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REAL TIME TRAFFIC PREDICTION FOR PHYSICAL STORES

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REAL TIME TRAFFIC PREDICTION FOR PHYSICAL STORES

ABSTRACT

A traffic predictor system can be used to predict customer traffic to physical stores. The system receives data describing search queries from a population of users. The system identifies intents of the population of users based on the search queries from the population of users. The intents may include local intent, i.e., intent to visit a physical store, and/or a product intent, i.e., intent to obtain a product. The system determines probabilities that the identified intents will lead to customers visiting the store. Subsequently, the system can generate traffic predictions for stores based on the determined probabilities for the identified intents.

PROBLEM STATEMENT

Physical stores constitute a major part of some retail businesses. Retail businesses may depend on a major share of their revenue to come from the selling of products through their physical stores. However, operating costs associated with running physical stores are high, and businesses look to optimize such operating costs. Customer traffic predictions is an important factor in optimizing operating costs as businesses can adjust staffing and product stock levels based on the traffic predictions. At present, there are no reliable techniques to predict customer traffic to physical retail stores. Furthermore, existing techniques to predict customer traffic do not help stores optimize product stock levels to satisfy the demand of customers. A system that provides reliable traffic predictions for physical stores is described below.

DETAILED DESCRIPTION

The systems and techniques described in this disclosure relate to a store traffic predictor system. The system can be implemented for use in an Internet, an intranet, or another client and server environment. The system can be implemented as program instructions locally on a client device or implemented across a client device and server environment. The system can also be implemented across a server and multiple client devices.

Fig. 1 illustrates an example method 100 for predicting customer traffic at stores. The method can be performed by a system that predicts the customer traffic, for example, the store traffic predictor system.

The traffic predictor system receives data describing search queries from a population of users (110). The system receives the search queries from one or more user sessions at one or more search engines. The search queries can be transmitted by the users to a search engine when searching for a particular store and/or product or service. In such instances, the search queries include the name of a product or service that the user is interested in procuring from a physical store. Example search queries include “tablets in nearby store,” “chinese food take out,” and “furniture store.” The system may distinguish received search queries that include a store or products/services intent from other general search queries. For example, the system can deploy a classifier that distinguishes search queries with a store or product intent, e.g., “tablets in nearby store” and “chinese food take out,” from search queries without a store or product intent, such as “how to tie a knot” or “how to shave.” The system may store the received search queries in a local or remote, e.g., cloud, database.

The system then identifies intents of the population of users based on the search queries (120). The identified intents can be a local intent, a product intent, or both a local and product intent. A search query with a local intent can indicate an intent for a local location. For example, user query “Best Buy nearby” indicates that the user is looking for “Best Buy” stores nearby the user’s location. A search query with a product intent can indicate an intent for any product that the user might be interested in. For example, user query “cell phones” indicates that the user is looking for cell phones. A search query with both a local and product intent can indicate an intent for a product that the user is interested in from a specific local location. For example, user query “cell phones at nearby Best Buy” indicates that the user is interested in cell phones from a nearby Best Buy store. For queries where the local intent or product intent cannot be determined, e.g., “cell phone,” the system can analyze other search queries made by the user. For example, if a current search query from a user has an ambiguous intent, the system can determine the intent of a previous search query made by the user and apply the intent to the current search query. The system can assign an intent with each received user query. The intent and query pairs can be stored in a local or remote, e.g., cloud, database.

The system then determines probabilities for the population of users that they will visit stores in a particular period of time based on the identified intents (130). Probabilities can be generated for stores that have local intents identified from the search queries or stores identified from a pre-curated list. A probability can be generated for each identified intent and store pair. Additionally, different probabilities for intent and store pairs can be generated for different periods of time. For example, from the query “Best Buy nearby,” the system identifies that the user has an intent to visit Best Buy, and that there is 50% probability that the user will visit Best

Buy within the next hour. Additionally, the system can determine that there is a 30% probability that the user will visit Best Buy within the next 6 hours, 10% probability within the next 24 hours, and 5% probability within the next week, and so on.

