# DQBarge: Improving data-quality tradeoffs in large-scale Internet services

#### **Michael Chow**

Kaushik Veeraraghavan, Jason Flinn, Michael Cafarella





# Complex Internet services

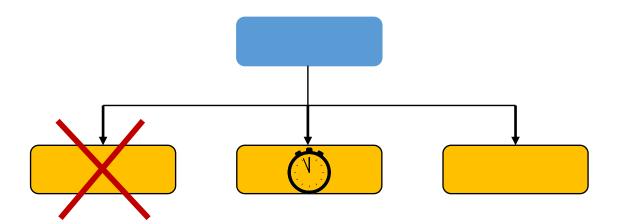
Composed of hundreds of software components

Requests have response time goals



# Balancing response time goals

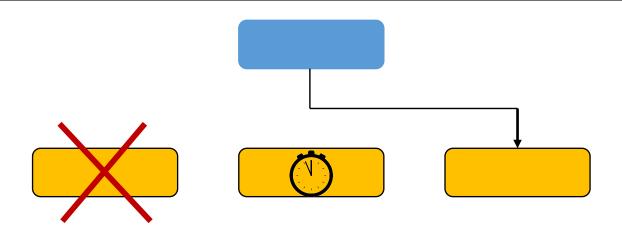
- Components have response time goals
  - Lower-level components unaware of response goals
  - Lower-level components may fail

