Identifying Task-based Sessions in Search Engine Query Logs

Gabriele Tolomei

Ca' Foscari University of Venice
ISTI-CNR, Pisa
Italy

February, 12 2011

Agenda

- Introduction
- Contributions
- Experiments and Results
- Conclusions and Future Work

Agenda

- Introduction
- Contributions
- Experiments and Results
- Conclusions and Future Work

Problem Statement: TSDP

Task-based Session Discovery Problem:

Discover sets of possibly non contiguous queries issued by users of Web Search Engines for carrying out specific **tasks** using Query Log Mining techniques

Motivation

- Everyone who is now at WSDM 2011 has dealt with a lot of "stuff" for organizing her/his attendance

Motivation

- Everyone who is now at WSDM 2011 has dealt with a lot of "stuff" for organizing her/his attendance
- Conference Web site is full of useful information but still some tasks have to be performed (e.g., book flight, reserve hotel room, rent car, etc.)

Motivation

- Everyone who is now at WSDM 2011 has dealt with a lot of "stuff" for organizing her/his attendance
- Conference Web site is full of useful information but still some tasks have to be performed (e.g., book flight, reserve hotel room, rent car, etc.)
- In the last Web era this means to search for suitable contents over the Internet about achieving those tasks

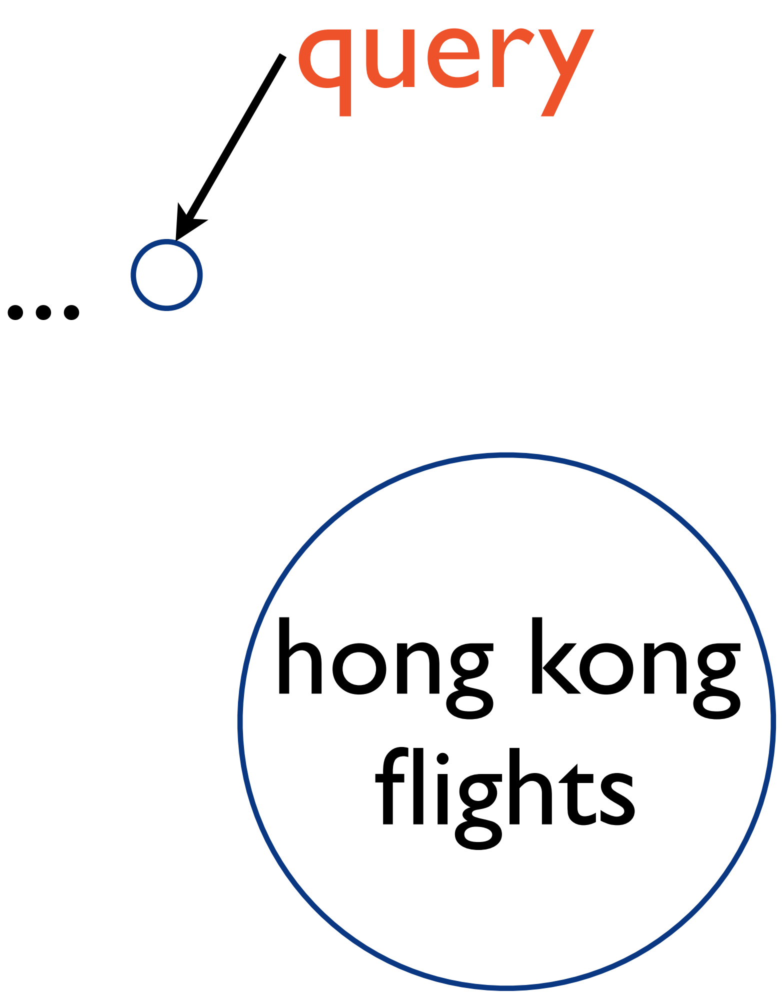
Motivation

- Everyone who is now at WSDM 2011 has dealt with a lot of "stuff" for organizing her/his attendance
- Conference Web site is full of useful information but still some tasks have to be performed (e.g., book flight, reserve hotel room, rent car, etc.)
- In the last Web era this means to search for suitable contents over the Internet about achieving those tasks
    - Formulate information needs by means of a set of queries issued to a Web Search Engine (WSE)

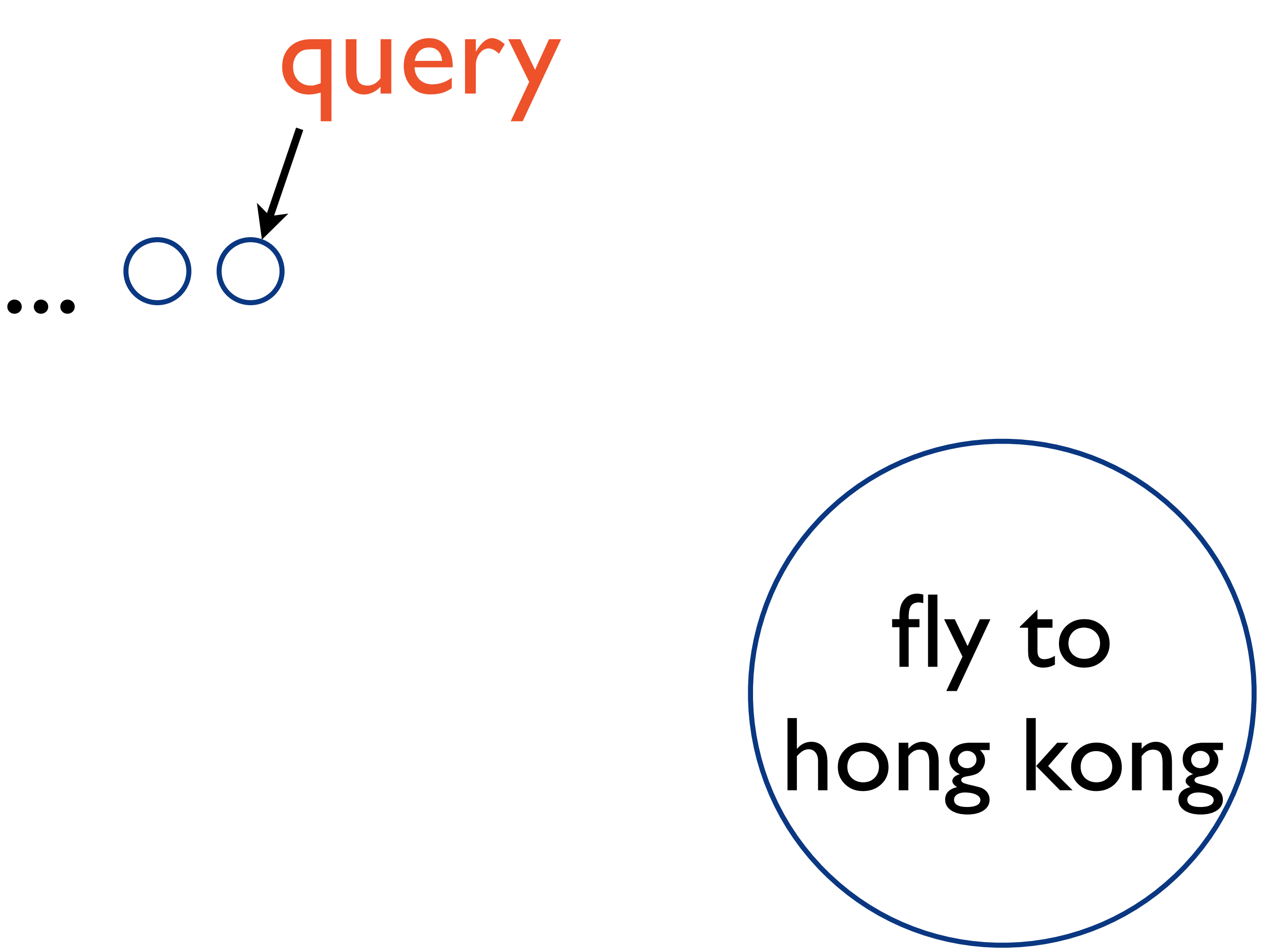
Motivation

- Everyone who is now at WSDM 2011 has dealt with a lot of "stuff" for organizing her/his attendance
- Conference Web site is full of useful information but still some tasks have to be performed (e.g., book flight, reserve hotel room, rent car, etc.)
- In the last Web era this means to search for suitable contents over the Internet about achieving those tasks
    - Formulate information needs by means of a set of queries issued to a Web Search Engine (WSE)
    - Possibly, interleave searches with other information needs (e.g., reading sport news)

