Cross-Device Search

George D. Montañez, Ryen White, Xiao Huang

Carnegie Mellon University Microsoft Research Microsoft

CIKM 2014

Nov. 6th, 2014

George D. Montañez, Ryen White, Xiao Huang Cross-Device Search

Why Look At Cross-Device Search?

Why Look At Cross-Device Search?



- The number of smart and web capable devices is rapidly increasing.
- Multi-device users on a commercial search engine: **5%** of all users.
- Multi-device user query volume: 16% of total volume.
- Previous research has not investigated search on gaming consoles, or focused on device-device transitions.

Data Extraction Method Query Counts User Device-type Counts

Search Log Dataset

- Looked at several months of search and mobile log data, for English speaking US market.
- Obtained users who were logged in to search engine during this period, with unique identifier for each user.
- Filtered abnormal queries (e.g., from automated bots) and queries without necessary metadata.
- \sim 2 billion total queries, \sim 33 million users.

Data Extraction Method Query Counts User Device-type Counts



Table: Query Counts

Description	Total	%
Queries	2,271,142,893	100.00
Multi-Device User Queries	370,865,428	16.33
PC Queries	2,074,083,054	91.32
Smartphone Queries	53,939,886	2.38
Tablet Queries	137,979,833	6.08
Xbox Queries	1,854,422	0.08

Data Extraction Method Query Counts User Device-type Counts

Device-Type Counts

Table: User Device-type Counts

Device(s)	Users	%
Any Device(s)	33,221,253	100.00
More Than One Device	1,675,272	5.04
One Device	31,545,981	94.96
Two Devices	1,585,018	4.77
Three Devices	89,834	0.27
Four Devices	420	< 0.01
PC	31,770,955	95.63
Smartphone	1,301,717	3.92
Tablet	1,863,783	5.61
Xbox	50,744	0.15

Query Topic Distributions Device Transitions

Cross-Device Analysis

We characterized:

- Search behavior for different device types, i.e., topical interests on different devices
- How topical interests shifted over the course of the day
- Device-transition behavior, i.e., how did users transition among devices

Query Topic Distributions Device Transitions

Topical Interest by Device-Type

CHANGE IN TOPIC PROBABILITY (BY DEVICE)



George D. Montañez, Ryen White, Xiao Huang Cross-Device Search

Query Topic Distributions Device Transitions

Changes in Topic Distributions Per Device, Per Hour

TOPICS WITH LARGEST CHANGE IN PER HOUR TOPIC PROBABILITY







George D. Montañez, Ryen White, Xiao Huang

Cross-Device Search

Query Topic Distributions Device Transitions

Markov Transition Probability Graphs

- Maximum likelihood estimates for device transitions conditioned on the previous device
- Most transitions are self-transitions



Figure: Device transition probabilities %

George D. Montañez, Ryen White, Xiao Huang Cross-Device Search

Device Transitions

Markov Transition Probability Graphs - Cont.

- Only consider transitions between different devices •
- Most transition mass leads to PC
- Significant interplay between PC-smartphone and PC-tablet



Figure: Cross-device transition probabilities % Cross-Device Search

George D. Montañez, Rven White, Xiao Huang

Query Topic Distributions Device Transitions

Previous Query Topic To Next Device

- Relationship between previous query topic and the device of next query
- Events and Nightlife query increases likelihood of using a gaming console
- Celebrities query increases likelihood of using a tablet



Prediction Task Prediction Datasets Experimental Set-up Results

Predicting the Next Device

• Given a previous query, time of day and associated topical, spatial and temporal context, can we predict the next device a user will use?

Prediction Task Prediction Datasets Experimental Set-up Results

Predicting the Next Device

- Given a previous query, time of day and associated topical, spatial and temporal context, can we predict the next device a user will use?
- Answer: Yes, with high accuracy, precision and recall.

Prediction Task Prediction Datasets Experimental Set-up Results

Predicting the Next Device

- Given a previous query, time of day and associated topical, spatial and temporal context, can we predict the next device a user will use?
- Answer: Yes, with high accuracy, precision and recall.
- Knowing which device is next can allow for device-appropriate content gathering and better query-sense disambiguation.

Prediction Task Prediction Datasets Experimental Set-up Results

Prediction Datasets

- Created three datasets from primary dataset: Main, Balanced (50/50 mix of cross-device/same-device transitions), and Cross-Device Only.
- Features: Previous Device, Previous Query Topics, Previous Query Length, Previous Location, etc.
- Computed global and user-specific transition statistics as features from separate historical data.

