A Compression Framework for User Profiles

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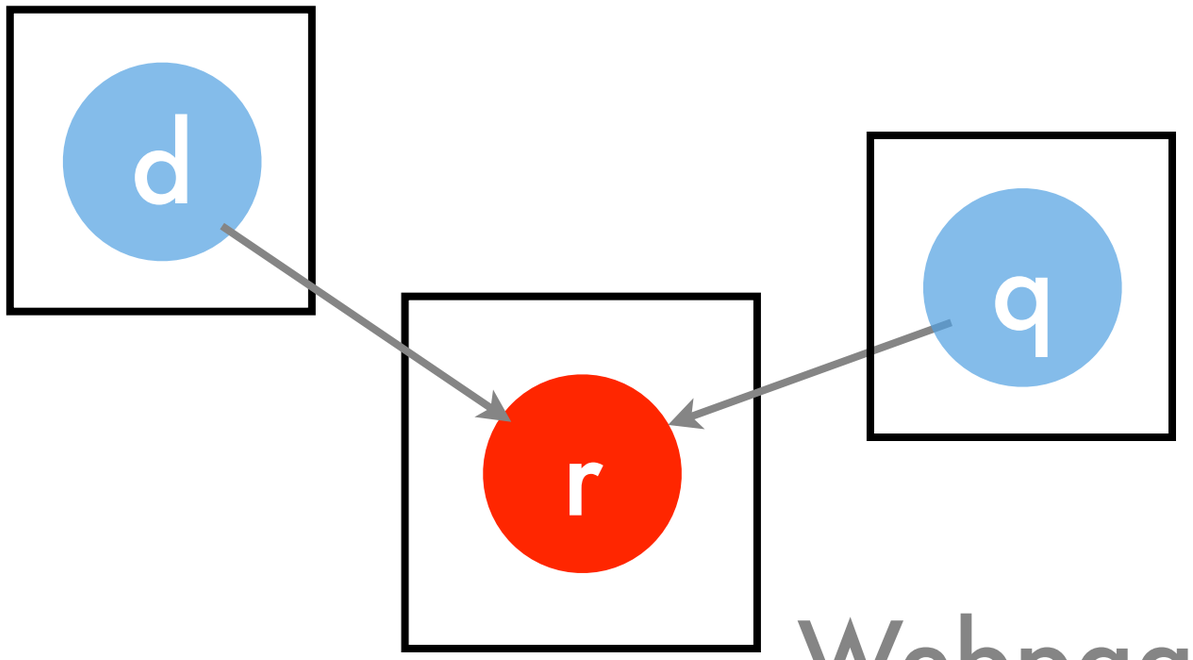
Outline

- User profiling
- Compression Framework
  - Term extraction using information geometry
  - Compression for clustering
  - Hierarchical formulation
- Experiments
- Discussion

