User Modeling for Interactive User-Adaptive Collection Structuring

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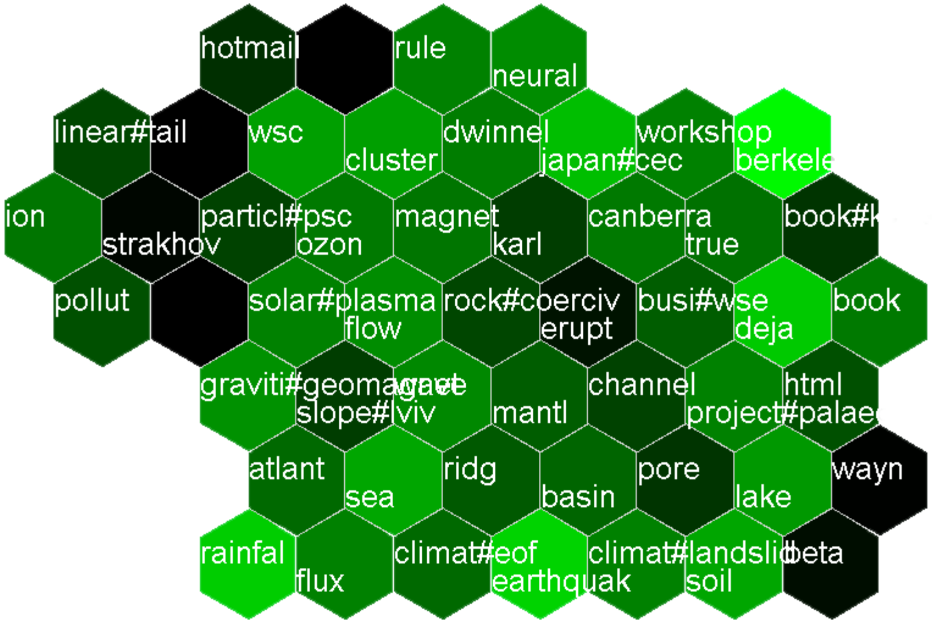
Contents