A classifier can be run on session queries to generate the probabilities users will visit stores within different time periods. The classifier looks at features from a collection of session search queries and related user interactions and predicts the probability the sessions will lead to users visiting stores after the sessions. The features can include the queries itself. For example, the classifier can determine that query “Best Buy nearby” indicates a high probability the user will visit Best Buy within the day. The features can also include the type of device, e.g., desktop, tablet, laptop, mobile, the queries are submitted from. For example, the classifier can determine that there is a higher probability users will visit Best Buy when the query “Best Buy nearby” is submitted from a mobile device than a desktop device. The features can further include the distance of the user, or distance of the device used to submit the queries, from the store. For example, the classifier can determine that there is an inverse relationship between the distance of the user from the store and the probability the user will visit the store. The features can further include user interactions with the search results that can be used to predict the probability the user will visit the store, e.g., the search results the user selects, the duration the user stays within a selected search result, a request for directions to the store, a selection of a map of the store, or movement of a cursor over the address of the store. For example, the classifier can determine that there is a high probability the user will visit Best Buy if the user selects the search result link for Best Buy. The classifier can determine the probability is even higher if the user stays within the Best Buy website for a significant period of time.

The classifier can also use the identified product intent of search queries to predict the probability users will visit stores within various periods of time. The type of product a user is searching for can help predict how soon the user will go to a store to purchase the product. For example, for user query “Refrigerator stores near me,” the system identifies “refrigerator” as the product intent, and determines that there is a higher probability that the user will visit the refrigerator store in the distant future, e.g., in a month, than in the near future, e.g., in a day or week. As a further example, for user query “Thai food near me,” the system identifies “Thai food” as the product intent, and determines that there is a lower probability that the user will visit the Thai restaurant in the distant future than in the near future..

The classifier can be trained on conversion metrics data, i.e., when the user actually visits a store, based on features from session search queries and related user interactions, as described above.

The system generates traffic predictions for the store based on the determined probabilities for the population of users (140). The system can combine the probabilities generated for the stores, products, and time periods to generate the predicted traffic for the stores for different periods of time. The system can then relay the traffic prediction to the stores in the form of a web dashboard or as an alert.

Fig. 2 is a block diagram of an exemplary environment that shows components of a system for implementing the techniques described in this disclosure. The environment includes client devices 210, servers 230, and network 240. Network 240 connects client devices 210 to servers 230. Client device 210 is an electronic device. Client device 210 may be capable of requesting and receiving data/communications over network 240. Example client devices 210 are

personal computers (e.g., laptops), mobile communication devices, (e.g. smartphones, tablet computing devices), set-top boxes, game-consoles, embedded systems, and other devices 210' that can send and receive data/communications over network 240. Client device 210 may execute an application, such as a web browser 212 or 214 or a native application 216. Web applications 213 and 215 may be displayed via a web browser 212 or 214. Server 230 may be a web server capable of sending, receiving and storing web pages 232. Web page(s) 232 may be stored on or accessible via server 230. Web page(s) 232 may be associated with web application 213 or 215 and accessed using a web browser, e.g., 212. When accessed, webpage(s) 232 may be transmitted and displayed on a client device, e.g., 210 or 210'. Resources 218 and 218' are resources available to the client device 210 and/or applications thereon, or server(s) 230 and/or web page(s) accessible therefrom, respectively. Resources 218' may be, for example, memory or storage resources; a text, image, video, audio, JavaScript, CSS, or other file or object; or other relevant resources. Network 240 may be any network or combination of networks that can carry data communication.

The subject matter described in this disclosure can be implemented in software and/or hardware (for example, computers, circuits, or processors). The subject matter can be implemented on a single device or across multiple devices (for example, a client device and a server device). Devices implementing the subject matter can be connected through a wired and/or wireless network. Such devices can receive inputs from a user (for example, from a mouse, keyboard, or touchscreen) and produce an output to a user (for example, through a display and/or a speaker). Specific examples disclosed are provided for illustrative purposes and do not limit the scope of the disclosure.