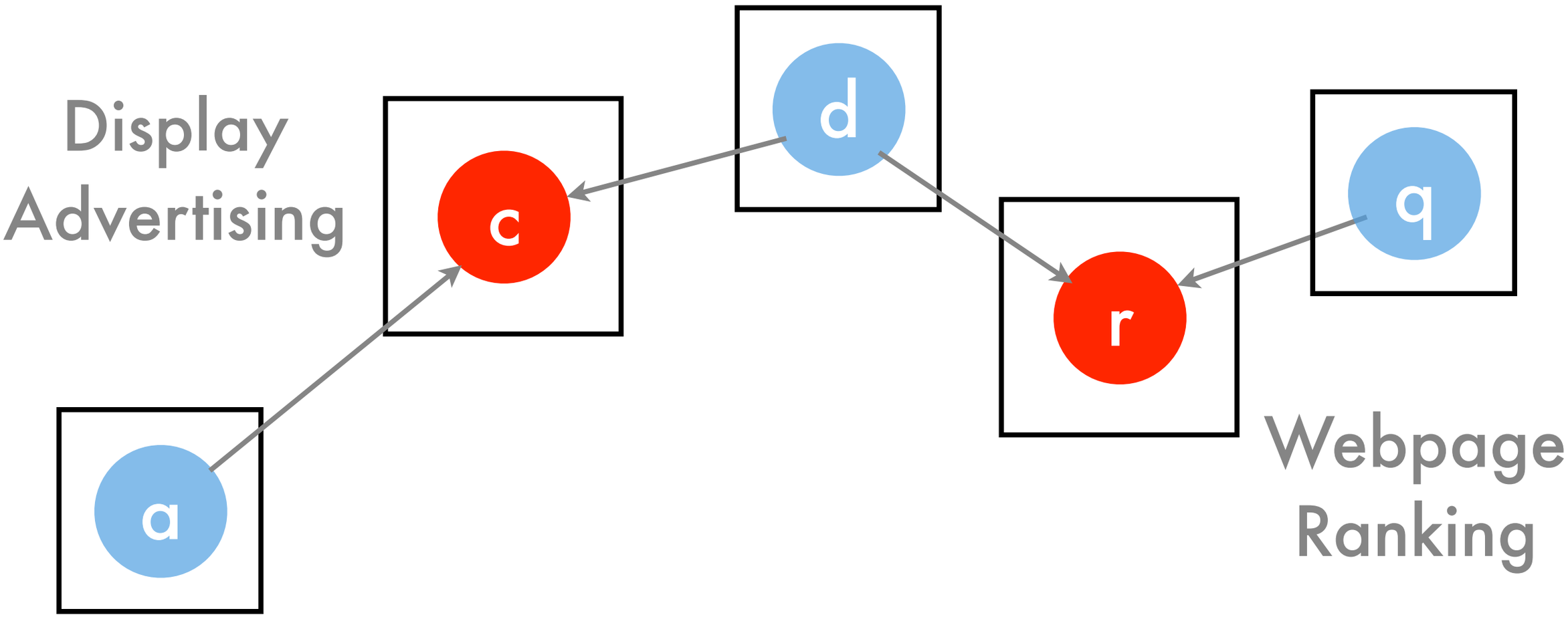
Why user profiling

Why user profiling



Webpage Ranking

Why user profiling



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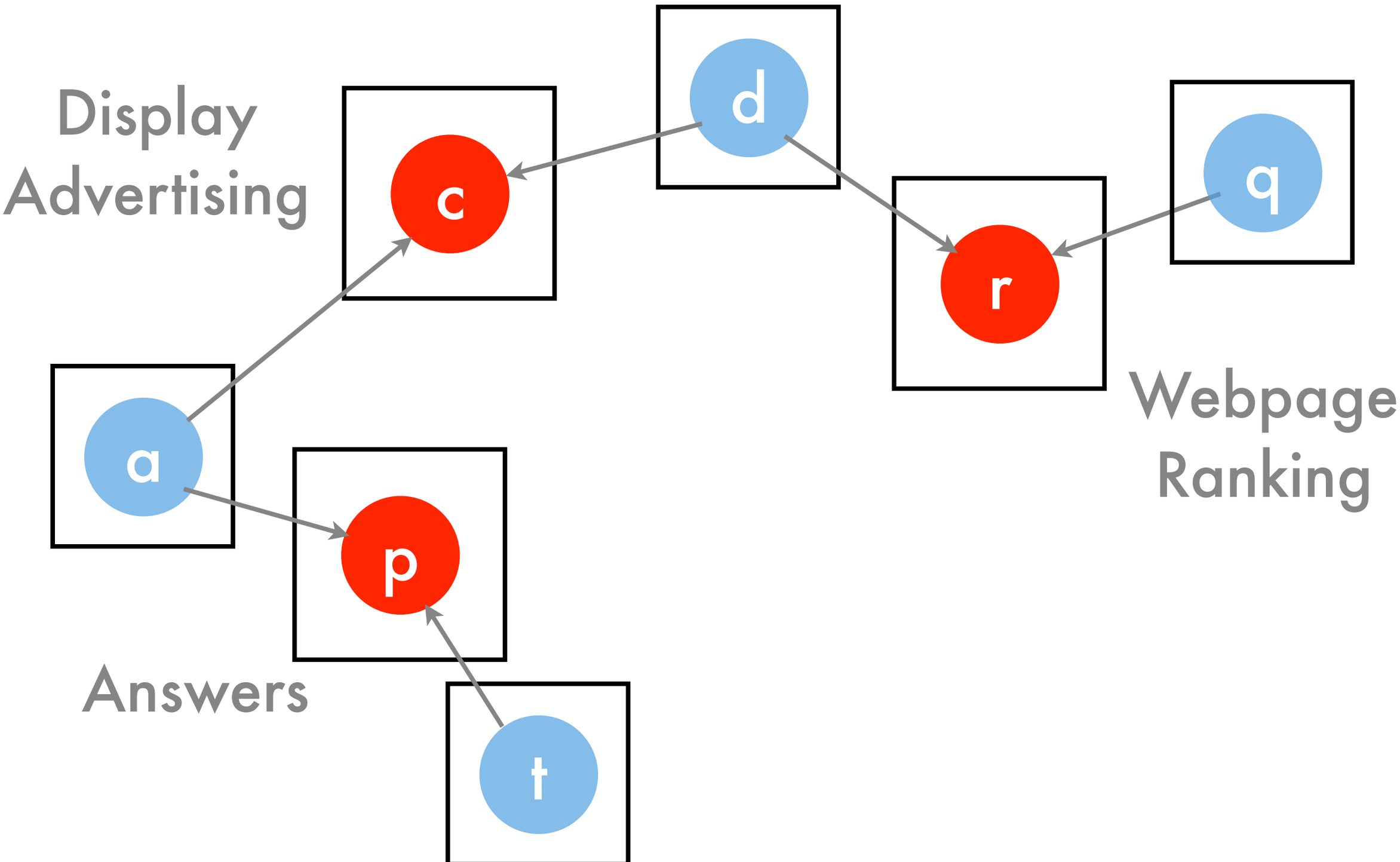