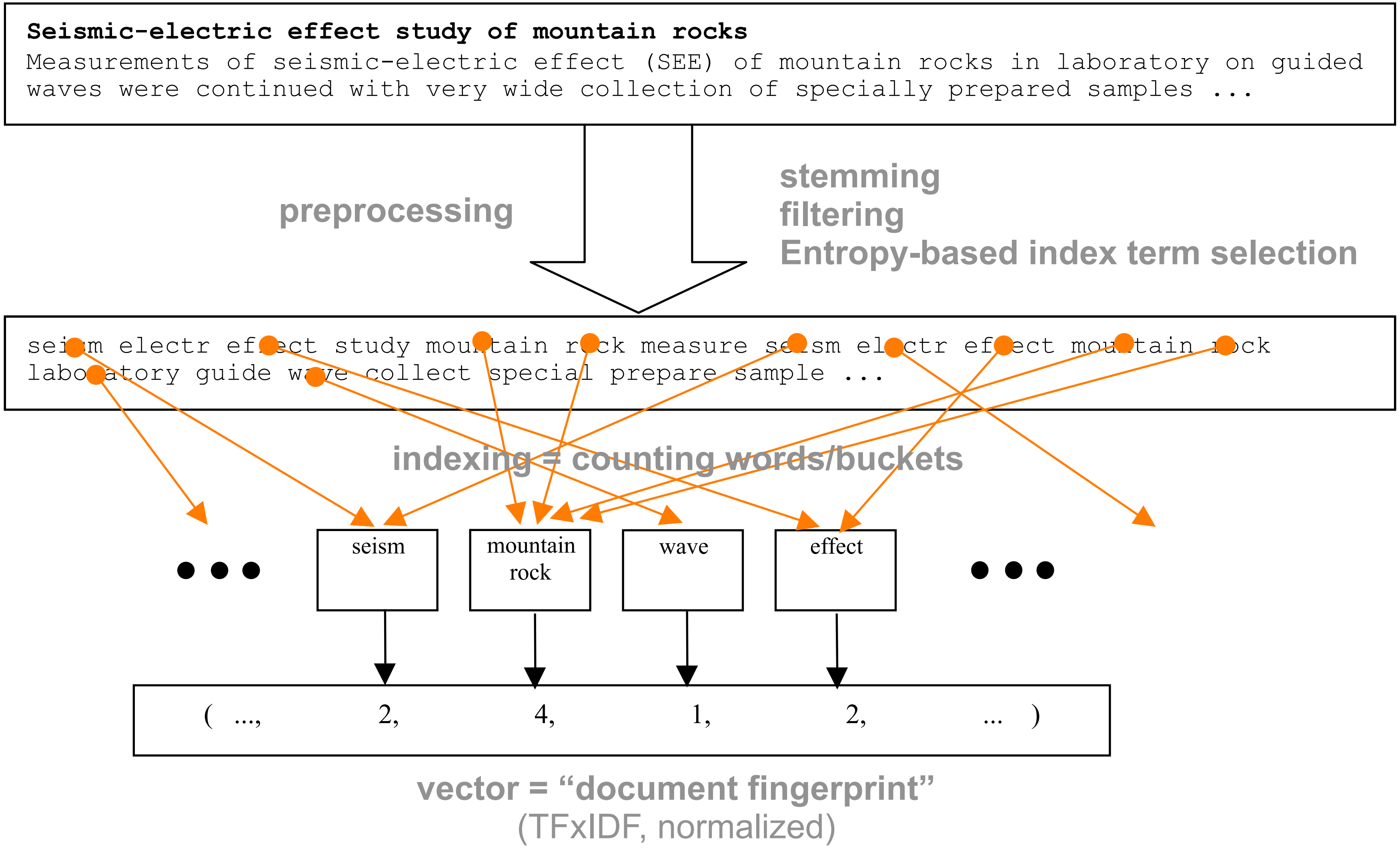
Motivation

- Scenario: exploration of conference proceedings
- Generate an overview map



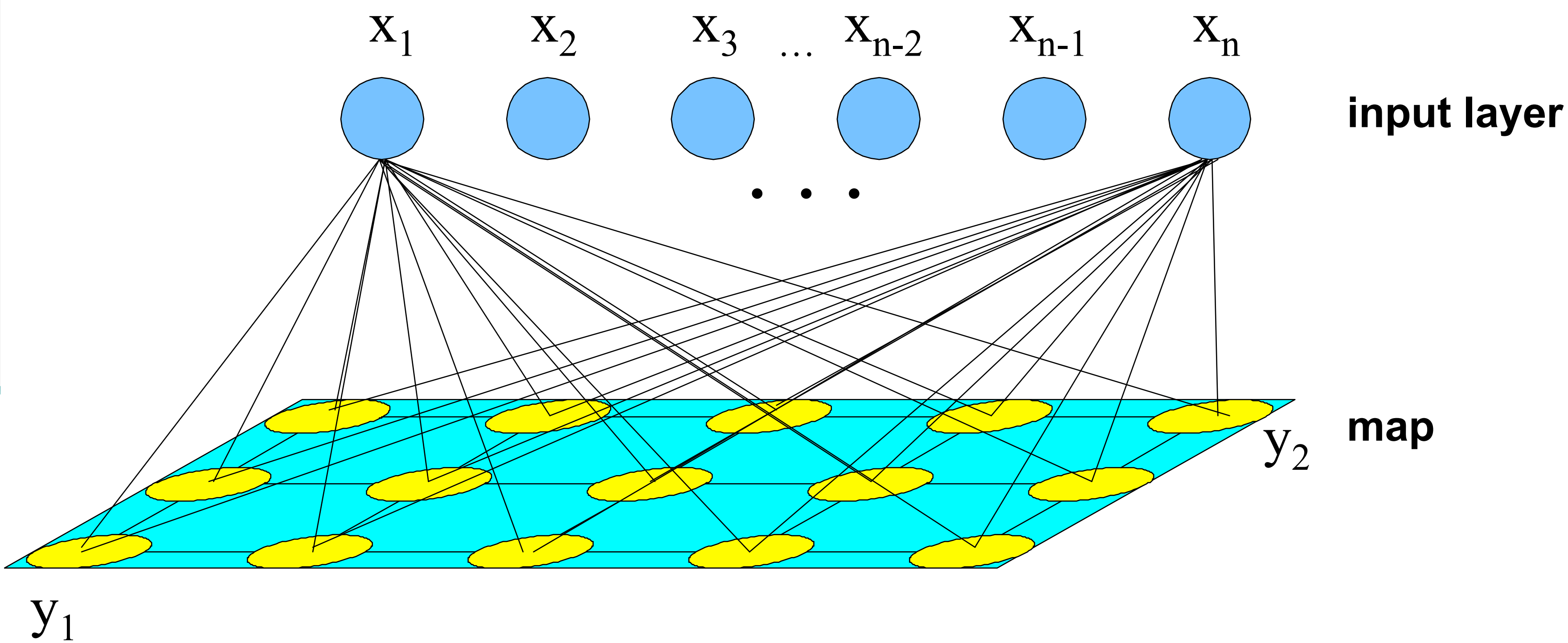
- Better: individual structuring
  - … learned from user-interaction with the map (reassigning objects by drag & drop actions)