The Big Picture



The Big Picture

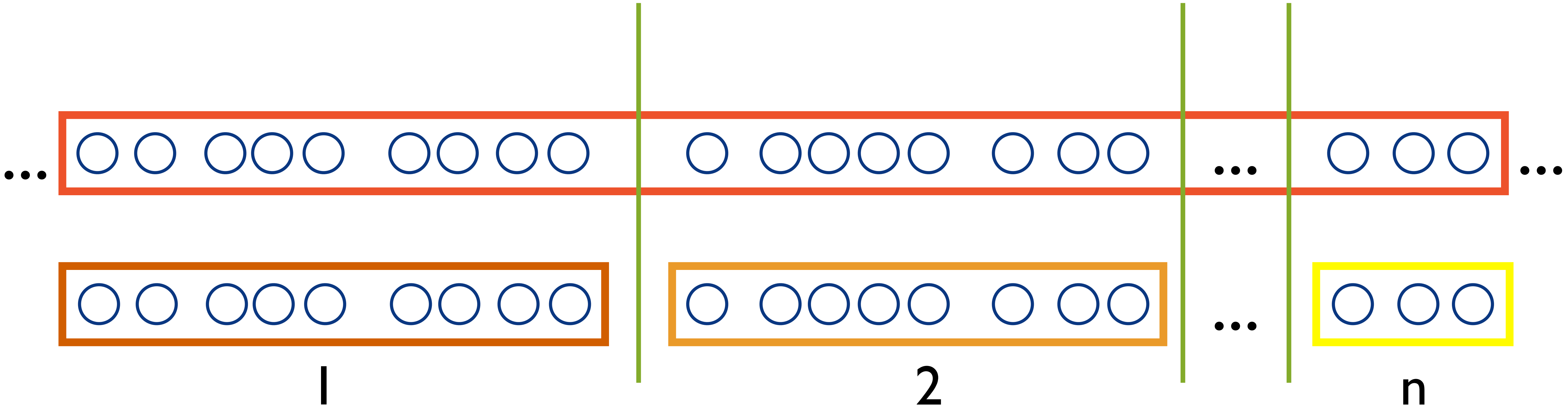


The Big Picture

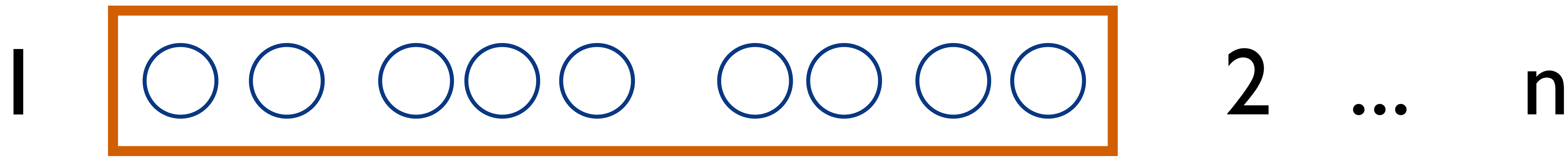
The Big Picture

The Big Picture

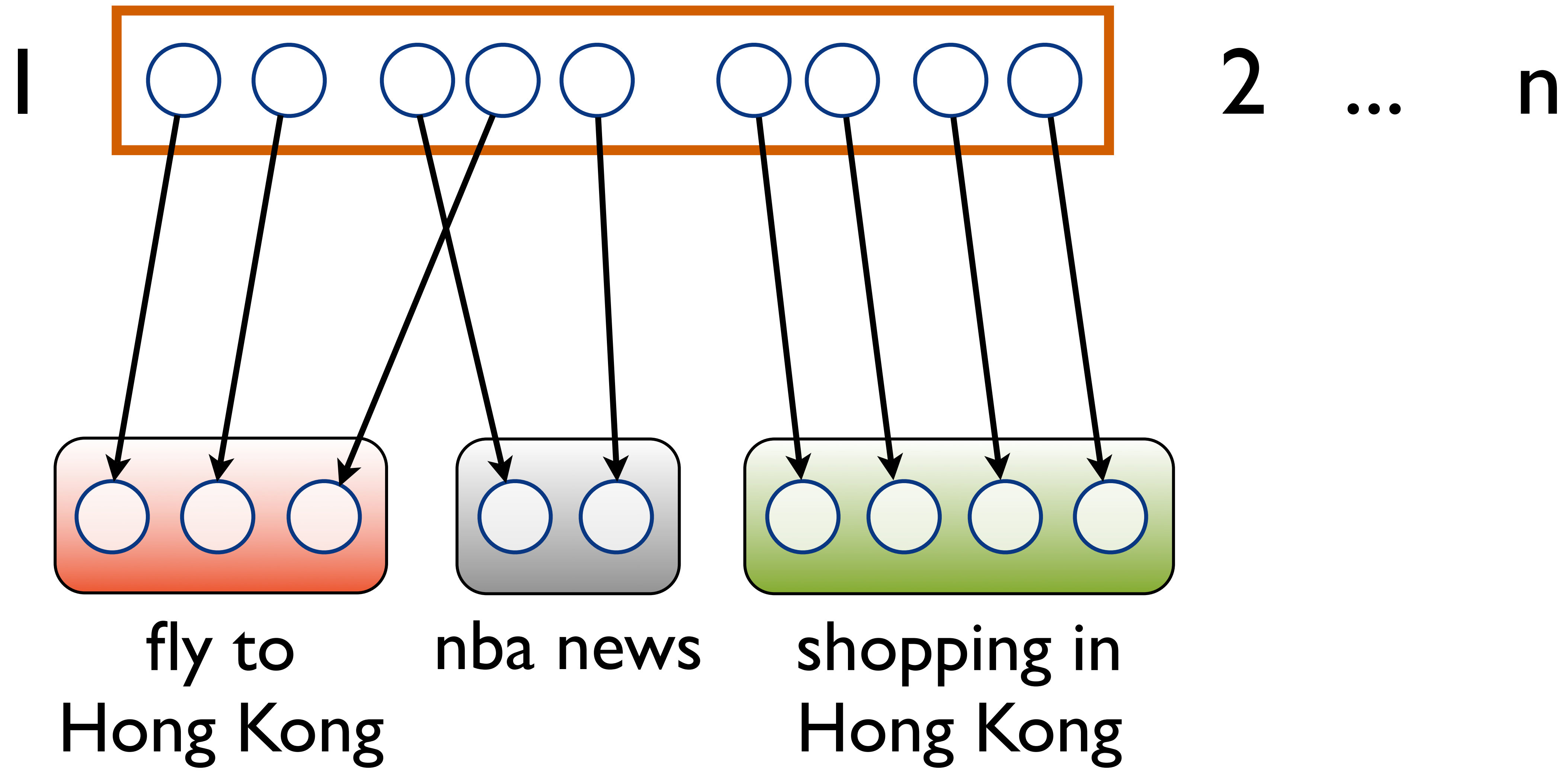
The Big Picture



The Big Picture



The Big Picture



wsdm 2011 Hong Kong

Related Work

- Previous work on session identification can be classified into:

1. time-based
2. content-based
3. mixed-heuristics (combining 1. and 2.)

Related Work: time-based

- Silverstein *et al.* [1] firstly defined the concept of "session":
    - 2 adjacent queries (q_i, q_{i+1}) are part of the same session if their time submission gap is at most 5 minutes

Related Work: time-based

- Silverstein *et al.* [1] firstly defined the concept of "session":
  - 2 adjacent queries (q_i, q_{i+1}) are part of the same session if their time submission gap is at most 5 minutes
- He and Göker [2] used different timeouts to split user sessions (from 1 to 50 minutes)

Related Work: time-based

- Silverstein *et al.* [1] firstly defined the concept of "session":
    - 2 adjacent queries (q_i, q_{i+1}) are part of the same session if their time submission gap is at most 5 minutes
- He and Göker [2] used different timeouts to split user sessions (from 1 to 50 minutes)
- Radlinski and Joachims [3] introduced query chains, i.e., sequence of queries with similar information need

Related Work: time-based

- Silverstein *et al.* [1] firstly defined the concept of "session":
  - 2 adjacent queries (q_i, q_{i+1}) are part of the same session if their time submission gap is at most 5 minutes
- He and Göker [2] used different timeouts to split user sessions (from 1 to 50 minutes)
- Radlinski and Joachims [3] introduced query chains, i.e., sequence of queries with similar information need
- Jansen and Spink [4] described a session as the time gap between the first and last recorded timestamp on the WSE server

Related Work: time-based

- Silverstein *et al.* [1] firstly defined the concept of "session":
  - 2 adjacent queries (q_i, q_{i+1}) are part of the same session if their time submission gap is at most 5 minutes
- He and Göker [2] used different timeouts to split user sessions (from 1 to 50 minutes)
- Radlinski and Joachims [3] introduced query chains, i.e., sequence of queries with similar information need
- Jansen and Spink [4] described a session as the time gap between the first and last recorded timestamp on the WSE server

PROs

✓ ease of implementation

CONs

✓ unable to deal with multi-tasking behaviors

Related Work: content-based

- Some work exploit lexical content of the queries for determining a topic shift in the stream, i.e., session boundary [5, 6, 7]

Related Work: content-based

- Some work exploit lexical content of the queries for determining a topic shift in the stream, i.e., session boundary [5, 6, 7]

- Several string similarity scores have been proposed, e.g., Levenstein, Jaccard, etc.

Related Work: content-based

- Some work exploit lexical content of the queries for determining a topic shift in the stream, i.e., session boundary [5, 6, 7]
- Several string similarity scores have been proposed, e.g., Levenstein, Jaccard, etc.
- Shen *et al.* [8] compared "expanded representation" of queries
  - expansion of a query q is obtained by concatenating titles and Web snippets for the top-50 results provided by a WSE for q

wsdm 2011 Hong Kong

Related Work: content-based

- Some work exploit lexical content of the queries for determining a topic shift in the stream, i.e., session boundary [5, 6, 7]
- Several string similarity scores have been proposed, e.g., Levenstein, Jaccard, etc.
- Shen *et al.* [8] compared "expanded representation" of queries
  - expansion of a query q is obtained by concatenating titles and Web snippets for the top-50 results provided by a WSE for q

PROs

✓ effectiveness improvement

CONs

✓ *vocabulary-mismatch problem*: e.g., ("nba", "kobe bryant")

Related Work: mixed

- He *et al.* [6] extend their previous work to consider both temporal and lexical features

Related Work: mixed

- He *et al.* [6] extend their previous work to consider both temporal and lexical features
- Boldi *et al.* [9] introduce the query-flow graph as a model for representing WSE log data
    - session identification as Traveling Salesman Problem

Related Work: mixed

- He *et al.* [6] extend their previous work to consider both temporal and lexical features
- Boldi *et al.* [9] introduce the query-flow graph as a model for representing WSE log data
  - session identification as Traveling Salesman Problem
- Jones and Klinkner [10] address a problem similar to the TSDP
  - hierarchical search: mission vs. goal
  - supervised approach: learn a suitable binary classifier to detect whether two queries (q_i, q_j) belong to the same task or not

Related Work: mixed

- He *et al.* [6] extend their previous work to consider both temporal and lexical features
- Boldi *et al.* [9] introduce the query-flow graph as a model for representing WSE log data
  - session identification as Traveling Salesman Problem
- Jones and Klinkner [10] address a problem similar to the TSDP
  - hierarchical search: mission vs. goal
  - supervised approach: learn a suitable binary classifier to detect whether two queries (q_i, q_j) belong to the same task or not

PROs

✓ effectiveness improvement

CONs

✓ computational complexity

Agenda

- Introduction
- Contributions
- Experiments and Results
- Conclusions and Future Work

Our Approach

- Formalize the Task-based Session Discovery Problem

wsdm 2011 Hong Kong

Our Approach

- Formalize the Task-based Session Discovery Problem
- Analyze a long-term WSE log of queries

Our Approach

- Formalize the Task-based Session Discovery Problem
- Analyze a long-term WSE log of queries
- Build a ground-truth of tasks by manually grouping a sample of task-related queries in the given WSE log

Our Approach

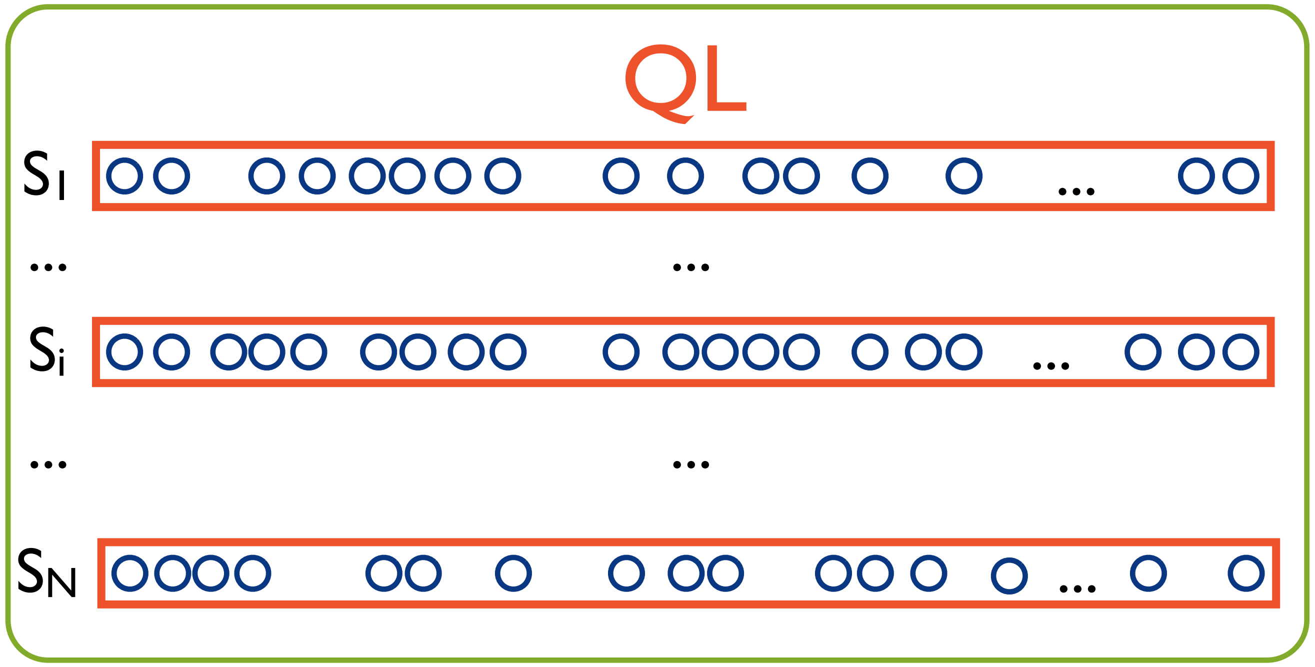
- Formalize the Task-based Session Discovery Problem
- Analyze a long-term WSE log of queries
- Build a ground-truth of tasks by manually grouping a sample of task-related queries in the given WSE log
- Perform some statistics on top of the ground-truth