Prediction Task Prediction Datasets Experimental Set-up Results

Features

Туре	Features and Counts			
Previous Device	Previous Device Flag (x4)			
Query Length	Query Length			
Hour	Previous Query Local Hour Flag (x24)			
Topic	Previous Query Topic Flags (×15)			
Topic	Current Query Topic Flags (x15)			
	Global Device Probabilities (x4)			
	Global Device-Device Transition			
Global Stats	Probabilities (×16)			
	Global Cross-Device Transition			
	Probabilities (×12)			
	Global Device Avg. Transition			
Global Temporal Stats	Delay (×4)			
	Global Device-Device Avg.			
	Transition Delay (x16)			

Prediction Task Prediction Datasets Experimental Set-up Results



Туре	Features and Counts			
	Number of Historical User Samples			
	Number of Historical User Cross-			
	Device Samples			
	User Device Probabilities (×4)			
	User Device-Device Transition			
User Stats	Probabilities (×16)			
	User Cross-Device Transition			
	Probabilities (×12)			
	User Cross-Device Destination			
	Device Probabilities (x4)			
	User IsDeviceDominant Flags (×4)			
	User IsCrossDeviceDominant Flags (x4)			
	User Device Avg. Transition Delay (×4)			
User Temporal Stats	User Device-Device Avg. Transition			
	Delay (×16)			

Prediction Task Prediction Datasets Experimental Set-up Results

Experimental Set-up

- 5-Fold cross-validation on subsample of 250,000 records from each set.
- **Baseline Methods:** Most Frequent Label, Uniform Guessing, Stratified Guessing.
- **Models:** L1 Logistic Regression and Gradient Boosting Trees Ensemble Classifiers.
- Metrics: Accuracy, Precision, Recall, F1-score, Multiclass Log-Loss.

Prediction Task Prediction Datasets Experimental Set-up **Results**

Predict Next Device - Main

- Both models show significant improvement over baseline methods
- Previous device state is the strongest feature for next device prediction

Method	Accuracy	Avg. Precision	Avg. Recall	Avg. F1-Score	Log-Loss
Baseline Method - Most Frequent Label	0.648	0.420	0.648	0.510	12.157
Baseline Method - Stratified	0.489	0.489	0.489	0.489	0.883
Baseline Method - Uniform	0.250	0.488	0.250	0.309	1.386
Gradient Boosting Trees Classifier L1 Logistic Regression	0.982*** 0.983***	0.982*** 0.983***	0.982*** 0.983***	0.982*** 0.983***	0.097*** 0.089***

(Statistical significance assessed by two-tailed paired t-test, with: $* < \alpha = .05$, $** < \alpha = .01$, $*** < \alpha = .00$)

Prediction Task Prediction Datasets Experimental Set-up Results

Predict Device Switch (Balanced)

- Predict whether a user switched device between queries.
- Balanced transition dataset: transition instances equally split among the "same device" and "different device" class label
- A non-trivially important task in scenarios when a new query is issued without corresponding device-type info

Method	Accuracy	Avg. Precision	Avg. Recall	Avg. F1-Score	Log-Loss
Baseline Method - Most Frequent Label	0.499	0.249	0.499	0.332	17.320
Baseline Method - Stratified	0.498	0.498	0.498	0.498	0.693
Baseline Method - Uniform	0.501	0.501	0.501	0.501	1.386
Gradient Boosting Trees Classifier	0.787***	0.788***	0.787***	0.786***	0.462***
L1 Logistic Regression	0.779***	0.782***	0.779***	0.778***	0.484***

(Statistical significance assessed by two-tailed paired t-test, with: * < α = .05, ** < α = .01, *** < α = .001)

Prediction Task Prediction Datasets Experimental Set-up Results

Predict Device Switch - Feature Ablations

Feature Group	Accuracy	Avg. Precision	Avg. Recall	Avg. F1-Score	Log-Loss
Baseline	0.589	0.591	0.589	0.587	0.676
Baseline+Q	0.589	0.591	0.589	0.587	0.674***
Baseline+Q+PT	0.599***	0.602***	0.599***	0.596***	0.665***
Baseline+Q+PT+PH	0.608***	0.609***	0.608***	0.607***	0.661***
Baseline+Q+PT+PH+U1	0.660***	0.661***	0.660***	0.660***	0.615***
Baseline+Q+PT+PH+U1-2	0.665***	0.666***	0.665***	0.664***	0.610***
Baseline+Q+PT+PH+U1-4	0.668***	0.668***	0.668***	0.668***	0.607***
Baseline+Q+PT+PH+U1-6	0.673***	0.674***	0.673***	0.673***	0.601***
${\sf Baseline}{+}{\sf Q}{+}{\sf PT}{+}{\sf PH}{+}{\sf U1}{-}{\sf 6}{+}{\sf G}$	0.674***	0.674***	0.674***	0.673***	0.602***
Baseline+Q+PT+PH+U1-6+G+CT	0.675***	0.675***	0.675***	0.675***	0.599***
$Baseline{+}Q{+}PT{+}PH{+}U1{-}6{+}G{+}DT$	0.778***	0.782***	0.778***	0.778***	0.485***
All Features	0.779***	0.782***	0.779***	0.778***	0.484***