Document Representation



Self-Organizing Map (SOM)

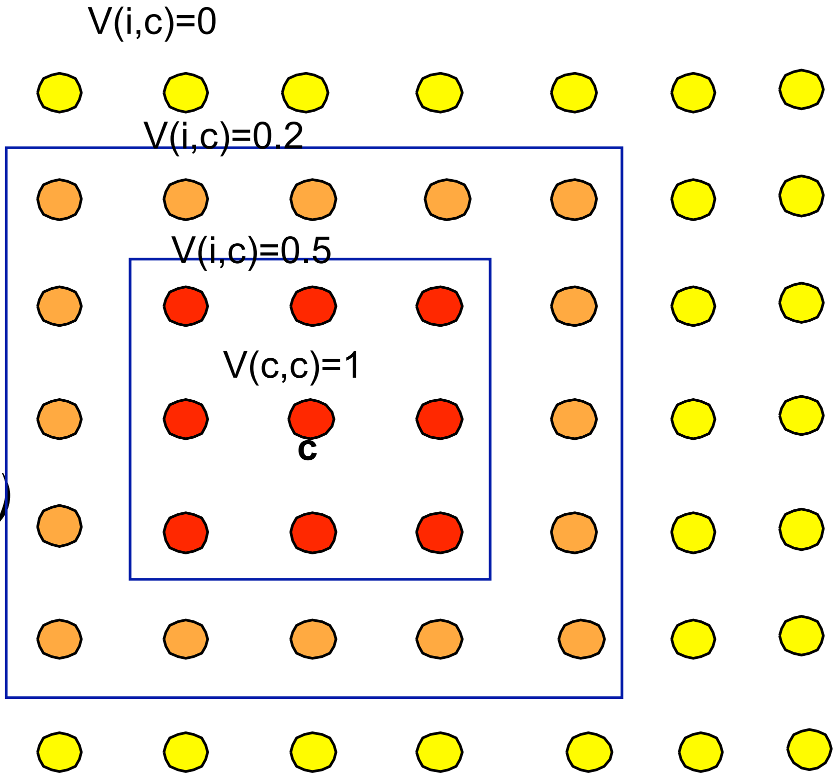
- Projection of high-dimensional data vectors to lower dimensional data space (usually 2D) under preservation of neighbourhood relations