Our Approach

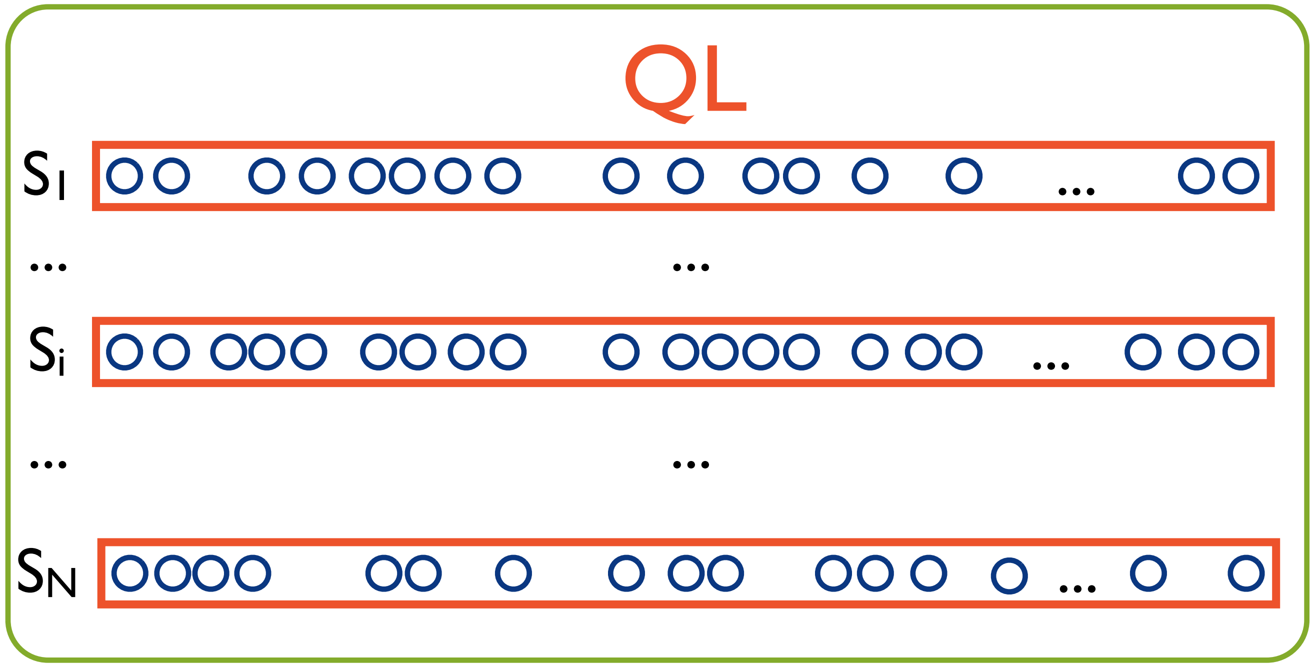
- Formalize the Task-based Session Discovery Problem
- Analyze a long-term WSE log of queries
- Build a ground-truth of tasks by manually grouping a sample of task-related queries in the given WSE log
- Perform some statistics on top of the ground-truth
- Propose several techniques for addressing the TSDP