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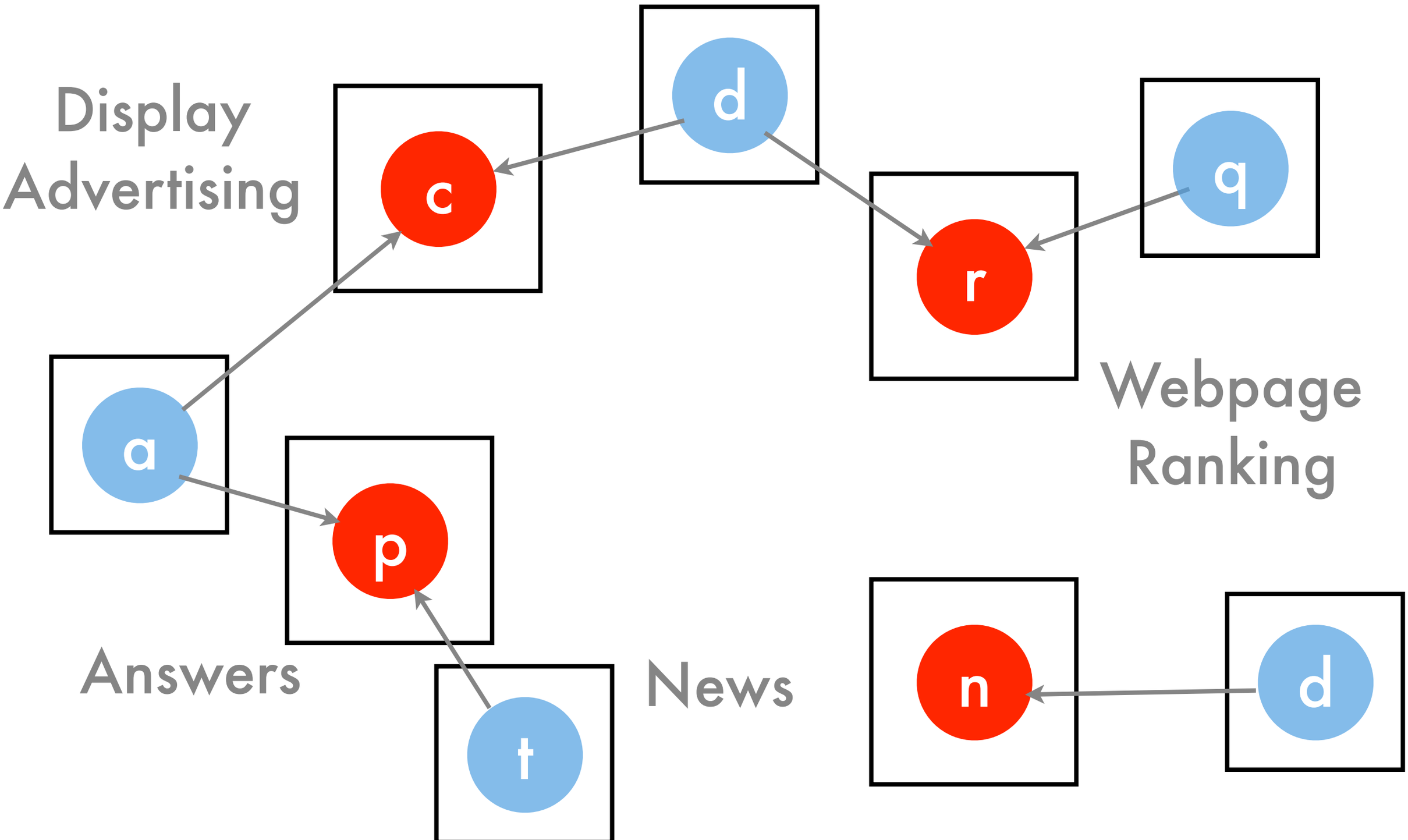