SOM Learning

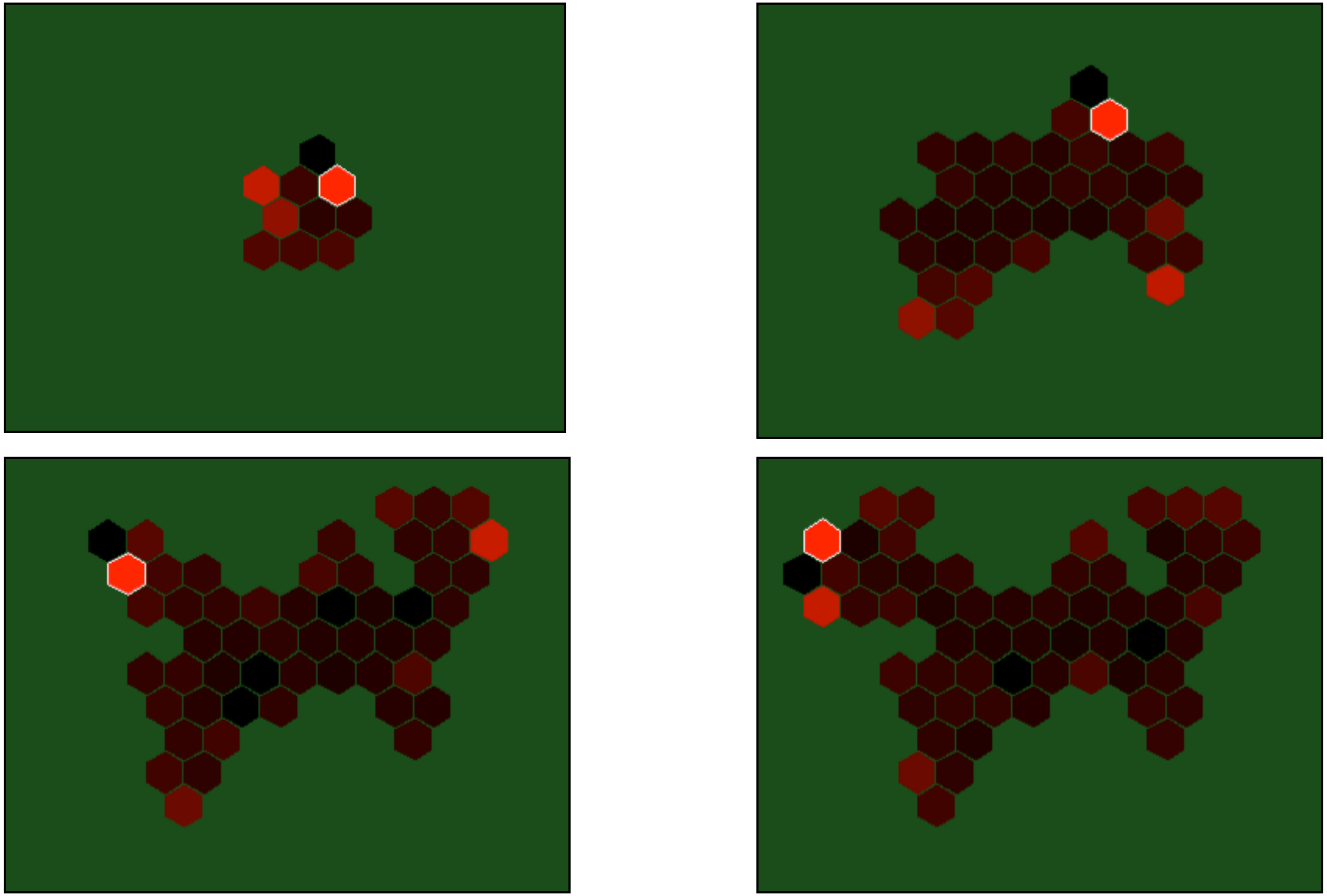
- competitive learning
- additionally neighborhood relations defined
- all vectors w_i in a neighbor-hood of the winner neuron c are adjusted:

