it is driven by a determination of optimal AP/SSID based on a number of spatiotemporal and parametric factors fed to a ML model trained for AP selection. Per the techniques, for example, a client may connect to an AP with a weaker RSSI if the AP is associated with a better history of user experience as compared to a nearer AP with stronger RSSI. As another example, per the techniques, a client may autonomously roam across APs or SSIDs, if conditions point to the optimality of switching APs or SSIDs. In this manner, the techniques address the sticky client syndrome, where a client maintains a previously made connection even when a better alternative becomes available.

Per the techniques, a client device, especially if stationary, can also be configured to try out different APs before settling on an AP or SSID. Also, a client with multi-technology, multi-radio capabilities can establish a multi-link connection, e.g., a simultaneous connection to more than one AP to achieve superior quality of service. In this regard, a client can reject a stronger AP in lieu of two weaker APs, if the sum of the bandwidths of the weaker APs is more than the bandwidth of the stronger AP.

Further to the descriptions above, a user may be provided with controls allowing the user to make an election as to both if and when systems, programs or features described herein may enable collection of user information (e.g., information about a user's social network, social actions or activities, profession, a user's preferences, or a user's current location), and if the user is sent content or communications from a server. In addition, certain data may be treated in one or more ways before it is stored or used, so that personally identifiable information is removed. For example, a user's identity may be treated so that no personally identifiable information can be determined for the user, or a user's geographic location may be generalized where location information is obtained (such as to a city, ZIP code, or state level), so that a particular location of a user cannot be determined. Thus, the user may have control over what information is collected about the user, how that information is used, and what information is provided to the user.

CONCLUSION

This disclosure utilizes machine learning models trained to intelligently select a wireless access point or an SSID based on multiple factors, e.g., neighboring APs, neighboring clients, historical service information, signal and interference levels, ping jitter, time-of-day, day-of-week, etc. Per the techniques, the selected AP is associated with a best overall score as determined by the machine learning model based on several factors. The selected AP therefore is not necessarily the AP with the strongest signal or geographically nearest to the client device making the selection. User experience is improved by selecting the AP in this manner.

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