# BANDIT ALGORITHMS FOR SOCIAL-AWARE SEARCH

Meeting ALICIA

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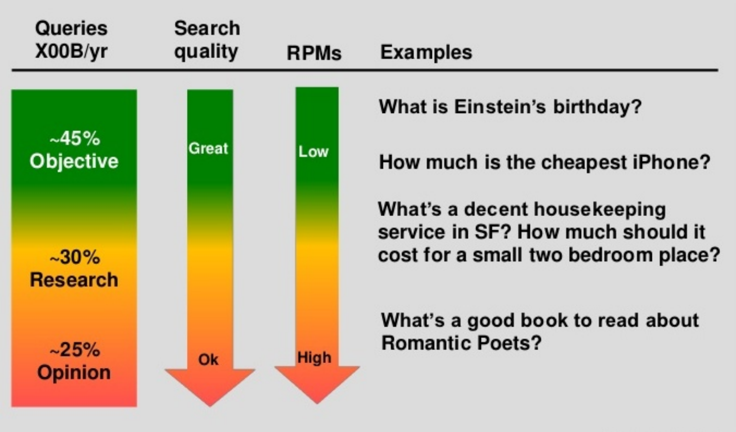
Can the search engine learn the correct setting for a (user, context, query) tuple?

# Understanding query nature and context




Classic web search is great for objective queries, but the subjective ones bring the most revenues.

# Full-personalization goal

- Learn and refine profiles
- Understand and model context: how to set the $\alpha$ value in social search, depending on the context?

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- An unknown two-dimensional parameter $\alpha$ is to estimate
- Linear reward $r_t = x_t^T \alpha + \epsilon_t$
- Choose a vector $x$ according to the previously seen chosen items and rewards.

# Experimental setup (1/2)

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Input:

- weighted-graph $G$
- triples $(user, item, tag)$

General workflow:

- Input: ($query$, $seeker$)

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General workflow:

- Input: (*query*, *seeker*)
- Objective: show a **unique** item *i* (to be changed in the future)
- If *i* was tagged by *seeker*: **click**, else, **no click**.

# Improving results – Clustering

(*query*, *seeker*) input should probably influence the $\alpha$ to choose

1. Cluster queries: obvious impact

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S. Li et al.
*Data-Dependent Clustering in Exploration-Exploitation Algorithms.*
2015.

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- Define a model to improve results using clustering
- Define a model to improve results using social network to speed up learning

Thank you.
Questions?

D. Jiang, K. W.-T. Leung, J. Vosecky and W. Ng
*Personalized Query Suggestion With Diversity Awareness.*
In ICDE, pages 400-411, 2014.

C. Gentille et al.
*Online Clustering of Bandits.*
In ICML, 2014.

S. Li et al.
*Data-Dependent Clustering in Exploration-Exploitation Algorithms.*
2015.

# References II


S. Buccapatnam et al.
*Stochastic Bandits Side Observations on Networks.*
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