$$\forall i : w_i = w_i + v(c,i) \cdot \delta \cdot (w_i - x(t))$$

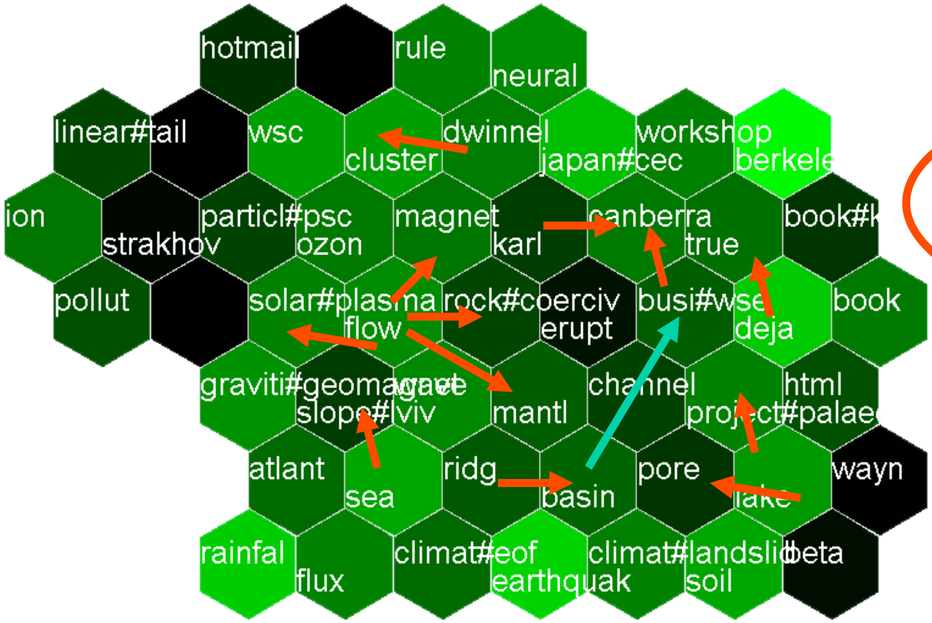


- $v(i,c)$: neighborhood function
- δ : learning rate

Growing SOM



Generic Adaptation Approach



- User manually moves a document
- Similarity measure is adapted
- Other documents are automatically assigned to other cells

Generic Adaptation Approach

- Standard similarity measure for documents x_j and x_k: inner product:

$$sim(x_j, x_k) = \sum_{l=1}^{m} x_{jl} \cdot x_{kl}$$

  (assuming normalized feature vectors)
- Introduction of feature weights w_l to personalize similarity:

$$sim(x_j, x_k) = \sum_{l=1}^{m} x_{jl} \cdot w_l \cdot x_{kl}$$

- Initial weights are 1.0
- Weight vector w is used as user model

Generic Adaptation Approach

- Document d assigned to cluster c_s:

$$sim(c_s, d) > sim(c_i, d) \quad \forall i \neq s$$

- Moving d to cluster c_t:

$$sim(c_t, d) > sim(c_i, d) \quad \forall i \neq t$$

- i.e. change weights w_l such that:

$$\sum_{l=1}^{m} x_{jl} \cdot w_l \cdot c_{tl} > \sum_{l=1}^{m} x_{jl} \cdot w_l \cdot c_{sl} \quad \forall s \neq t$$

How can these weights be computed?

Problems & Limitations

- So far: heuristics to compute new weights
- No limitations for values of the weights
  - Extreme weighting schemes
- No formal guaranty that all manually moved objects are assigned to their target cell
- No additional constraints (e.g. to increase interpretability)
- New approach: using Quadratic Optimization

Quadratic Optimization

- minimize change of weight vector w

$$\min_{w \in \Re^m} \sum_{l=1}^{m} \left(w_l - 1\right)^2$$

- weights should be non-negative

$$w_l \geq 0 \quad \forall 1 \leq l \leq m$$

- sum of the weights should be m (dictionary size)

$$\sum_{l=1}^{m} w_l = m$$

- keep all manually moved objects at their position

$$\sum_{l=1}^{m} x_{jl} \cdot w_l \cdot c_{tl} > \sum_{l=1}^{m} x_{jl} \cdot w_l \cdot c_{sl} \quad \forall s \neq t$$

Evaluation by User Simulation

modify objects by adding random features
learn map on modified objects
repeat
  select an object o to be moved
  select most similar cell c for o according to user
  move o to c
until o could not be moved

