Web Research: Open Problems

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To find and state key open algorithmic problems for future web technologies
Intro: Criteria and Questionnaire
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Problem 1: Large-Scale Filtering
Outline

1. Intro: Criteria and Questionnaire
2. Problem 1: Large-Scale Filtering
3. Problem 2: Large-Scale Matching
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1 Intro: Criteria and Questionnaire
2 Problem 1: Large-Scale Filtering
3 Problem 2: Large-Scale Matching
4 Problem 3: Tag Propagation
1. Intro: Criteria and Questionnaire
2. Problem 1: Large-Scale Filtering
3. Problem 2: Large-Scale Matching
4. Problem 3: Tag Propagation
5. Problem 4: Structure Discovery
INTRO

What are my personal criteria for choosing open problems?

What kind of questions should I answer about proposed problems?
Criteria

- Ultimate relation to technology challenge
- Familiarity with the corresponding applied field
- Interplay of several basic fields
- Freshness (hence, badly formalized)
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Your favorite criteria?
Questionnaire

- Technology challenge?
- Sample formalization?
- Basic fields involved?
- Research workflow?
- Your constructive feedback?
- References? Similar Ideas? [To be done]
My style is

1. At first, think independently (e.g. pose new problems)
2. Only after that look into literature
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Hence, the following problems might be already known and heavily studied!
PROBLEM 1

Large-Scale Filtering

What are the fastest algorithms for personal news aggregation?
Personal news aggregation:

Every user has a preference profile:
specified information sources, keywords, tags(topics),
popularity, references to the preferences of others

Every news item has its own description:
text, votes and recommendations, tags,
author reputation, comments
1.1. Challenge

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**Filtering problem:**
To find, say, ten most appropriate news items
for every user
1.2. Formalization

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Data structures for storing all profiles and all news?
1.3. Fields Involved

- Text classification, kNN algorithms
- Computational Geometry
- Data Structures
- Compression (sparse sets)
- Linear Algebra (singular decomposition trick)
- What else?
1.4. Workflow

1. Find fast algorithms for all-to-all filtering problem
2. Suggest data structures for storing profiles and news
3. Study filtering in dynamic settings: with profiles and descriptions quickly evolving in time
4. Describe spam prevention mechanisms for large filtering systems
1.5. Constructive Feedback

Do you know related results?

What is the most important theoretical question in this problem?

How to make my formalization better?
PROBLEM 2

Large-Scale Matching

What is the most effective algorithm for distributing sponsored links among all websites?
2.1. Challenge

Effective sponsored links (ads) distribution:
Every ad has a target description
Every website has an audience description
2.1. Challenge

**Effective sponsored links (ads) distribution:**
- Every ad has a target description
- Every website has an audience description

**Business objective:**
- Maximize ratio clicks/displays
2.2. Formalization

• Every website’s audience profile is a normalized red vector in $n$-dimensional space
2.2. Formalization

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- We use cosine measure for similarity.
- Computational problem: compute matching between ads and websites that satisfy some constraints and minimize the sum of distances (ad - website).
2.3. Fields Involved

- Computational Geometry
- Linear Algebra (singular decomposition trick)
- Data Structures
- Compression (sparse sets)
- Game theory
- Optimization
- What else?
2.4. Workflow

1. State ads distribution as an optimization problem
2. Find algorithms that can approximately solve this problem faster than \((\#\text{websites}) \times (\#\text{ads})\)
3. Introduce feedback to the model: after every click on any ad we receive some additional knowledge about the world and can use it for improvement of our matching
2.5. Constructive Feedback

Do you know related results?

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PROBLEM 3

Tag Propagation

How to extend partial categorization of websites to the whole web?
3.1. Challenge

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People use millions of keywords (tags)
There are billions of webpages
We have very sparse training collection of pairs (website, tag)
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Get a fast algorithm that can characterize any given website
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- People use millions of keywords (tags)
- There are billions of webpages
- We have **very sparse** training collection of pairs (website, tag)

**Goal:**
- Get a fast algorithm that can characterize any given website

**Applications:**
- Ads targeting
- Search results annotations
- Automatic web directories
3.2. Formalization

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T_k(i) = T_{k-1}(i) + \alpha \sum_{j \text{ links to } i} T_{k-1}(j)
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- Computational problem: use some preprocessing for initial tag distribution and then for every given website compute quickly ten tags with the highest rank
3.3. Fields Involved

- Data Structures
- Compression (sparse sets)
- Numerical Analysis (speed of convergence)
- What else?
3.4. Workflow

1. Define formulas for tag “propagation”
2. Construct a fast algorithm for computing, say, ten most relevant tags of arbitrary website
Do you know related results?

What is the most important theoretical question in this problem?

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PROBLEM 4

**Structure Discovery**

Consider keywords we use in everyday life. Can we suggest an algorithm that computes the most appropriate hierarchy of these keywords?
4.1. Challenge

We can collect many huge data sets: call graphs, shopping histories, search histories social networks, RSS subscription graph
HOW TO BENEFIT FROM THEM?
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Example: hierarchy discovery
We have some folksonomy
How to compute “optimal” tags hierarchy?
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Example: hierarchy discovery
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Applications:
Visualization and better navigation
Solving synonymy problem
4.2. Formalization

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- We want to compute the optimal **AND-OR** tree of tags.
- Optimal means minimal correctness violation.
- Correctness: sons of OR vertex should be disjoint, parent set contains children sets, etc...
4.3. Fields Involved

- Computational Biology (phylogeny algorithms)
- Approximate algorithms
- What else?
4.4. Workflow

1. Fix a format of tag description and define an optimality criteria for hierarchy of tags
2. Construct a fast algorithm for computing optimal hierarchy
3. Study interplay with algorithms for constructing phylogenency tree
4.5. Constructive Feedback

Do you know related results?

What is the most important theoretical question in this problem?

How to make my formalization better?
We discuss four problems. Which one do you like the most?

1. Large-Scale Filtering
2. Large-Scale Matching
3. Tag Propagation
4. Structure Discovery
Main points

My homepage: http://logic.pdmi.ras.ru/~yura/

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- Technology challenges: personal aggregation, effective ads, usage of huge data collection
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- Key algorithmic challenge: large-scale algorithms that are faster than naive (usually quadratic) approaches
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Thanks! Questions?