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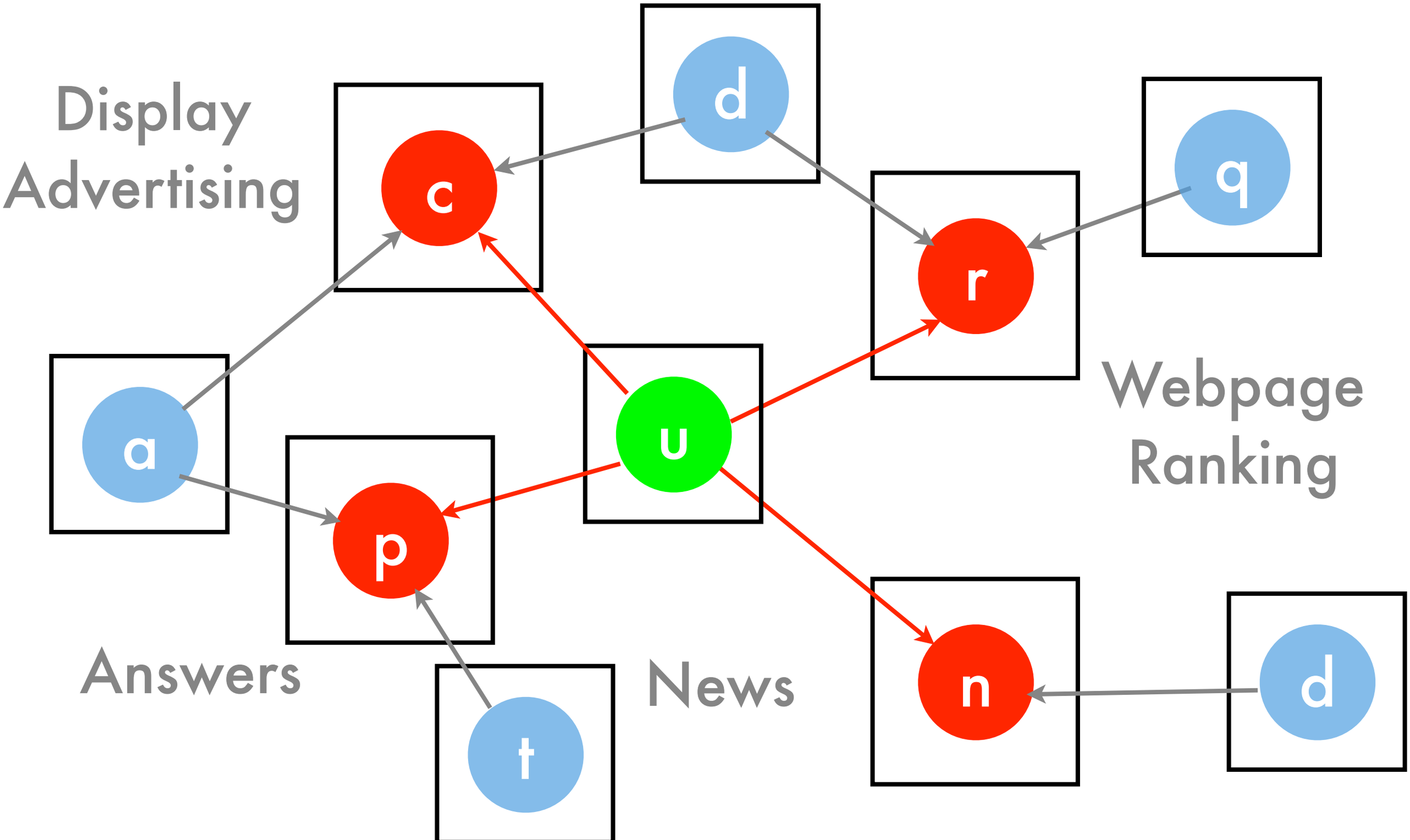
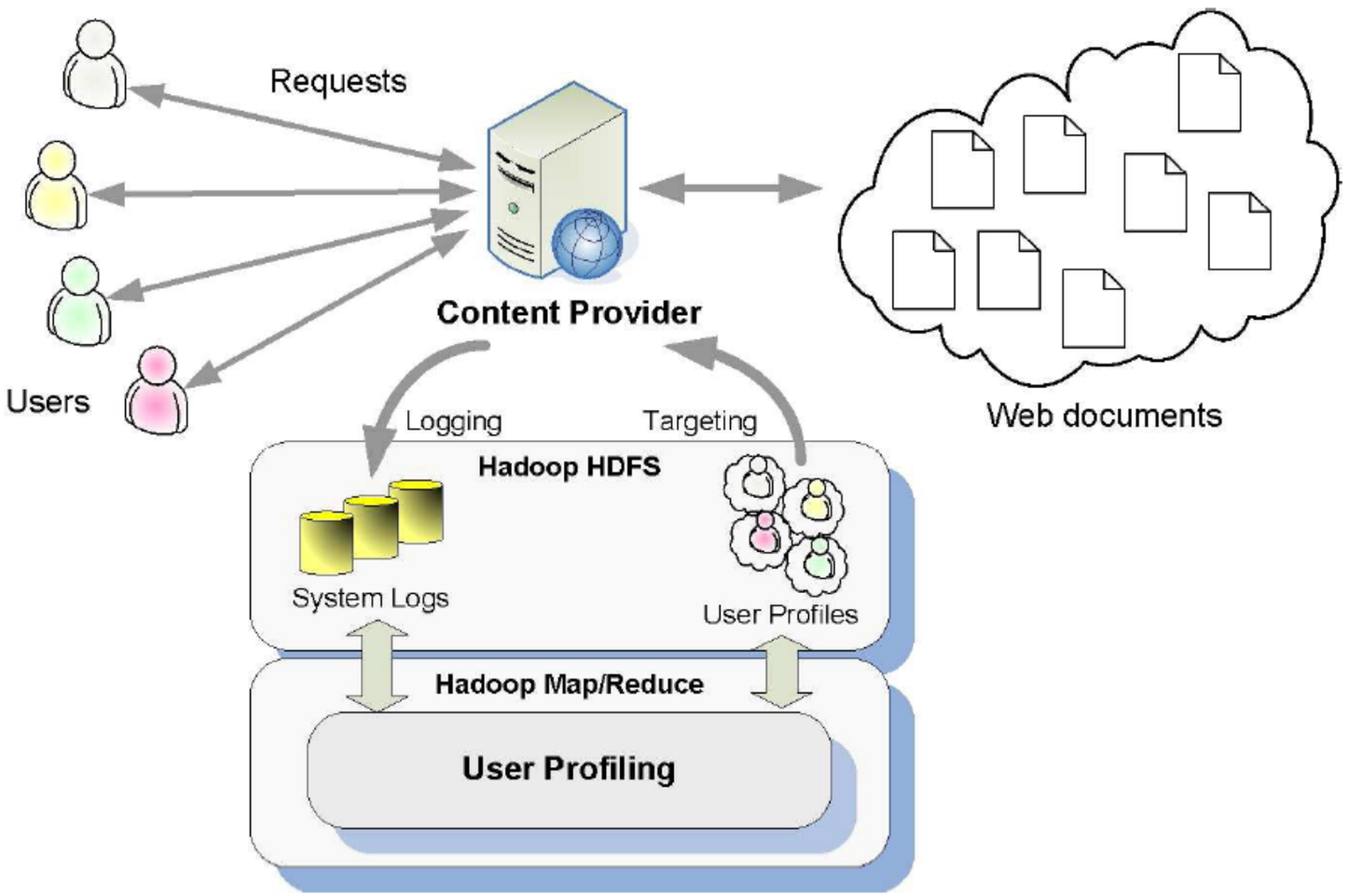