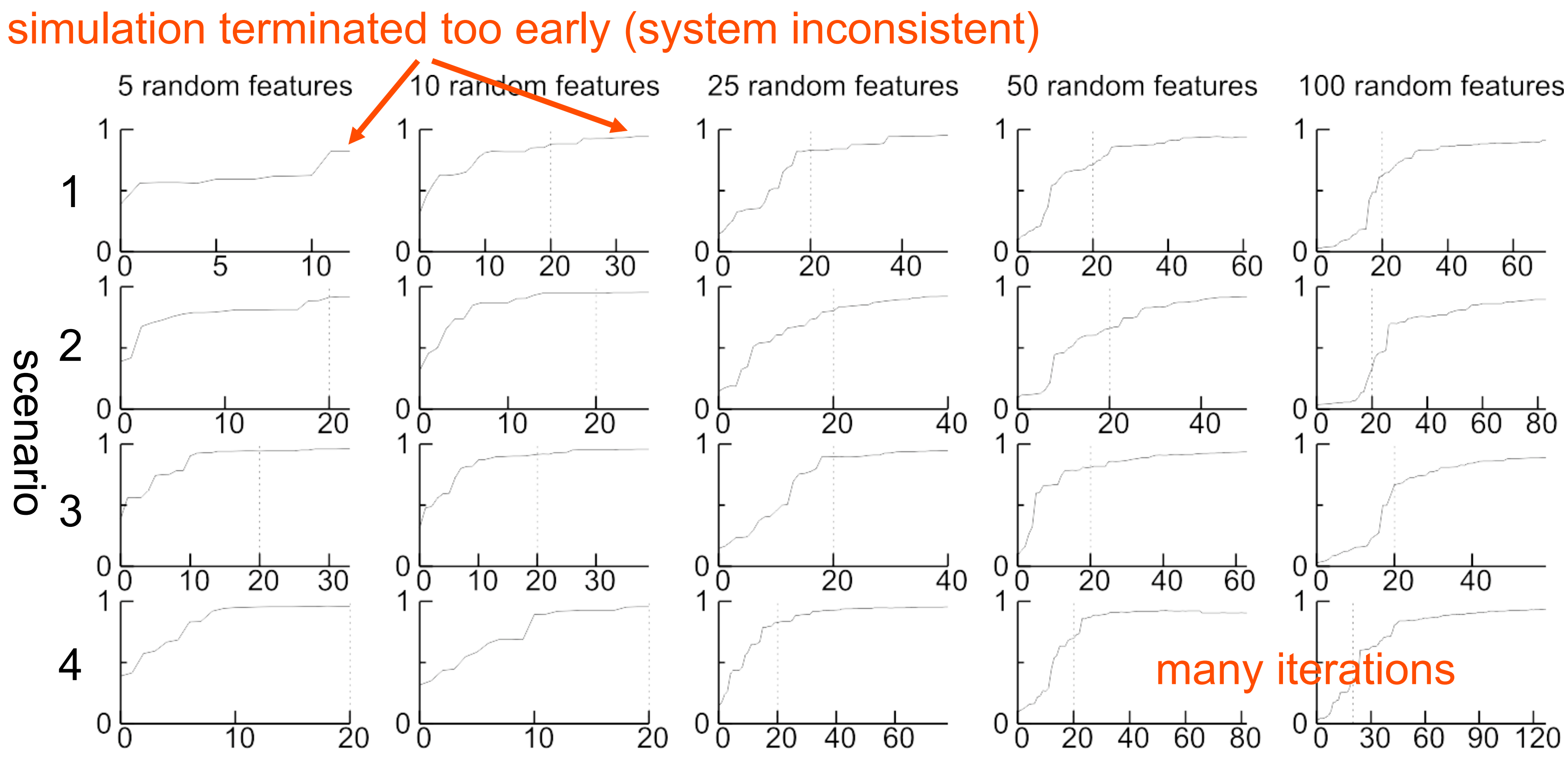
		cell selection	
		greedy	random
object selection	greedy	scenario 1	scenario 3
	random	scenario 2	scenario 4

Experiment 1 - Setup

- 1914 documents from a scientific news archive represented by 800 index terms
- no class information
- Greedy selection heuristic:
  - Cell with lowest average pairwise (ground truth) similarity
  - Object with lowest average pairwise (ground truth) similarity with all other objects in the cell
- Target cell selection:
  - Cell with highest (ground truth) similarity

Experiment 1 - Results

- Top-10 precision increased to 0.82-0.97 (mean 0.93)
- Moving ~1% of the collection was sufficient
- Random selection did not yield worse results