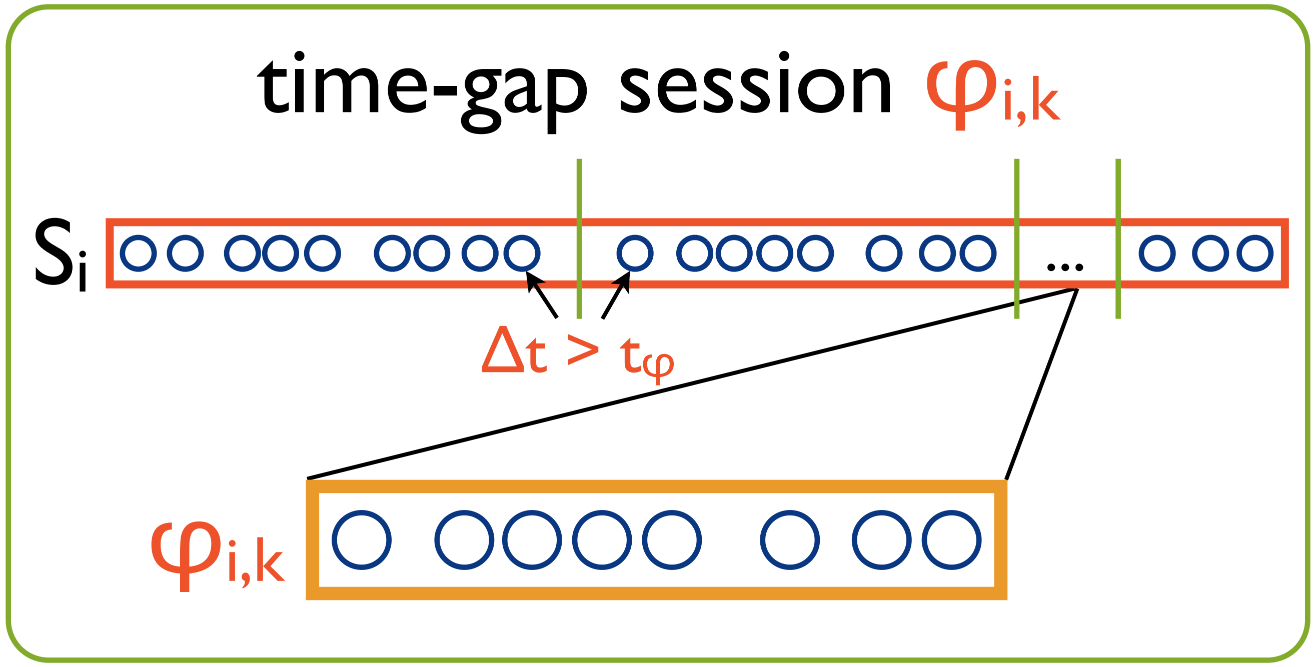
wsdm 2011 Hong Kong

Theoretical Model

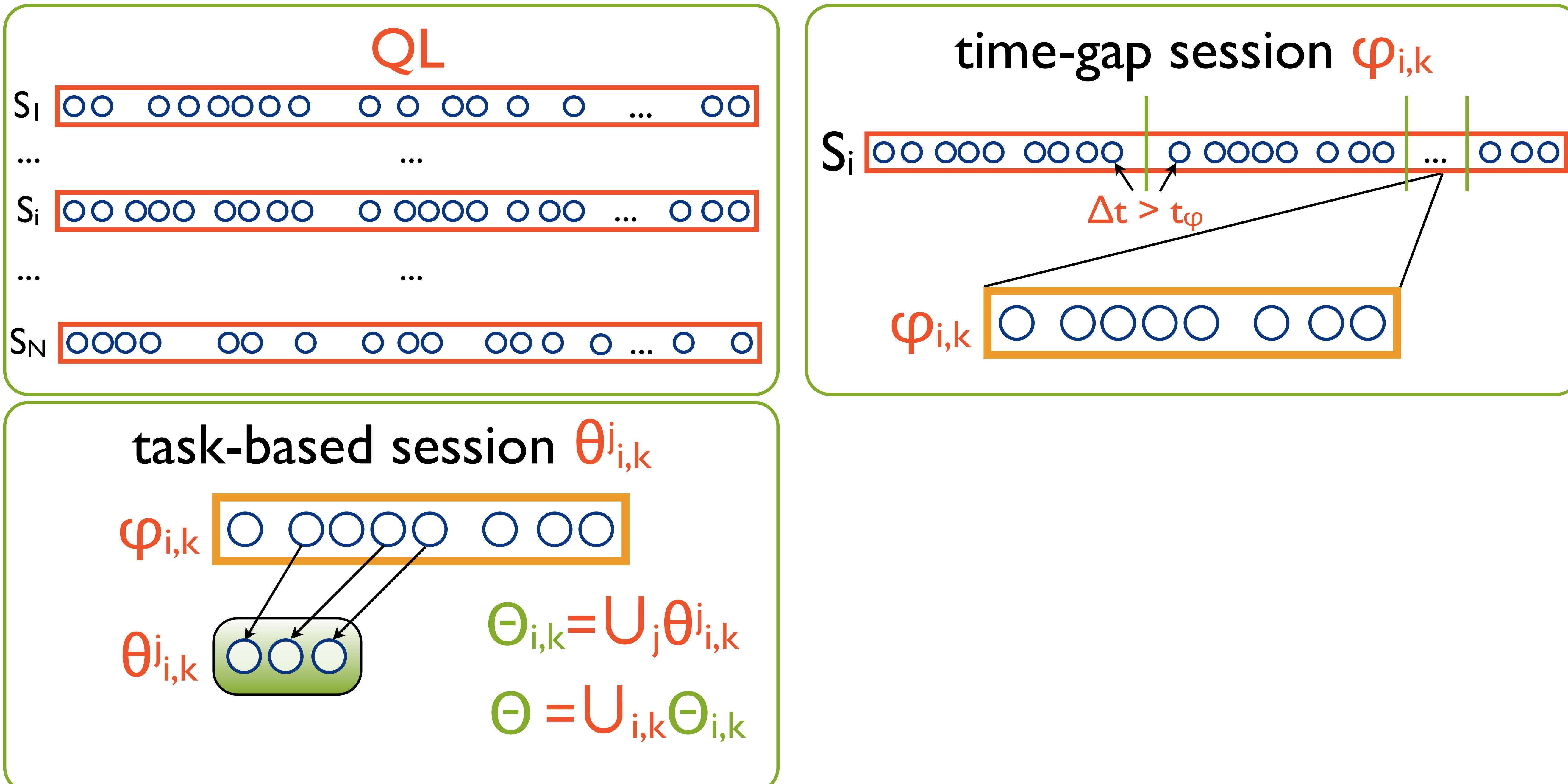


Theoretical Model



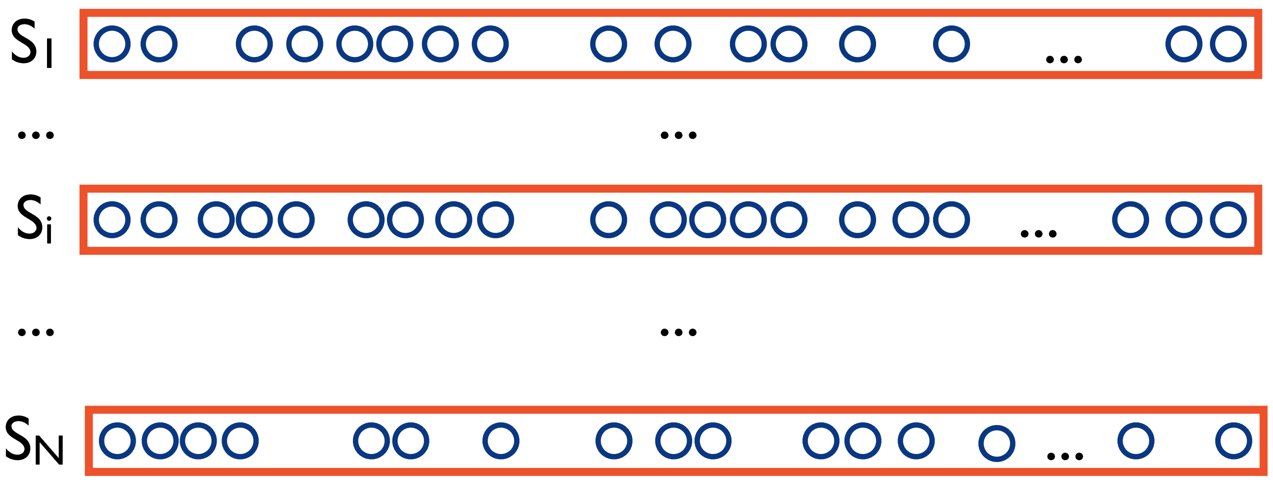


Theoretical Model

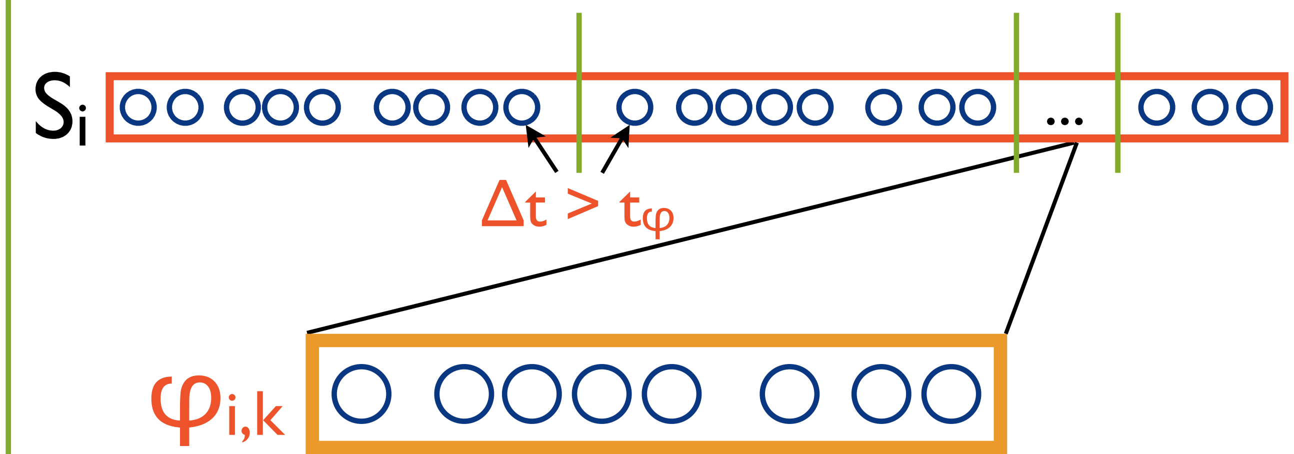


Theoretical Model

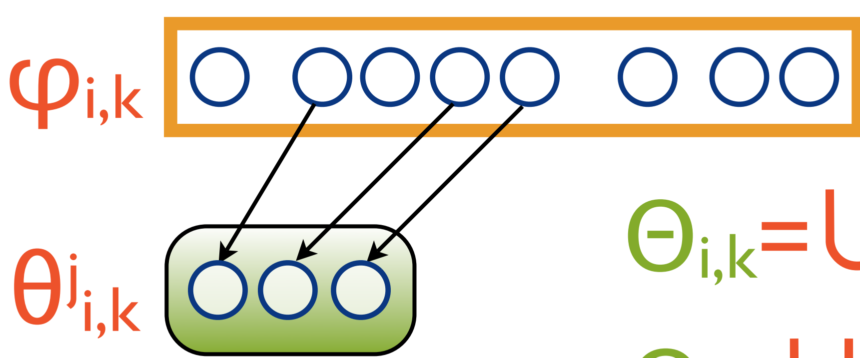
QL



time-gap session $\varphi_{i,k}$



task-based session $\theta^j_{i,k}$



$$\Theta_{i,k} = \cup_j \theta^j_{i,k}$$

$$\Theta = \cup_{i,k} \Theta_{i,k}$$

TSDP

- ✓ $\Theta_{i,k}$ set of actual task-based sessions of $\varphi_{i,k}$
- ✓ $C_{i,k}$ set of task-based sessions of $\varphi_{i,k}$ discovered using partitioning strategy π
- ✓ $\Theta = \cup_{i,k}\Theta_{i,k}$ and $C_\pi = \cup_{i,k} C_{i,k}$
- ✓ Find the best partitioning π^* such that:

$$\pi^* = \mathrm{argmax}_\pi\ \xi(\Theta, C_\pi)$$

where ξ measures the quality of C_π w.r.t. Θ

Data Set: AOL Query Log

Original Data Set

- ✓ 3-months collection
- ✓ ~20M queries
- ✓ ~657K users

Data Set: AOL Query Log

Original Data Set

- ✓ 3-months collection
- ✓ ~20M queries
- ✓ ~657K users

Sample Data Set

- ✓ 1-week collection
- ✓ ~100K queries
- ✓ 1,000 users
- ✓ removed empty queries
- ✓ removed "non-sense" queries
- ✓ removed stop-words
- ✓ applied Porter stemming algorithm

Data Analysis: query time gap

- Devise a value t_{φ}, such that two adjacent queries whose time gap is smaller than t_{φ} should be considered part of the same time-gap session

Data Analysis: query time gap

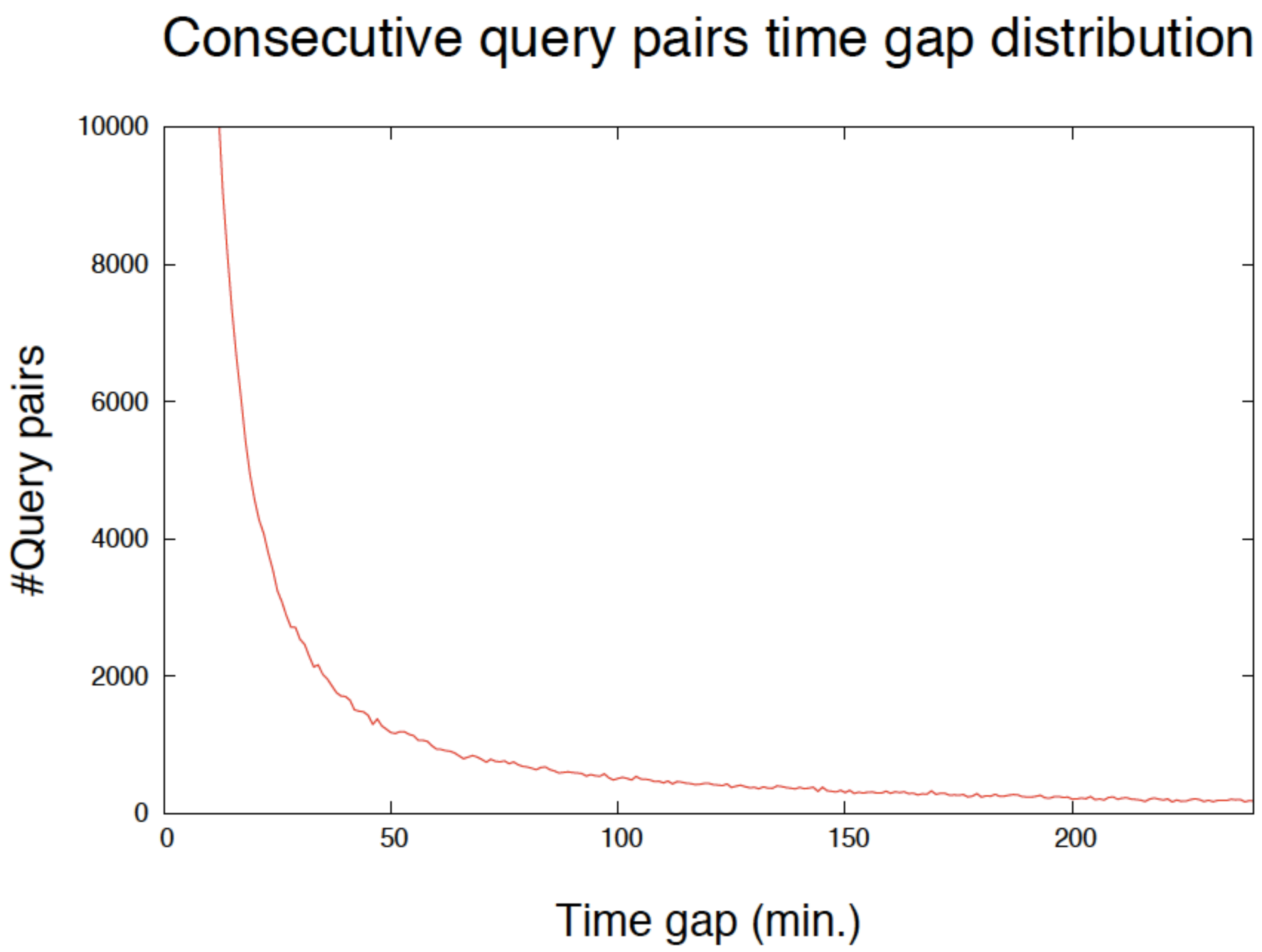
- Devise a value t_φ, such that two adjacent queries whose time gap is smaller than t_φ should be considered part of the same time-gap session
- Analyze the distribution of time gaps between all the adjacent query pairs (q_i, q_{i+1}) in the original collection

Data Analysis: query time gap

- Devise a value t_φ, such that two adjacent queries whose time gap is smaller than t_φ should be considered part of the same time-gap session
- Analyze the distribution of time gaps between all the adjacent query pairs (q_i, q_{i+1}) in the original collection
- power-law distribution

$$\boxed{p(x) \propto L(x)\, x^{-\alpha} \quad (\alpha > 1)}$$

Data Analysis: query time gap



Data Analysis: query time gap

- Compute the cumulative probability distribution in order to find x' such that $Pr(X \leq x') = P(x') = \lambda$
  - $\lambda = \mu + \sigma = 0.5 + 0.341 = 0.841$ (mean + std. deviation of a Gaussian distribution)
  - estimation of $\alpha = 1.58$
  - $P(x') = \lambda = 0.841$

wsdm 2011 Hong Kong

Data Analysis: query time gap

- Compute the cumulative probability distribution in order to find x' such that $Pr(X \leq x') = P(x') = \lambda$
  - $\lambda = \mu + \sigma = 0.5 + 0.341 = 0.841$ (mean + std. deviation of a Gaussian distribution)
  - estimation of $\alpha = 1.58$
  - $P(x') = \lambda = 0.841 \longrightarrow \boxed{x' \sim 26 \text{ minutes}}$
- This means 84.1% of consecutive query pairs are issued within 26 minutes
  - x' can be used as the threshold t_φ
  - compliant with often used 30-minutes threshold

Ground-truth: construction

- Long-term sessions of sample data set are first split using the time threshold devised before (i.e., 26 minutes)
    - obtaining several time-gap sessions

Ground-truth: construction

- Long-term sessions of sample data set are first split using the time threshold devised before (i.e., 26 minutes)
    - obtaining several time-gap sessions
- Human annotators group queries that they claim to be task-related inside each time-gap session

Ground-truth: construction

- Long-term sessions of sample data set are first split using the time threshold devised before (i.e., 26 minutes)
  - obtaining several time-gap sessions
- Human annotators group queries that they claim to be task-related inside each time-gap session
- Represents the "optimal" task-based partitioning Θ manually built from actual WSE query log data