User profiling data



- Page views
- Queries
- Comments
- Clicks
- Timestamps

Previous work

- Bag of tokens (unordered set of activities)
  - "page views about banking"
  - "queries about cars"
- Represent user as distribution over tokens
  - Laplace smoothing for events
  - Background distribution is uniform over users
- Kullback Leibler divergence weighting

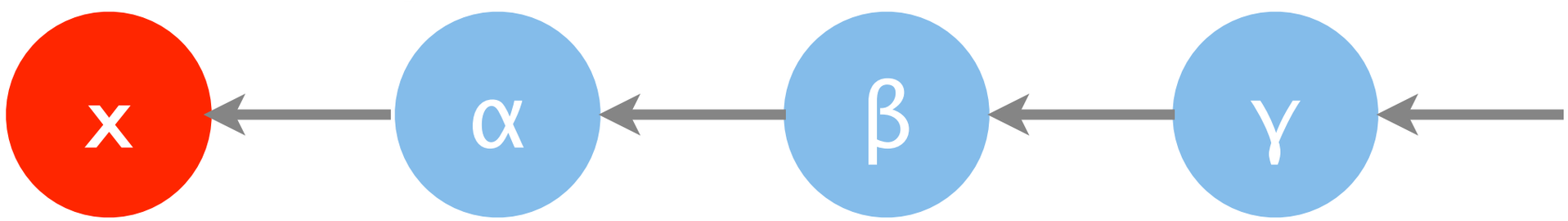
  (Konopnicki et al., 2010)
  - KL divergence between user distribution and background (#bits to encode u)
  - Term weight proportional to KL contribution

$$D(p\|q) = \sum_t p(t) \log \frac{p(t)}{q(t)}$$

term weight

Compression Framework

- Basic Idea
  - Encode objects by most meaningful subset of activities relative to background
  - Do this hierarchically
- Hierarchical probabilistic model



- Encoding

$$p(x) = \int p(x|\alpha)p(\alpha|\beta)p(\beta|\gamma)\ldots d\alpha d\beta d\gamma$$