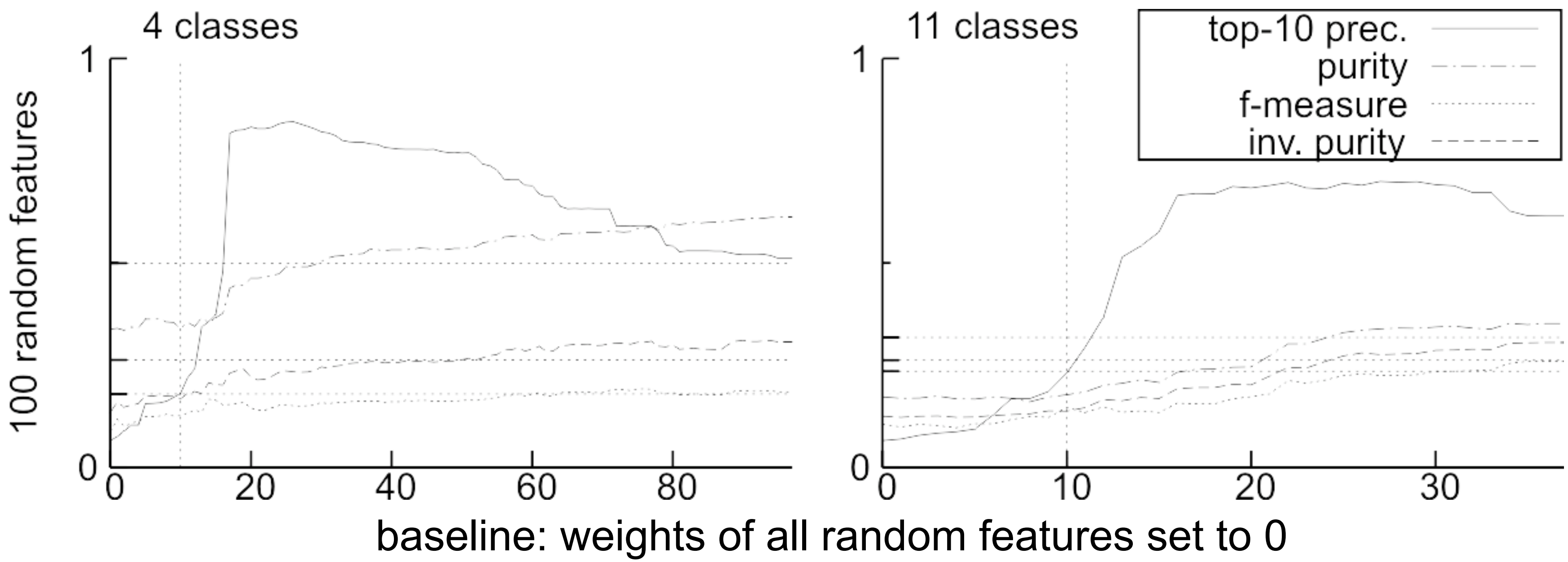


Experiment 2 - Setup

- 10% (947 documents) from the *Banksearch dataset* (pre-classified into 4/11 classes) represented by 800 index terms
- Greedy selection heuristic:
  - Cell with highest frequency difference of minority-majority class(es)
  - Object belonging to a minority class with lowest average pairwise (ground truth) sim. with all other objects in the cell
- Target cell selection:
  - Cell with highest (ground truth) similarity having the class of the object to be moved as majority class

Experiment 2 - Results

- *Purity, inverse purity and f-measure* came close to / exceeded the baseline (due to additional information)
- Top-10 precision decreased after a peak (not optimized by heuristic)
- Manually moving 1-2% of all objects was sufficient



Conclusions

- Proposed and evaluated method for user-adaptive collection structuring based on quadratic optimization
- User model: personalized similarity measure
- Only tested for text – other (non-sparse) data might lead to different performance

- Future Work:
  - Open problem: Sometimes no solution
  - Application to multimedia data
  - User study with “real” users

Information Retrieval Group

Thank you for your attention!