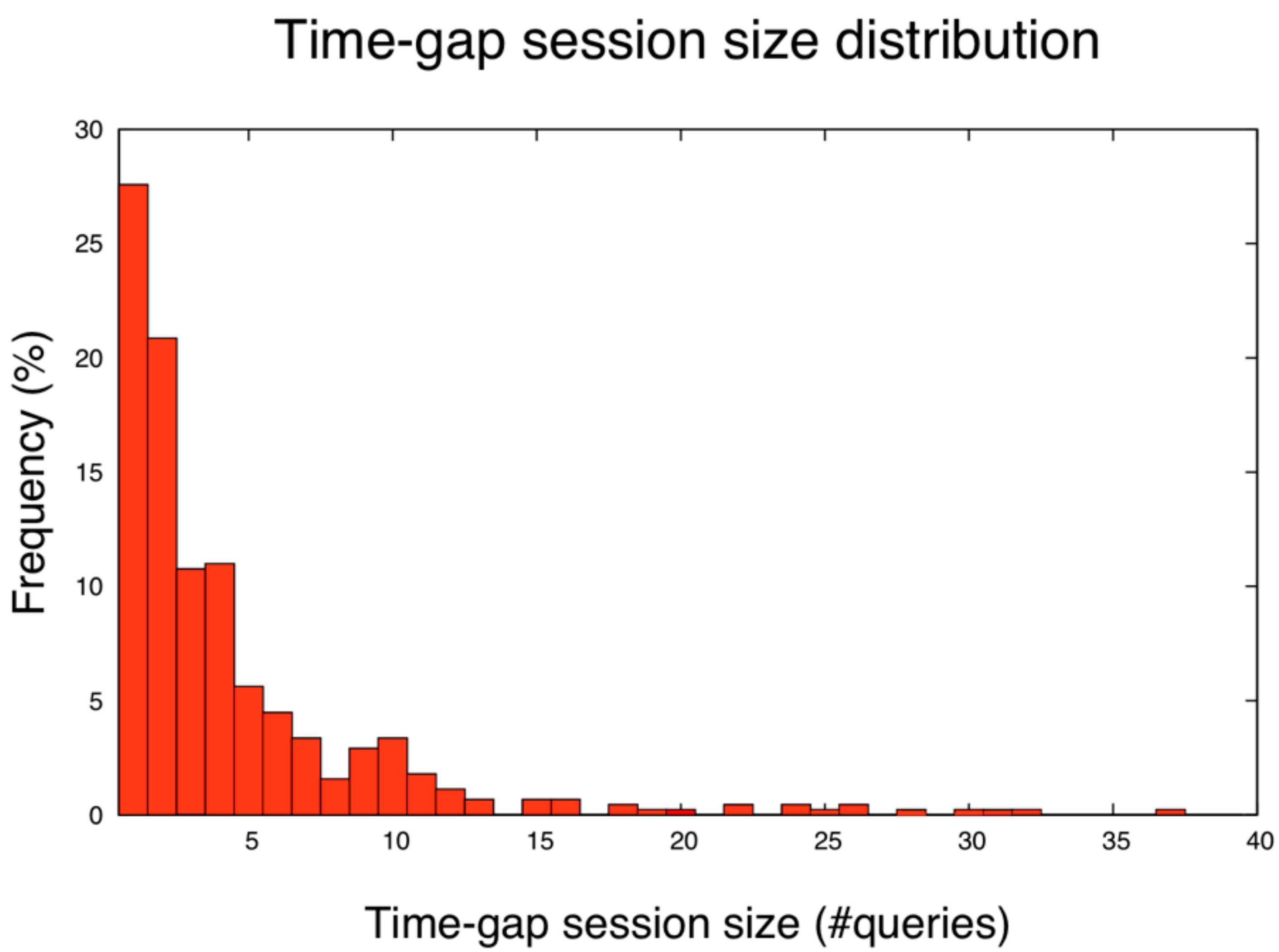
Ground-truth: construction

- Long-term sessions of sample data set are first split using the time threshold devised before (i.e., 26 minutes)
    - obtaining several time-gap sessions
- Human annotators group queries that they claim to be task-related inside each time-gap session
- Represents the "optimal" task-based partitioning Θ manually built from actual WSE query log data
- Useful both for statistical purposes and evaluation of automatic task-based session discovery methods

Ground-truth: statistics

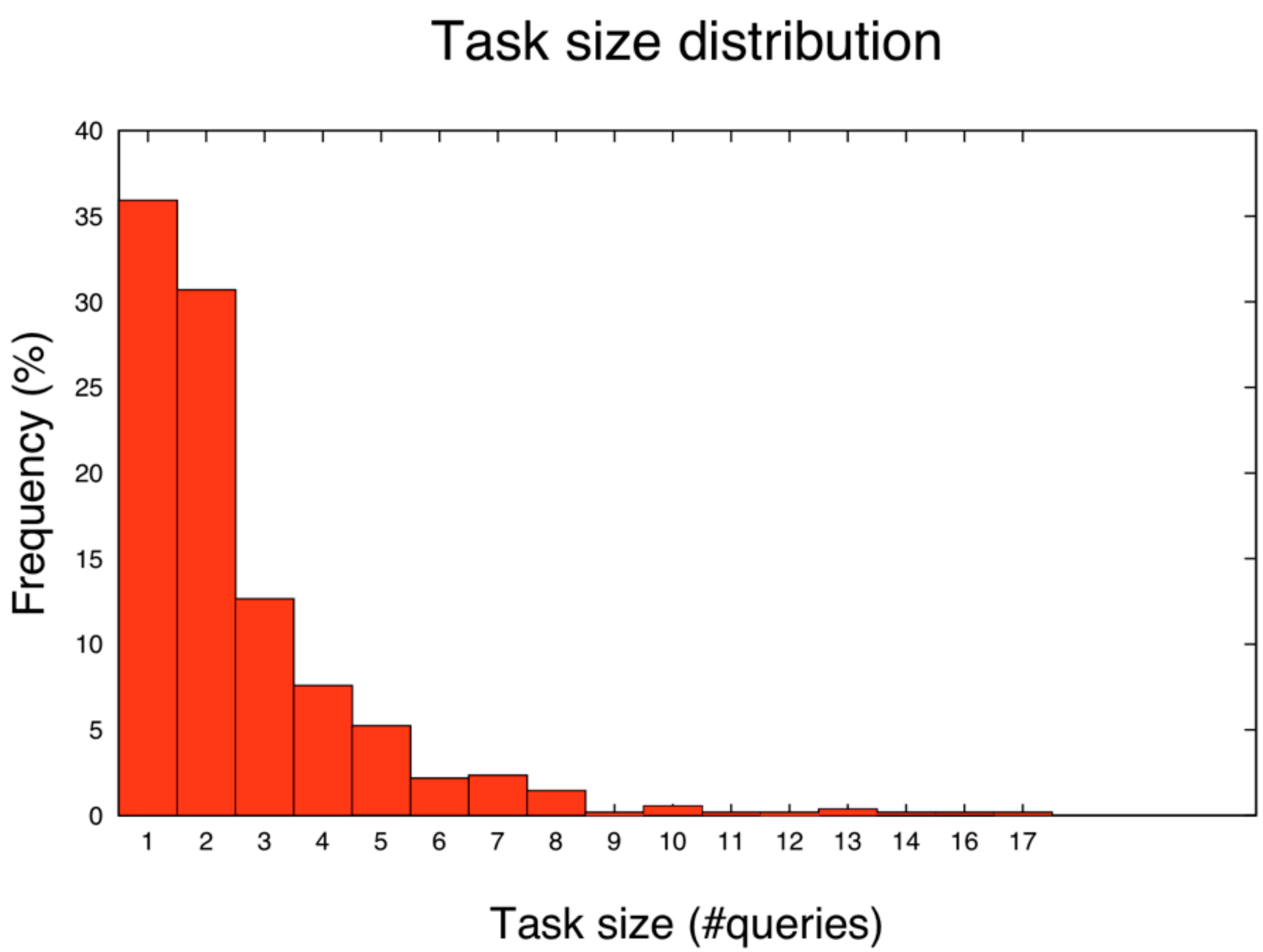
- ✓ 2,004 queries
- ✓ 446 time-gap sessions
- ✓ 1,424 annotated queries
- ✓ 307 annotated time-gap sessions
- ✓ 554 detected task-based sessions

Ground-truth: statistics



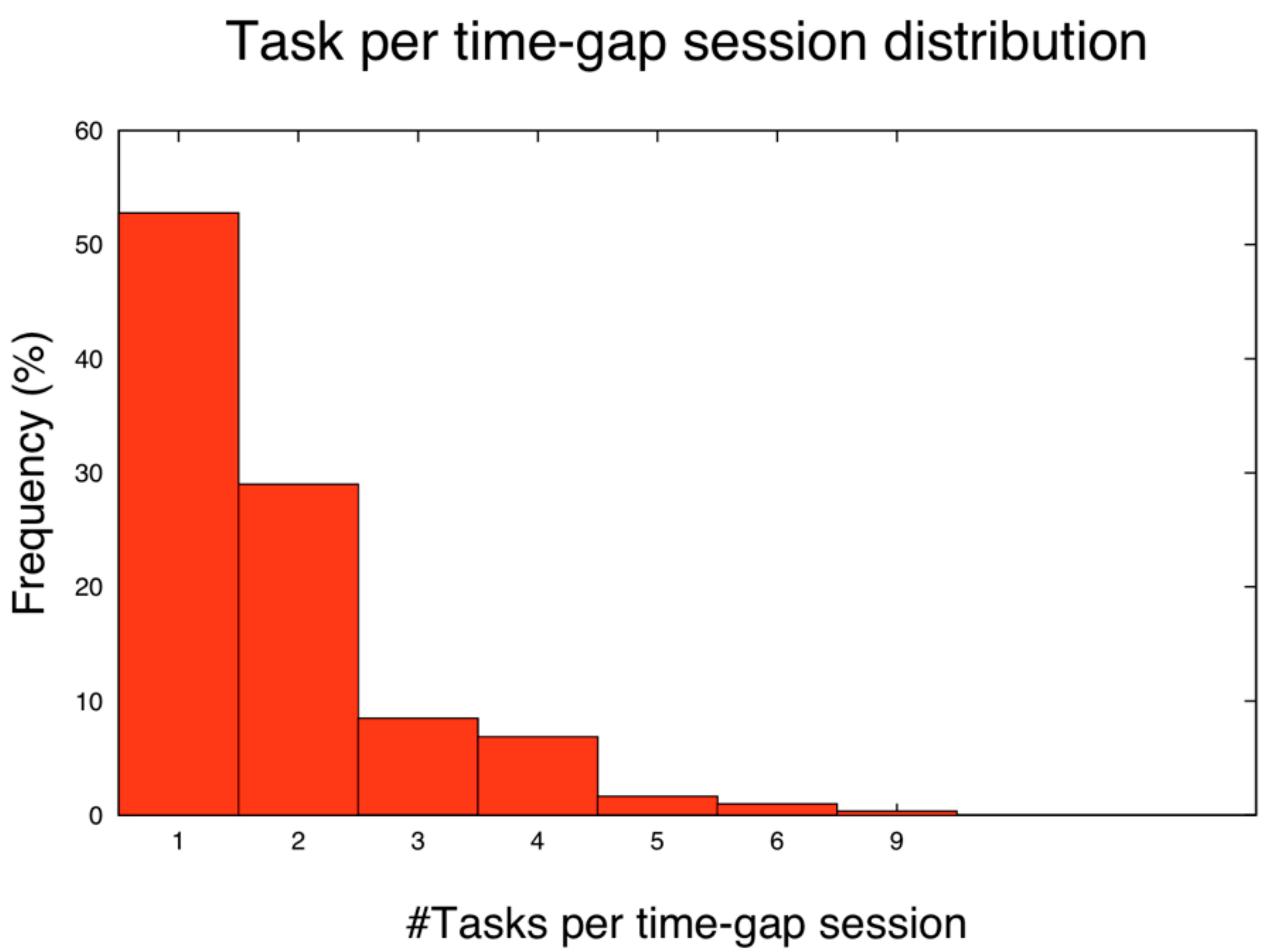
- ✓ 4.49 avg. queries per time-gap session
- ✓ more than 70% time-gap session contains at most 5 queries