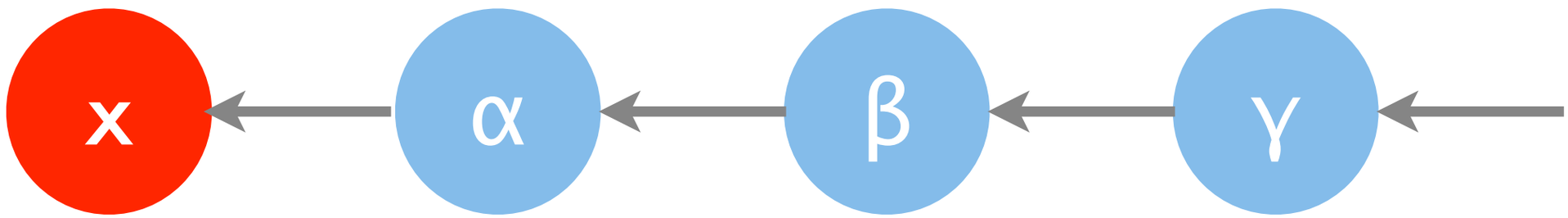
  - Stagewise compression for key terms

$$D(p(x|\gamma)\|p(x))$$ cluster relative to background

$$D(p(x|\beta)\|p(x|\gamma))$$ user relative to cluster

Compression Framework

General model



Compression Framework

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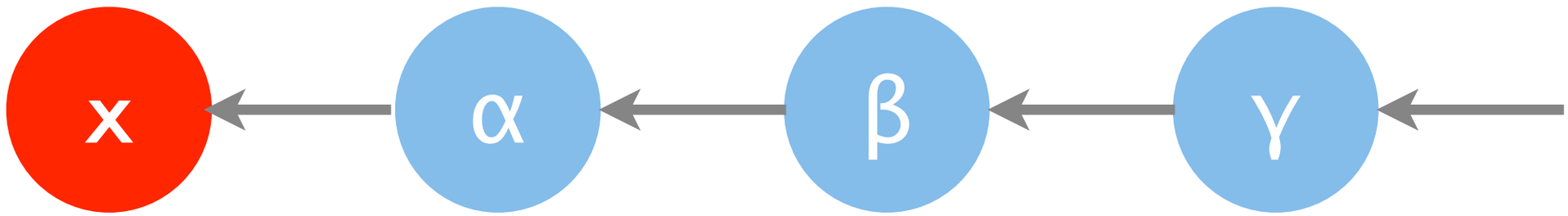
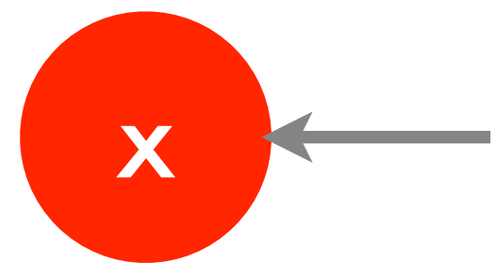


Konopnicki et al. 2010
One stage encoding

encode user tokens
relative to background



Compression Framework

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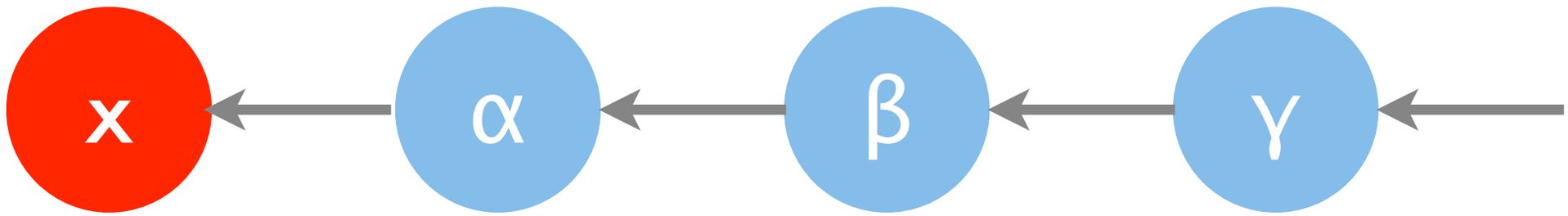

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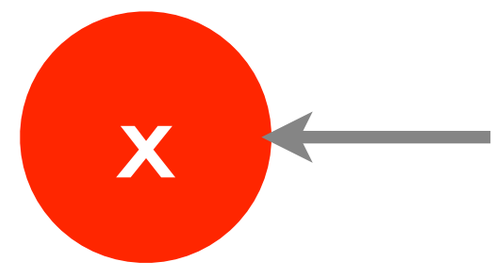
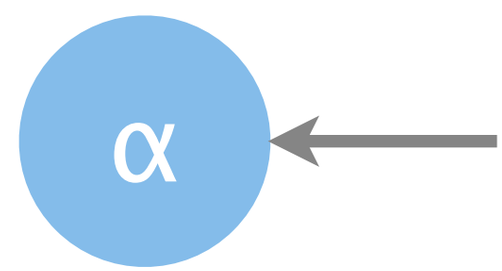
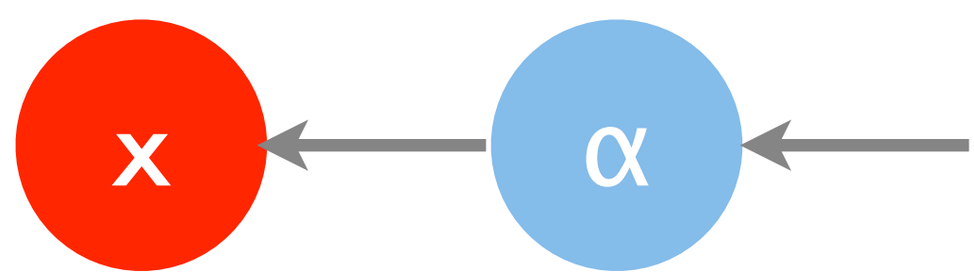


Our model
Two stage encoding

encode **cluster** tokens
relative to background



encode **user** tokens
relative to **cluster**



Why?

- Meaningful features
  - Cluster ID is often meaningless
  - Activity / tokens often user interpretable
  - Retain user interpretable representation
  - ‘tokens are the best features’
- Simplicity
- Flexibility
  - Extend this to general hierarchical models
  - Smoothing via hierarchy of latent parameters
- Data reduction