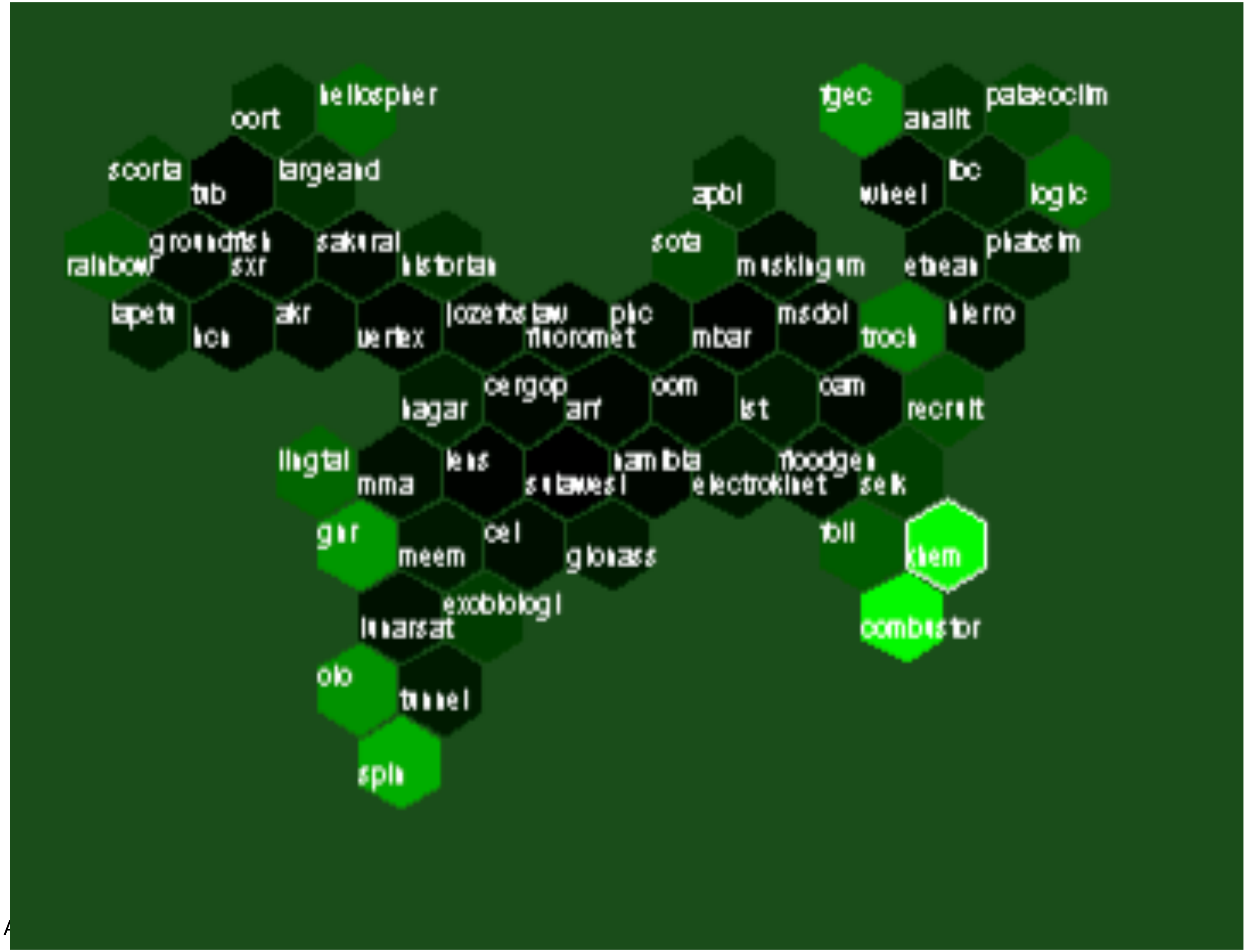
Experimental Setup

- User study:
  - expensive, time consuming, not objective
- Alternative way: simulate user actions
  - User (ground truth) similarity = initial similarity measure on unmodified objects

Experimental Setup

- User study:
  - expensive, time consuming, not objective
- Alternative way: simulate user actions
  - 2 similarity measures:
  - Select and move object according to a ground truth similarity
  - Measure impact

Growing SOM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heliospher
palaeoclim
logic
wheel
rainbow
groundfish
sakurai
historian
muskingum
vertex
fluoromet
mbar
recruit
hagar
meem
glonass
exobiologi
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tunnel
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