Ground-truth: statistics



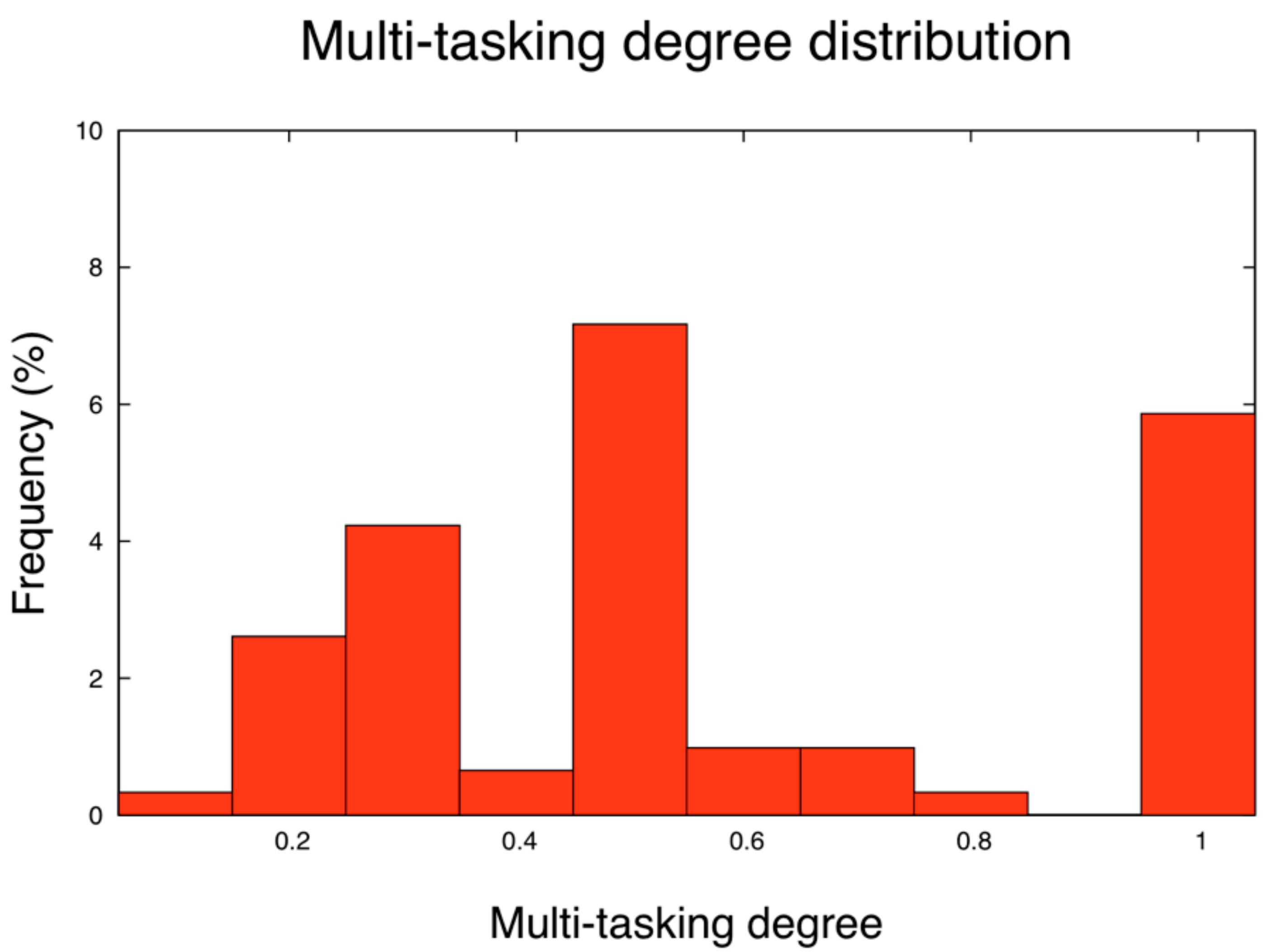
- ✓ 2.57 avg. queries per task
- ✓ ~75% tasks contains at most 3 queries

Ground-truth: statistics



- ✓ 1.80 avg. task per time-gap session
- ✓ ~47% time-gap session contains more than one task (multi-tasking)
- ✓ 1,046 over 1,424 queries (i.e., ~74%) included in multi-tasking sessions

Ground-truth: statistics



- ✓ overlapping degree of multi-tasking sessions
- ✓ jump occurs whenever two queries of the same task are not originally adjacent
- ✓ ratio of task in a time-gap session that contains at least one jump

TSDP: approaches

1) TimeSplitting-t

Description:

The idea is that if two consecutive queries are far away enough then they are also likely to be unrelated.

Two consecutive queries (q_i, q_{i+1}) are in the same task-based session if and only if their time submission gap is lower than a certain threshold t.

wsdm 2011 Hong Kong

TSDP: approaches

1) TimeSplitting-t

Description:

The idea is that if two consecutive queries are far away enough then they are also likely to be unrelated.

Two consecutive queries (q_i, q_{i+1}) are in the same task-based session if and only if their time submission gap is lower than a certain threshold t.

PROs:

- ✓ ease of implementation
- ✓ $O(n)$ time complexity (linear in the number n of queries)

wsdm 2011 Hong Kong

TSDP: approaches

1) TimeSplitting-t

Description:

The idea is that if two consecutive queries are far away enough then they are also likely to be unrelated.

Two consecutive queries (q_i, q_{i+1}) are in the same task-based session if and only if their time submission gap is lower than a certain threshold t.

PROs:

- ✓ ease of implementation
- ✓ $O(n)$ time complexity (linear in the number n of queries)

CONs:

- ✓ unable to deal with multi-tasking
- ✓ unawareness of other discriminating query features (e.g., lexical content)

TSDP: approaches

1) TimeSplitting-t

Description:
The idea is that if two consecutive queries are far away enough then they are also likely to be unrelated.
Two consecutive queries (q_i, q_{i+1}) are in the same task-based session if and only if their time submission gap is lower than a certain threshold t.

PROs:
- ✓ ease of implementation
- ✓ $O(n)$ time complexity (linear in the number n of queries)

CONs:
- ✓ unable to deal with multi-tasking
- ✓ unawareness of other discriminating query features (e.g., lexical content)

Methods: TS-5, TS-15, TS-26, etc.

wsdm 2011 Hong Kong

TSDP: approaches

1) TimeSplitting-t

Description:
The idea is that if two consecutive queries are far away enough then they are also likely to be unrelated.
Two consecutive queries (q_i, q_{i+1}) are in the same task-based session if and only if their time submission gap is lower than a certain threshold t.

PROs:
- ✓ ease of implementation
- ✓ $O(n)$ time complexity (linear in the number n of queries)

CONs:
- ✓ unable to deal with multi-tasking
- ✓ unawareness of other discriminating query features (e.g., lexical content)

Methods: TS-5, TS-15, TS-26, etc.

2) QueryClustering-m

Description:
Queries are grouped using clustering algorithms, which exploit several query features. Clustering algorithms assembly such features using two different distance functions for computing query-pair similarity.
Two queries (q_i, q_j) are in the same task-based session if and only if they are in the same cluster.

TSDP: approaches

1) TimeSplitting-t

Description:
The idea is that if two consecutive queries are far away enough then they are also likely to be unrelated.
Two consecutive queries (q_i, q_{i+1}) are in the same task-based session if and only if their time submission gap is lower than a certain threshold t.

PROs:
- ✓ ease of implementation
- ✓ O(n) time complexity (linear in the number n of queries)

CONs:
- ✓ unable to deal with multi-tasking
- ✓ unawareness of other discriminating query features (e.g., lexical content)

Methods: TS-5, TS-15, TS-26, etc.

2) QueryClustering-m

Description:
Queries are grouped using clustering algorithms, which exploit several query features. Clustering algorithms assembly such features using two different distance functions for computing query-pair similarity.
Two queries (q_i, q_j) are in the same task-based session if and only if they are in the same cluster.

PROs:
- ✓ able to detect multi-tasking sessions
- ✓ able to deal with "noisy queries" (i.e., outliers)

TSDP: approaches

1) TimeSplitting-t

Description:
The idea is that if two consecutive queries are far away enough then they are also likely to be unrelated.
Two consecutive queries (q_i, q_{i+1}) are in the same task-based session if and only if their time submission gap is lower than a certain threshold t.

PROs:
- ✓ ease of implementation
- ✓ $O(n)$ time complexity (linear in the number n of queries)

CONs:
- ✓ unable to deal with multi-tasking
- ✓ unawareness of other discriminating query features (e.g., lexical content)

Methods: TS-5, TS-15, TS-26, etc.

2) QueryClustering-m

Description:
Queries are grouped using clustering algorithms, which exploit several query features. Clustering algorithms assembly such features using two different distance functions for computing query-pair similarity.
Two queries (q_i, q_j) are in the same task-based session if and only if they are in the same cluster.

PROs:
- ✓ able to detect multi-tasking sessions
- ✓ able to deal with "noisy queries" (i.e., outliers)

CONs:
- ✓ $O(n^2)$ time complexity (almost quadratic in the number n of queries due to all-pairs-similarity computational step)

TSDP: approaches

1) TimeSplitting-t

Description:
The idea is that if two consecutive queries are far away enough then they are also likely to be unrelated.
Two consecutive queries (q_i, q_{i+1}) are in the same task-based session if and only if their time submission gap is lower than a certain threshold t.

PROs:
- ✓ ease of implementation
- ✓ $O(n)$ time complexity (linear in the number n of queries)

CONs:
- ✓ unable to deal with multi-tasking
- ✓ unawareness of other discriminating query features (e.g., lexical content)

Methods: TS-5, TS-15, TS-26, etc.

2) QueryClustering-m

Description:
Queries are grouped using clustering algorithms, which exploit several query features. Clustering algorithms assembly such features using two different distance functions for computing query-pair similarity.
Two queries (q_i, q_j) are in the same task-based session if and only if they are in the same cluster.