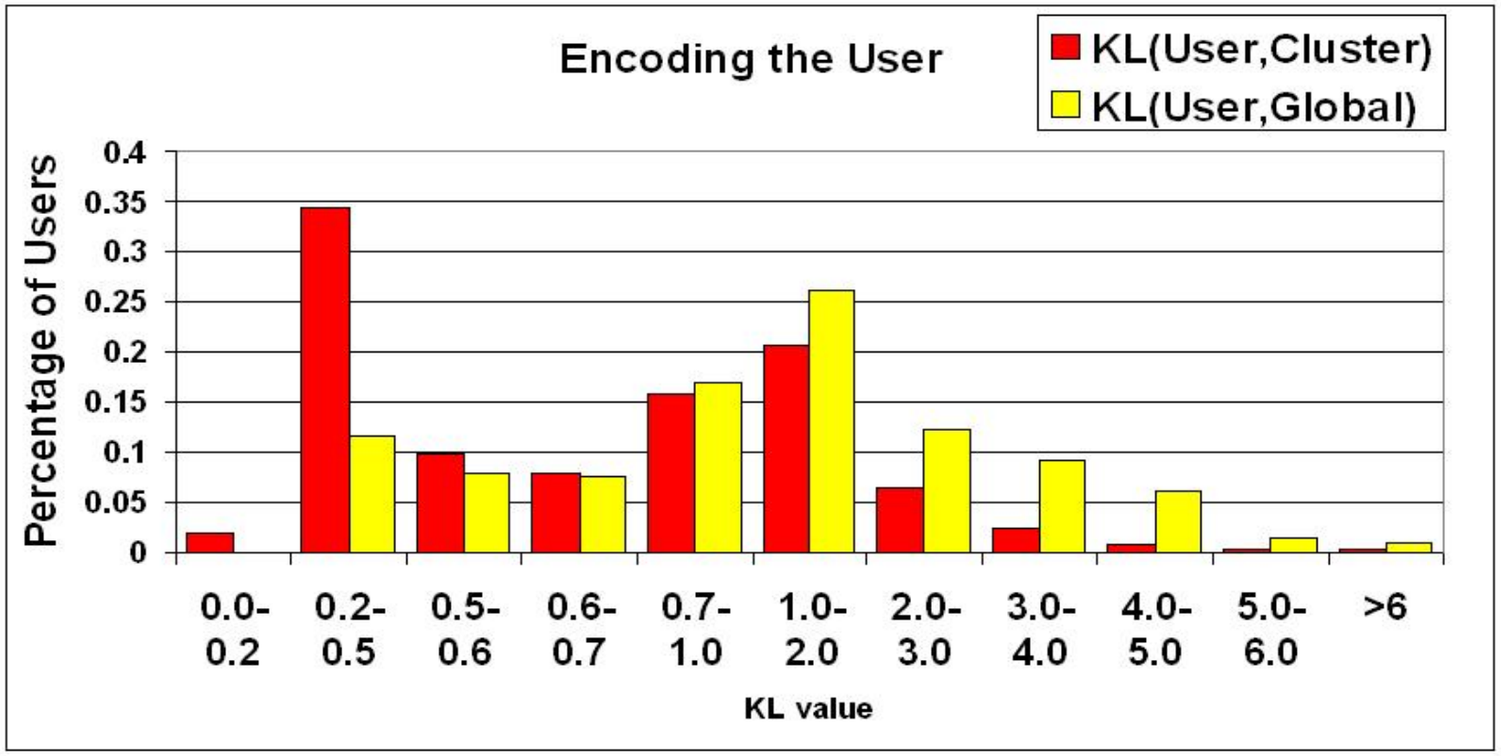
  (think information theoretic frequent item sets)

Dataset

- 1 million users at Yahoo!
- 55 day period (1/1-2/25/2010)
- Sample data (user interpretable)

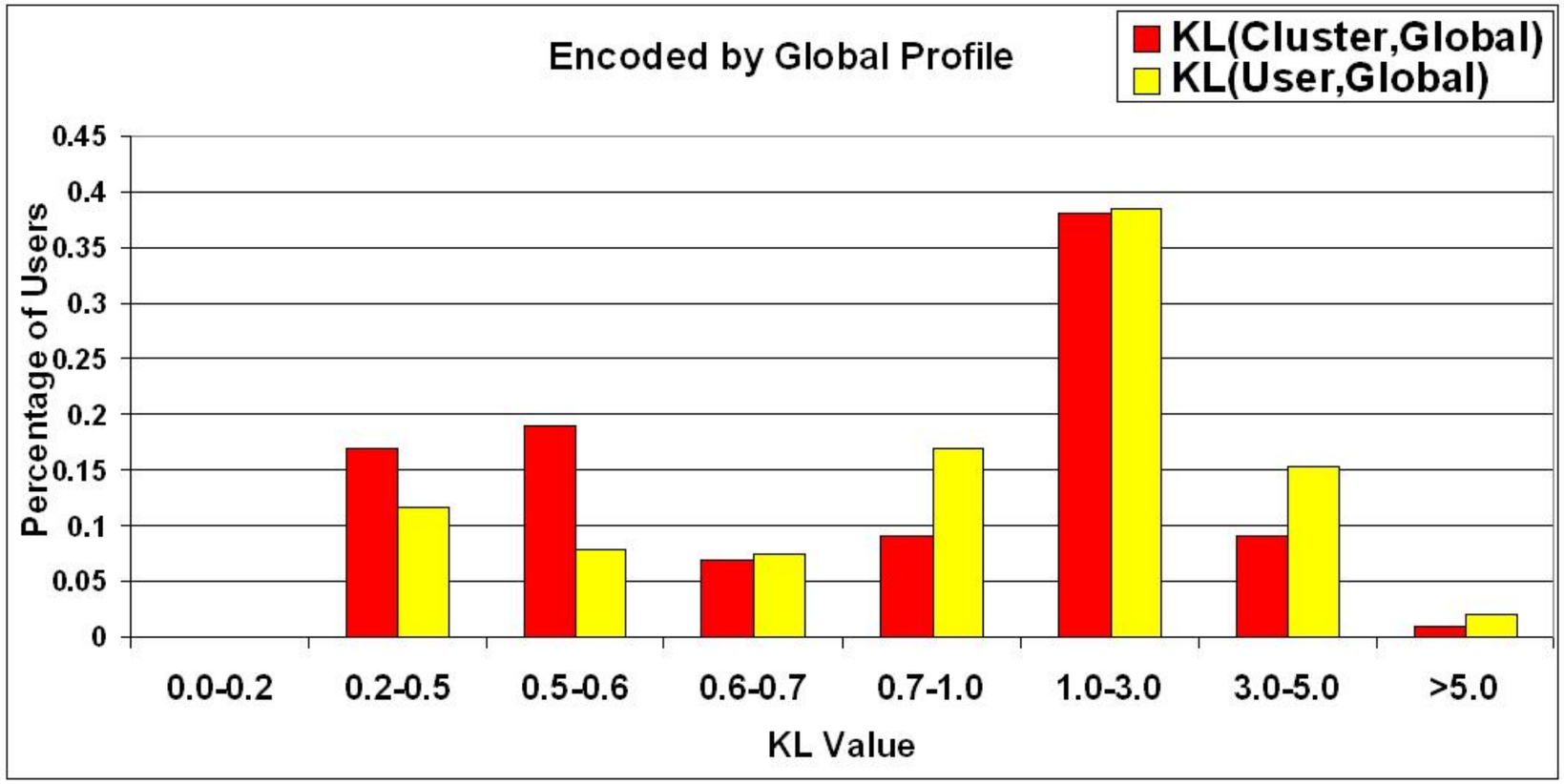
  User ID,
  cpv_Technology/Online Community=20,
  cpv_Technology/Internet Services=35,
  cpv_Technology=40