DRAWINGS

100

110

Receives data describing search queries from a population of users



120

Identifies intents of the population of users based on the search queries



130

Determines probabilities for the population of users that they will visit stores in a particular period of time based on the identified intents



140

Generates traffic predictions for the store based on the determined probabilities for the population of users

Fig. 1

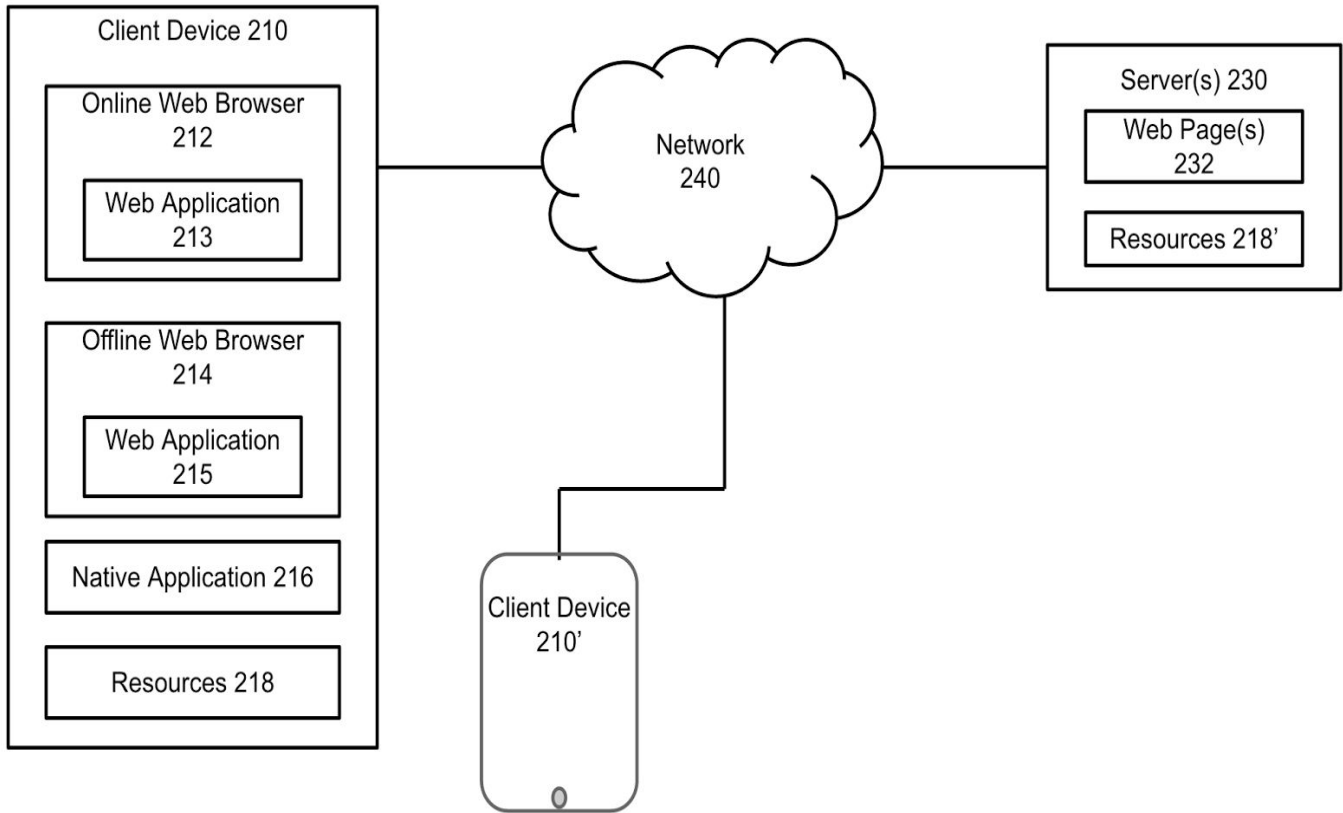


Fig. 2