PROs:
- ✓ able to detect multi-tasking sessions
- ✓ able to deal with "noisy queries" (i.e., outliers)

CONs:
- ✓ $O(n^2)$ time complexity (almost quadratic in the number n of queries due to all-pairs-similarity computational step)

Methods: QC-Means, QC-Scan, QC-wcc, and QC-htc

Query Features

Content-based ($\mu_{content}$)

- ✓ two queries (q_i, q_j) sharing common terms are likely related
- ✓ $\mu_{jaccard}$: Jaccard index on query 3-grams

$$\mu_{jaccard}(q_1, q_2) = 1 - \frac{|T(q_1) \cap T(q_2)|}{|T(q_1) \cup T(q_2)|}$$

- ✓ $\mu_{levenstein}$: normalized Levenstein distance

$$\mu_{content}(q_1, q_2) = \frac{(\mu_{jaccard} + \mu_{levenstein})}{2}$$

Query Features

Content-based ($\mu_{content}$)

- ✓ two queries (q_i, q_j) sharing common terms are likely related
- ✓ $\mu_{jaccard}$: Jaccard index on query 3-grams

$$\mu_{jaccard}(q_1, q_2) = 1 - \frac{|T(q_1) \cap T(q_2)|}{|T(q_1) \cup T(q_2)|}$$

- ✓ $\mu_{levenstein}$: normalized Levenstein distance

$$\mu_{content}(q_1, q_2) = \frac{(\mu_{jaccard} + \mu_{levenstein})}{2}$$

Semantic-based ($\mu_{semantic}$)

- ✓ using Wikipedia and Wiktionary for "expanding" a query q
- ✓ "wikification" of q using vector-space model

$$\vec{C}(t) = (c_1, c_2, \ldots, c_W) \qquad \vec{C}(q) = \sum_{t \in q} \vec{C}(t)$$

- ✓ relatedness between (q_i, q_j) computed using cosine-similarity

$$rel(q_1, q_2) = \frac{\vec{C}(q_1) \cdot \vec{C}(q_2)}{|\vec{C}(q_1)||\vec{C}(q_1)|}$$

$$\mu_{wikification}(q_1, q_2) = 1 - rel(q_1, q_2)$$

$$\mu_{semantic}(q_1, q_2) = min(\mu_{wiktionary}, \mu_{wikipedia})$$

wsdm 2011 Hong Kong

Distance Functions: μ_1 vs. μ_2

✓ Convex combination μ_1

$$\mu_1 = \alpha \cdot \mu_{content} + (1 - \alpha) \cdot \mu_{semantic}$$

✓ Conditional formula μ_2

Idea: if two queries are close in term of lexical content, the semantic expansion could be unhelpful. Vice-versa, nothing can be said when queries do not share any content feature

$$\mu_2 = \begin{cases} \mu_{content} & \text{if } \mu_{content} < \mathbf{t} \\ \min(\mu_{content}, \mathbf{b} \cdot \mu_{semantic}) & \text{otherwise.} \end{cases}$$

✓ Both μ_1 and μ_2 relies on the estimation of some parameters, i.e., α, t, and b

✓ Use ground-truth for tuning parameters

QC-MEANS

- Centroid-based algorithm inspired by K-MEANS [11]

wsdm 2011 Hong Kong

QC-MEANS

- Centroid-based algorithm inspired by K-MEANS [11]
- The input parameter K, i.e., number of output clusters produced, is replaced with ρ

QC-MEANS

- Centroid-based algorithm inspired by K-MEANS [11]
- The input parameter K, i.e., number of output clusters produced, is replaced with ρ
- ρ defines the maximum radius of a centroid-based cluster

QC-MEANS

- Centroid-based algorithm inspired by K-MEANS [11]
- The input parameter K, i.e., number of output clusters produced, is replaced with ρ
- ρ defines the maximum radius of a centroid-based cluster
    - deals with the variance of sessions size

QC-MEANS

- Centroid-based algorithm inspired by K-MEANS [11]
- The input parameter K, i.e., number of output clusters produced, is replaced with ρ
- ρ defines the maximum radius of a centroid-based cluster
  - deals with the variance of sessions size
  - avoids to “apriori” specify the parameter K

QC-SCAN

- Density-based algorithm inspired by DB-SCAN [12]

QC-SCAN

- Density-based algorithm inspired by DB-SCAN [12]
- Produces clusters of several shapes (not only circles)

QC-SCAN

- Density-based algorithm inspired by DB-SCAN [12]
- Produces clusters of several shapes (not only circles)
- Deals with the presence of outliers in WSE log data (i.e., "noisy queries")

QC-SCAN

- Density-based algorithm inspired by DB-SCAN [12]
- Produces clusters of several shapes (not only circles)
- Deals with the presence of outliers in WSE log data (i.e., “noisy queries”)
- 2 input parameters needed as for classical DB-SCAN:

QC-SCAN

- Density-based algorithm inspired by DB-SCAN [12]
- Produces clusters of several shapes (not only circles)
- Deals with the presence of outliers in WSE log data (i.e., "noisy queries")
- 2 input parameters needed as for classical DB-SCAN:
  - minPts = minimum number of queries which a cluster has to be composed of

QC-SCAN

- Density-based algorithm inspired by DB-SCAN [12]
- Produces clusters of several shapes (not only circles)
- Deals with the presence of outliers in WSE log data (i.e., "noisy queries")
- 2 input parameters needed as for classical DB-SCAN:
  - minPts = minimum number of queries which a cluster has to be composed of
  - eps = neighborhood degree between queries in a cluster

QC-wcc

- Models each time-gap session φ as a weighted undirected graph $G_\varphi = (V, E, w)$

QC-wcc

- Models each time-gap session φ as a weighted undirected graph $G_\varphi = (V, E, w)$
  - set of nodes V are the queries in φ

QC-wcc

- Models each time-gap session φ as a weighted undirected graph $G_\varphi = (V, E, w)$
  - set of nodes V are the queries in φ
  - set of edges E are weighted by the similarity of the corresponding nodes

wsdm 2011 Hong Kong

QC-wcc

- Models each time-gap session φ as a weighted undirected graph $G_\varphi = (V, E, w)$
  - set of nodes V are the queries in φ
  - set of edges E are weighted by the similarity of the corresponding nodes
- Drop weak edges, i.e., with low similarity, assuming the corresponding queries are not related and obtaining G'_φ

QC-wcc

- Models each time-gap session φ as a weighted undirected graph $G_\varphi = (V, E, w)$
  - set of nodes V are the queries in φ
  - set of edges E are weighted by the similarity of the corresponding nodes
- Drop weak edges, i.e., with low similarity, assuming the corresponding queries are not related and obtaining G'_φ
- Clusters are built on the basis of strong edges by finding all the connected components of the pruned graph G'_φ

QC-wcc

- Models each time-gap session φ as a weighted undirected graph $G_\varphi = (V, E, w)$
  - set of nodes V are the queries in φ
  - set of edges E are weighted by the similarity of the corresponding nodes
- Drop weak edges, i.e., with low similarity, assuming the corresponding queries are not related and obtaining G'_φ
- Clusters are built on the basis of strong edges by finding all the connected components of the pruned graph G'_φ
- $O(m^2)$ time complexity where $m = |V|$

QC-HTC

- Variation of QC-WCC based on head-tail components

QC-HTC

- Variation of QC-WCC based on head-tail components
- Does not need to compute the full similarity graph

QC-HTC

- Variation of QC-WCC based on head-tail components
- Does not need to compute the full similarity graph
- Exploits the sequentiality of query submissions to reduce the number of similarity computations

QC-HTC

- Variation of QC-WCC based on head-tail components
- Does not need to compute the full similarity graph
- Exploits the sequentiality of query submissions to reduce the number of similarity computations
- Performs 2 steps:
  1. sequential clustering
  2. merging

QC-HTC: sequential clustering

- Partition each time-gap session into sequential clusters containing only queries issued in a row

QC-HTC: sequential clustering

- Partition each time-gap session into sequential clusters containing only queries issued in a row
- Each query in every sequential cluster has to be "similar enough" to the chronologically next one

QC-HTC: sequential clustering

- Partition each time-gap session into sequential clusters containing only queries issued in a row
- Each query in every sequential cluster has to be "similar enough" to the chronologically next one
- Need to compute only the similarity between one query and the next in the original data

QC-HTC: merging

- Merge together related sequential clusters due to multi-tasking

QC-HTC: merging

- Merge together related sequential clusters due to multi-tasking
- Hyp: a cluster is represented by its chronologically-first and last queries, i.e., head and tail, respectively

QC-HTC: merging

- Merge together related sequential clusters due to multi-tasking
- Hyp: a cluster is represented by its chronologically-first and last queries, i.e., head and tail, respectively
- Given two sequential clusters c_i, c_j and h_i, t_i, and h_j, t_j, their corresponding head and tail queries the similarity $s(c_i, c_j)$ is computed as follow:

QC-HTC: merging

- Merge together related sequential clusters due to multi-tasking
- Hyp: a cluster is represented by its chronologically-first and last queries, i.e., head and tail, respectively
- Given two sequential clusters c_i, c_j and h_i, t_i, and h_j, t_j, their corresponding head and tail queries the similarity $s(c_i, c_j)$ is computed as follow:

$$\boxed{s(c_i, c_j) = \min w(e(q_i, q_j)) \text{ s.t. } q_i \in \{h_i, t_i\} \text{ and } q_j \in \{h_j, t_j\}}$$

QC-HTC: merging

- Merge together related sequential clusters due to multi-tasking
- Hyp: a cluster is represented by its chronologically-first and last queries, i.e., head and tail, respectively
- Given two sequential clusters c_i, c_j and h_i, t_i, and h_j, t_j, their corresponding head and tail queries the similarity $s(c_i, c_j)$ is computed as follow:

$$\boxed{s(c_i, c_j) = \min w(e(q_i, q_j)) \text{ s.t. } q_i \in \{h_i, t_i\} \text{ and } q_j \in \{h_j, t_j\}}$$

  - c_i and c_j are merged as long as $s(c_i, c_j) > \eta$
  - h_i, t_i and h_j, t_j are updated consequently

QC-HTC: time complexity

- In the first step the algorithm computes the similarity only between one query and the next in the original data
  - O(m) where m is the size of the time-gap session

QC-HTC: time complexity

- In the first step the algorithm computes the similarity only between one query and the next in the original data
  - $O(m)$ where m is the size of the time-gap session
- In the second step the algorithm computes the pairwise similarity between each sequential cluster
  - $O(k^2)$ where k is the number of sequential clusters
  - if $k = \beta \cdot m$ with $0 \leq \beta \leq 1$ then time complexity is $O(\beta^2 \cdot m^2)$
  - e.g. $\beta = 1/2 \Rightarrow O(m^2/4) \Rightarrow$ 4 times better than QC-WCC

Agenda

- Introduction
- Contributions
- Experiments and Results
- Conclusions and Future Work

Setup

- Run and compare all the proposed approaches with:

Setup

- Run and compare all the proposed approaches with:
  - TS-26: time-splitting technique (baseline)

Setup

- Run and compare all the proposed approaches with:
  - TS-26: time-splitting technique (baseline)
  - QFG: session extraction method based on the query-flow graph model (state of the art)

Evaluation

- Measure the degree of correspondence between manually extracted tasks, i.e., ground-truth, and tasks output by algorithms

Evaluation

- Measure the degree of correspondence between manually extracted tasks, i.e., ground-truth, and tasks output by algorithms

a) F-measure

✓ evaluates the extent to which a task contains only and all the objects of a class

✓ combines p(i, j) and r(i, j) the precision and recall of task i w.r.t. class j

$$F(i,j) = \frac{2 \times p(i,j) \times r(i,j)}{p(i,j) + r(i,j)}$$

Evaluation

- Measure the degree of correspondence between manually extracted tasks, i.e., ground-truth, and tasks output by algorithms

a) F-measure

- ✓ evaluates the extent to which a task contains only and all the objects of a class
- ✓ combines p(i, j) and r(i, j) the precision and recall of task i w.r.t. class j

$$F(i,j) = \frac{2 \times p(i,j) \times r(i,j)}{p(i,j) + r(i,j)}$$

b) Rand

- ✓ pairs of objects instead of singleton
- ✓ f_{00}, f_{01}, f_{10}, f_{11}

$$R = \frac{f_{00} + f_{11}}{f_{00} + f_{01} + f_{10} + f_{11}}$$

Evaluation

- Measure the degree of correspondence between manually extracted tasks, i.e., ground-truth, and tasks output by algorithms

a) F-measure

✓ evaluates the extent to which a task contains only and all the objects of a class

✓ combines p(i, j) and r(i, j) the precision and recall of task i w.r.t. class j

$$F(i,j) = \frac{2 \times p(i,j) \times r(i,j)}{p(i,j) + r(i,j)}$$

b) Rand

✓ pairs of objects instead of singleton

✓ f_{00}, f_{01}, f_{10}, f_{11}

$$R = \frac{f_{00} + f_{11}}{f_{00} + f_{01} + f_{10} + f_{11}}$$

c) Jaccard

✓ pairs of objects instead of singleton

✓ f_{01}, f_{10}, f_{11}

$$J = \frac{f_{11}}{f_{01} + f_{10} + f_{11}}$$

Results: TS-t

Table 1: TS-5, TS-15, and TS-26.