Concentration by clusters



- Many users well represented by clusters
- Still meaningful divergence beyond clusters (clustering would oversimplify distribution)

Concentration by clusters



- Clusters capture overall distribution well
- Small set of users with significant deviation beyond cluster model (KL > 3.0)

Meaningful cluster features

Cluster ID	Important User Behaviors	KL Divergence
Cluster 1 (Technology Group)	cpv-Technology/Internet Services	0.3883
	cpv-Technology/Internet Services/Online Community	0.3854
	cpv-Technology	0.3840
	cpv-Technology/Internet Services/Online Community/Email	0.2829
	cpv-Technology/Internet Services/Online Community/Portals	0.2806
	cpv-Technology/Internet Services/Online Community/Photos	0.0122
Cluster 2 (Finance Group)	cadv-Finance	0.0365
	cadv-Finance/Credit Services	0.0274
	cadv-Finance/Insurance	0.0145
	cadv-Finance/Insurance/Automobile	0.0119
	cadv-Telecommunications/Cellular and Wireless Services	0.0081
	cadv-Technology/Consumer Electronics/Comms/Mobile/Cellular Telephones	0.0078

- Features ordered by relevance
- Represent cluster well
  - sparse encoding

Meaningful user features

User Index	Behavior set
User 1 Cluster 1	**cadv-Technology/Internet Services/Online Community**:134 **cpv-Technology/Internet Services/Online Community**:190 **cpv-Technology/Internet Services**:192 **cpv-Technology**:192 **cpv-Technology/Internet Services/Online Community/Email**:190 **cadv-Technology**:150 **cadv-Technology/Internet Services/Online Community/Email**:132 **cadv-Technology/Internet Services**:142 cadv-Finance/Insurance:52 cadv-Finance:52 cpv-Sports/Soccer:21 cpv-Sports/Auto Racing:32
User 2 Cluster 1	**cpv-Technology**:212 **cpv-Technology/Internet Services/Online Community**:212 **cpv-Technology/Internet Services**:212 **cpv-Technology/Internet Services/Online Community/Email**:212 cadv-Consumer Packaged Goods:18 cadv-Consumer Packaged Goods/Beauty and Personal Care:14 cadv-Life Stages/Parenting and Children/Baby:10 cadv-Life Stages:10
User 3 Cluster 2	**cadv-Finance/Credit Services**:72 **cadv-Finance**:190 **cadv-Finance/Investment/Discount Brokerages**:44 **cadv-Technology/Consumer Electronics/Communication/Mobile/Cellular Telephones**:34 **cadv-Technology/Consumer Electronics/Communication/Mobile**:104 cadv-Small Business and B2B:44 cadv-Life Stages:32 cadv-Retail:24

cluster specific

personalized

Advertising results

little click data

# conv	# ads	% win	profile AUC	base AUC
≥ 10	155	62%	0.57	0.56
$[10, 100]$	112	68%	0.55	0.53
≥ 100	43	47%	0.60	0.60

- Cluster smoothing helps most for users with little click data
- Subset at least as efficient as full set of features
- ... very preliminary results ...

Summary

- General compression framework
- Retains meaningful tokens
- Generalizes existing methods
- Todo: generative models (a la sequence memoizer for better representation)