Baseline = Previous Device

 $\mathsf{Q}=\mathsf{Previous}\;\mathsf{Query}\;\mathsf{Length}$

G = Global Transition Stats Features

PT = Previous Topic features

CT = Current Topic Features

PH = Previous Query Hour

U1 = Number of historical samples for the user and the number of cross-device samples for the user

U1-2 = U1 and user-specific device probabilities

U1-3 = U1, U2 and device-device pair transition probabilities

U1-4 = U1, U2, U3 and destination device transition probabilities

U1-5 = U1 through U4 and device conditioned transition probabilities

U1-6 = U1 through U5 and user-specific average transition times for device-device pairs

DT = Delay time (in seconds) between previous and current queries

All Features = All of the above feature sets

(Statistical significance assessed by two-tailed paired t-test, with: * < α = .05, ** < α = .01, *** < α = .001)

Prediction Task Prediction Datasets Experimental Set-up **Results**

Predict Next Device Given Device Switch

- A more difficult task
- The feature-based methods continue to significantly outperform the baselines

Method	Accuracy	Avg. Precision	Avg. Recall	Avg. F1-Score	Log-Loss
Baseline Method - Most Frequent Label	0.455	0.207	0.455	0.284	18.829
Baseline Method - Stratified	0.370	0.371	0.370	0.371	1.046
Baseline Method - Uniform	0.250	0.370	0.250	0.292	1.386
Gradient Boosting Trees Classifier L1 Logistic Regression	0.931*** 0.934***	0.931*** 0.933***	0.931*** 0.934***	0.931*** 0.933***	0.197*** 0.193***

(Statistical significance assessed by two-tailed paired t-test, with: * < α = .05, ** < α = .01, *** < α = .001)

Prediction Task Prediction Datasets Experimental Set-up Results

Predict Next Device Given Device Switch - Feature Ablations

- Previous device and searchers' own transition histories were the pirmary factors in the prediction
- Compactness is important of large scale search engines.

Feature Group	Accuracy	Avg. Precision	Avg. Recall	Avg. F1-Score	Log-Loss
Baseline+U1-6	0.932***	0.931***	0.932***	0.931***	0.196***
Baseline	0.781	0.642	0.781	0.703	0.496
Baseline+Q	0.781	0.642	0.781	0.703	0.496
Baseline+Q+PT	0.781	0.642	0.781	0.703	0.495
Baseline+Q+PT+PH	0.781	0.679	0.781	0.703	0.493
Baseline+Q+PT+PH+U1	0.781	0.716	0.781	0.703	0.491
Baseline+Q+PT+PH+U1-2	0.903***	0.903***	0.903***	0.898***	0.281***
Baseline+Q+PT+PH+U1-3	0.928***	0.927***	0.928***	0.927***	0.203***
Baseline+Q+PT+PH+U1-4	0.932***	0.932***	0.932***	0.931***	0.195***
Baseline+Q+PT+PH+U1-5	0.932***	0.932***	0.932***	0.931***	0.195***
Baseline+Q+PT+PH+U1-6	0.933***	0.932***	0.933***	0.932***	0.194***
${\sf Baseline+Q+PT+PH+U1-6+G}$	0.933***	0.932***	0.933***	0.932***	0.194***
Baseline+Q+PT+PH+U1-6+G+CT	0.933***	0.932***	0.933***	0.932***	0.194***
${\sf Baseline+Q+PT+PH+U1-6+G+DT}$	0.933***	0.933***	0.933***	0.932***	0.194***
All Features	0.934***	0.933***	0.934***	0.933***	0.193***
For Feature Group legend, see Table 1	9				

(Statistical significance assessed by two-tailed paired t-test, with: * < α = .05, ** < α = .01, *** < α = .001)

George D. Montañez, Ryen White, Xiao Huang

Summary Opportunities For Future Work The End

Summary

- We characterized temporal and topical aspects of cross-device search.
- Found that query content differed among device types and hour of day, often in intuitive ways.
- These differences and patterns can be successfully exploited to reliably predict the next device a user will transition to.
- Previous device can signal the next device, even when the devices differ.

Summary Opportunities For Future Work The End

Opportunities For Future Work

- Delay time prediction (anticipated time between devices)
- Session-level rather than query level predictions
- Qualitative investigations to complement our quantitative analysis
- Supporting device transitions (e.g., pre-fetching content suitable for the next device used)

Summary Opportunities For Future Work The End



Thank You!

George D. Montañez, Ryen White, Xiao Huang Cross-Device Search