	F-measure	Rand	Jaccard
TS-5	0.28	**0.75**	0.03
TS-15	0.28	0.71	0.08
TS-26	**0.65**	0.34	**0.34**

- 3 time thresholds used: 5, 15, and 26 minutes

Results: TS-t

Table 1: TS-5, TS-15, **and** TS-26.

	F-measure	Rand	Jaccard
TS-5	0.28	**0.75**	0.03
TS-15	0.28	0.71	0.08
TS-26	**0.65**	0.34	**0.34**

- 3 time thresholds used: 5, 15, and 26 minutes
- Note: TS-26 was used for splitting sample data set
  - task-based sessions concur with time-gap sessions

Results: QFG

Table 2: QFG: varying the threshold η.

	η	F-measure	Rand	Jaccard
QFG	0.1	0.68	0.47	0.36
	0.2	0.68	0.49	0.36
	0.3	0.69	0.51	0.37
	0.4	0.70	0.55	0.38
	0.5	0.71	0.59	0.38
	0.6	0.74	0.65	0.39
	0.7	**0.77**	**0.71**	**0.40**
	0.8	0.77	0.71	0.40
	0.9	0.77	0.71	0.40

✓ trained on a segment of our sample data set

✓ best results using $\eta = 0.7$

✓ vs. baseline:

- +16% F-measure
- +52% Rand
- +15% Jaccard

wsdm 2011 Hong Kong

Results: QC-MEANS

Table 3: QC-MEANS: μ_1 **vs.** μ_2.

QC-MEANS μ_1				
		F-measure	Rand	Jaccard
α	$(1-\alpha)$			
1	0	0.71	0.73	0.26
0.5	0.5	0.68	0.70	0.14
0	1	0.68	0.70	0.13

QC-MEANS μ_2				
		F-measure	Rand	Jaccard
t	b			
0.5	4	**0.72**	**0.74**	**0.27**

- ✓ max radius $\rho = 0.4$
- ✓ best results using μ_2
- ✓ vs. baseline:
  - +10% F-measure
  - +54% Rand
  - -21% Jaccard
- ✓ vs. QFG:
  - -6% F-measure
  - +4% Rand
  - -33% Jaccard

Results: QC-SCAN

Table 4: QC-SCAN: μ_1 vs. μ_2.

QC-SCAN μ_1				
		F-measure	Rand	Jaccard
α	$(1-\alpha)$			
1	0	0.77	0.71	0.17
0.5	0.5	0.74	0.68	0.06
0	1	0.75	0.68	0.07

QC-SCAN μ_2				
		F-measure	Rand	Jaccard
t	b			
0.5	4	**0.77**	**0.71**	**0.19**

- ✓ minPts = 2 and eps = 0.4
- ✓ best results using μ_2
- ✓ vs. baseline:
  - +16% F-measure
  - +52% Rand
  - -44% Jaccard
- ✓ vs. QFG:
  - same F-measure
  - same Rand
  - -53% Jaccard

Results: QC-wcc

Table 5: QC-wcc: μ_1 **vs.** μ_2 **varying the threshold** η**.**

QC-wcc μ_1 ($\alpha = 0.5$)			
η	F-measure	Rand	Jaccard
0.1	0.78	0.71	0.42
0.2	**0.81**	**0.78**	**0.43**
0.3	0.79	0.77	0.37
0.4	0.75	0.73	0.27
0.5	0.72	0.71	0.20
0.6	0.75	0.70	0.14
0.7	0.74	0.69	0.11
0.8	0.74	0.68	0.07
0.9	0.72	0.67	0.04

QC-wcc μ_2 ($t = 0.5, b = 4$)			
η	F-measure	Rand	Jaccard
0.1	0.67	0.45	0.33
0.2	0.78	0.71	0.42
0.3	**0.81**	**0.78**	**0.44**
0.4	0.81	0.78	0.41
0.5	0.80	0.77	0.37
0.6	0.78	0.75	0.32
0.7	0.75	0.73	0.23
0.8	0.71	0.70	0.15
0.9	0.69	0.68	0.08

- ✓ best results using μ_2 and $\eta = 0.3$
- ✓ vs. baseline:
  - +20% F-measure
  - +56% Rand
  - +23% Jaccard
- ✓ vs. QFG:
  - +5% F-measure
  - +9% Rand
  - +10% Jaccard

Results: QC-HTC

Table 6: QC-HTC: μ_1 **vs.** μ_2 **varying the threshold** η.

QC-HTC μ_1 ($\alpha = 0.5$)			
η	F-measure	Rand	Jaccard
0.1	0.78	0.72	0.41
0.2	**0.80**	**0.78**	**0.41**
0.3	0.78	0.76	0.35
0.4	0.75	0.73	0.25
0.5	0.73	0.70	0.18
0.6	0.75	0.70	0.13
0.7	0.74	0.69	0.10
0.8	0.74	0.68	0.06
0.9	0.72	0.67	0.03

QC-HTC μ_2 ($t = 0.5, b = 4$)			
η	F-measure	Rand	Jaccard
0.1	0.68	0.56	0.32
0.2	0.78	0.73	0.41
0.3	**0.80**	**0.78**	**0.43**
0.4	0.80	0.77	0.38
0.5	0.78	0.76	0.34
0.6	0.77	0.74	0.30
0.7	0.74	0.72	0.21
0.8	0.71	0.70	0.14
0.9	0.68	0.67	0.07

- ✓ best results using μ_2 and $\eta = 0.3$
- ✓ vs. baseline:
  - +19% F-measure
  - +56% Rand
  - +21% Jaccard
- ✓ vs. QFG:
  - +4% F-measure
  - +9% Rand
  - +8% Jaccard

wsdm 2011 Hong Kong

Results: best

Table 7: Best results obtained with each method.

	F-measure	Rand	Jaccard
TS-26 (*baseline*)	0.65	0.34	0.34
QFG $_{best}$ (*state of the art*)	0.77	0.71	0.40
QC-Means $_{best}$	0.72	0.74	0.27
QC-Scan $_{best}$	0.77	0.71	0.19
QC-wcc $_{best}$	**0.81**	**0.78**	**0.44**
QC-htc $_{best}$	0.80	0.78	0.43

Results: Wiki impact

Table 8: The impact of Wikipedia: μ_1 vs. μ_2

QC-HTC $_{\mu_1}$ $(\alpha = 1)$		QC-HTC $_{\mu_2}$ $(0.5, 4)$	
Query ID	Query String	Query ID	Query String
		63	los cabos
		64	cancun
65	hurricane wilma	65	hurricane wilma
68	hurricane wilma	68	hurricane wilma

- Benefit of using Wikipedia instead of only lexical content when computing query distance function

Results: Wiki impact

Table 8: The impact of Wikipedia: μ_1 vs. μ_2

QC-HTC $_{\mu_1}$ $(\alpha = 1)$		QC-HTC $_{\mu_2}$ $(0.5, 4)$	
Query ID	Query String	Query ID	Query String
		63	los cabos
		64	cancun
65	hurricane wilma	65	hurricane wilma
68	hurricane wilma	68	hurricane wilma

- Benefit of using Wikipedia instead of only lexical content when computing query distance function
- Capturing other two queries that are lexically different but somehow "semantically" similar

Agenda

- Introduction
- Contributions
- Experiments and Results
- Conclusions and Future Work

Conclusions

- Introduced the Task-based Session Discovery Problem
  - from a WSE log of user activities extract several sets of queries which are all related to the same task

Conclusions

- Introduced the Task-based Session Discovery Problem
  - from a WSE log of user activities extract several sets of queries which are all related to the same task
- Compared clustering solutions exploiting two distance functions based on query content and semantic expansion (i.e., Wiktionary and Wikipedia)

Conclusions

- Introduced the Task-based Session Discovery Problem
  - from a WSE log of user activities extract several sets of queries which are all related to the same task
- Compared clustering solutions exploiting two distance functions based on query content and semantic expansion (i.e., Wiktionary and Wikipedia)
- Proposed novel graph-based heuristic QC-HTC, lighter than QC-WCC, outperforming other methods in terms of F-measure, Rand and Jaccard index

Future Work

- Why should we stop here?

Future Work

- Why should we stop here?
- Once discovered, smaller tasks might be part of a bigger and more complex task, i.e., process

Future Work

- Why should we stop here?
- Once discovered, smaller tasks might be part of a bigger and more complex task, i.e., process
- The task "fly to Hong Kong" might be a step of the process "traveling to Hong Kong", which in turn could involve several other tasks...

Envision

- Make Web Search Engine the "universal driver" for executing our daily activities on the Web

Envision

- Make Web Search Engine the "universal driver" for executing our daily activities on the Web
- Once user types in a query, WSE should "infer the process" user aims to perform (if any) ⇒ serendipity!

Envision

- Make Web Search Engine the "universal driver" for executing our daily activities on the Web
- Once user types in a query, WSE should "infer the process" user aims to perform (if any) ⇒ serendipity!
- Results should be no longer only list of plain links but also processes (or part of those)

Envision

- Make Web Search Engine the "universal driver" for executing our daily activities on the Web
- Once user types in a query, WSE should "infer the process" user aims to perform (if any) ⇒ serendipity!
- Results should be no longer only list of plain links but also processes (or part of those)
- Recommendation of queries and/or Web pages both intra- and inter-task, which the process is composed of

task vs. query recommendation

wsdm 2011 Hong Kong

References

[1] Silverstein, Marais, Henzinger, and Moricz. "*Analysis of a very large web search engine query log*". In SIGIR Forum, 1999

[2] He and Göker. "*Detecting session boundaries from web user logs*". In BCS-IRSG, 2000

[3] Radlinski and Joachims. "*Query chains: Learning to rank from implicit feedback*". In KDD '05

[4] Jansen and Spink. "*How are we searching the world wide web?: a comparison of nine search engine transaction logs*". In IPM, 2006

[5] Lau and Horvitz. "*Patterns of search: Analyzing and modeling web query refinement*". In UM '99

[6] He and Harper. "*Combining evidence for automatic web session identification*". In IPM, 2002

[7] Ozmutlu and Çavdur. "*Application of automatic topic identification on excite web search engine data logs*". In IPM, 2005

[8] Shen, Tan, and Zhai. "*Implicit user modeling for personalized search*". In CIKM '05

[9] Boldi, Bonchi, Castillo, Donato, Gionis, and Vigna. "*The query-flow graph: model and applications*". In CIKM '08

[10] Jones and Klinkner. "*Beyond the session timeout: automatic hierarchical segmentation of search topics in query logs*". In CIKM '08

[11] MacQueen. "*Some methods for classification and analysis of multivariate observations*". In BSMSP, 1967

[12] Ester, Kriegel, Sander, and Xu. "*A density-based algorithm for discovering clusters in large spatial databases with noise*". In KDD '96

Thank You!