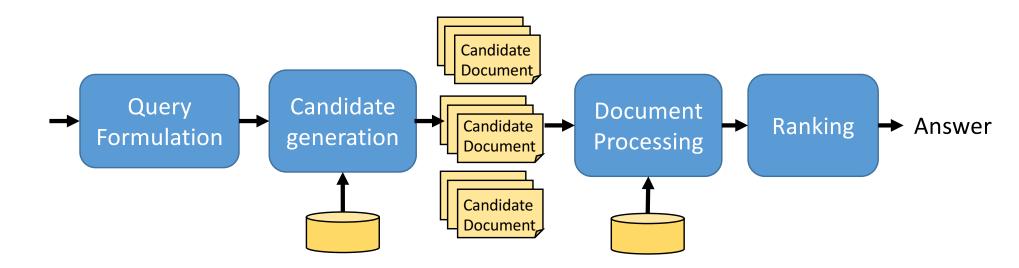


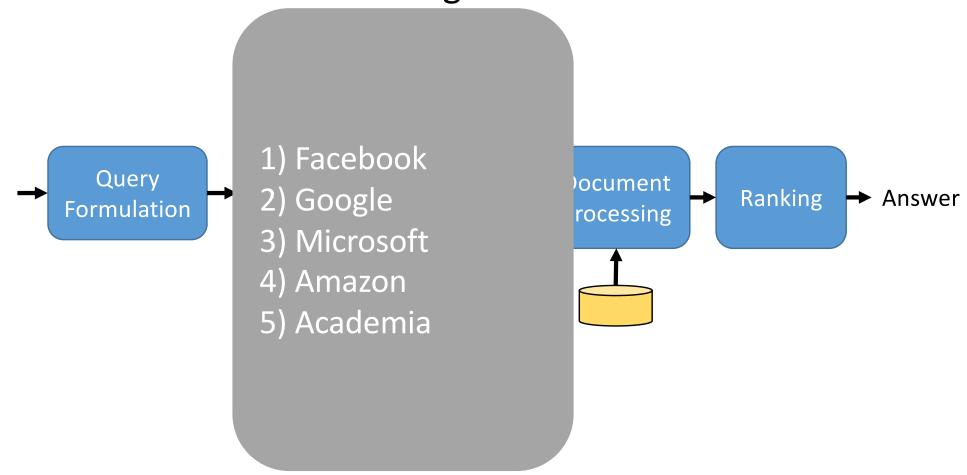
### **Data-quality tradeoff**

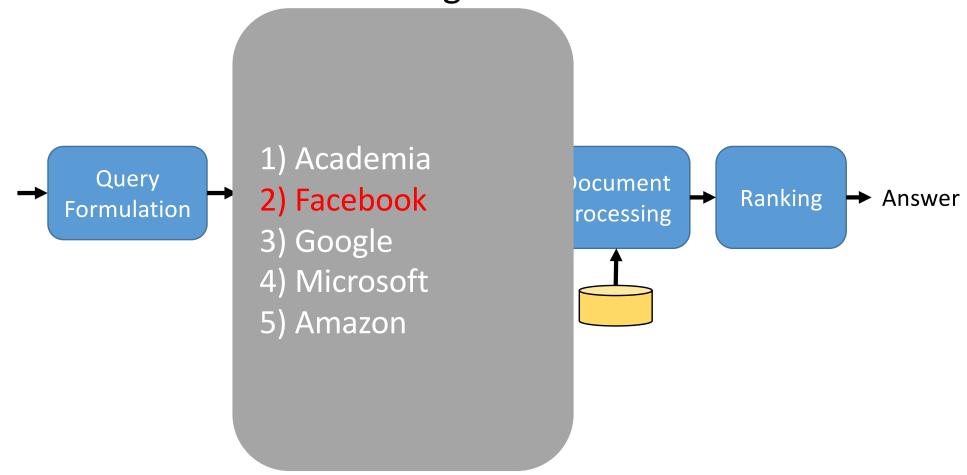
Explicit decision to return lower fidelity data

- Improve response time
- Minimize resource usage









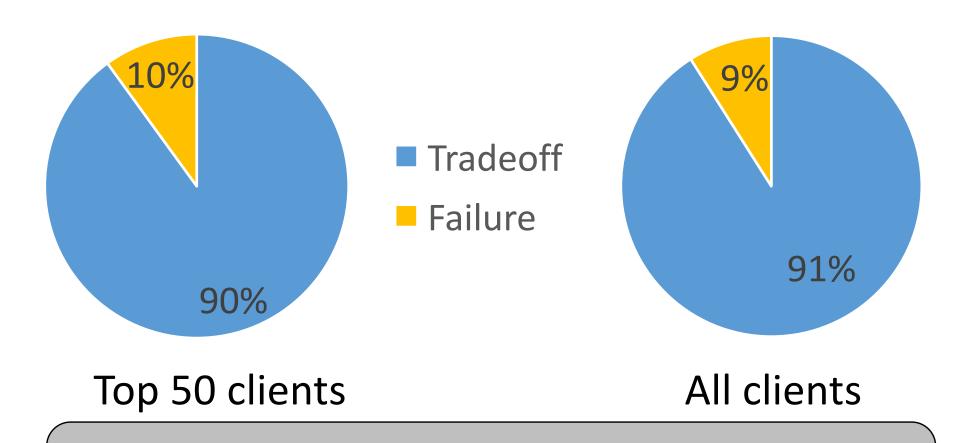
### Outline

- Motivation
- Study of data-quality tradeoffs at Facebook
- DQBarge
- Evaluation of DQBarge

### Study of tradeoffs at Facebook

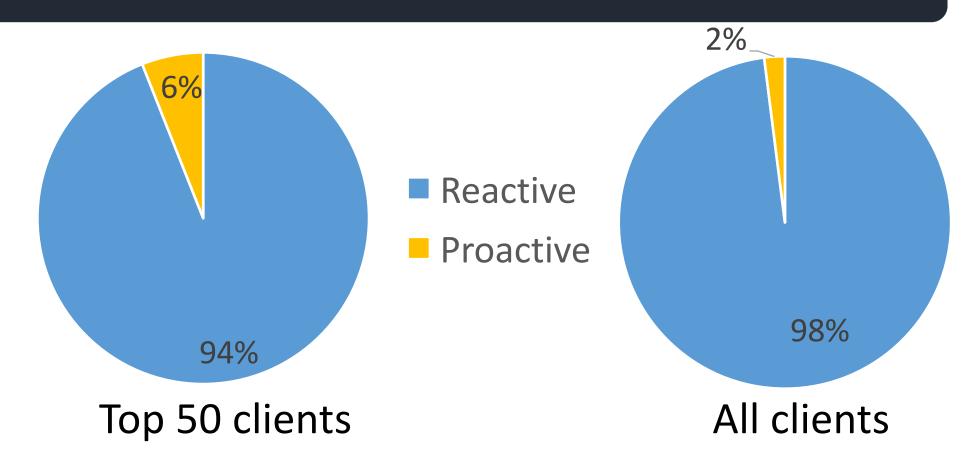
- Systematic study of a Facebook service
  - Laser, key-value store at Facebook [2015]
- Categorized tradeoffs made by all 463 clients

# >90% of clients perform tradeoffs



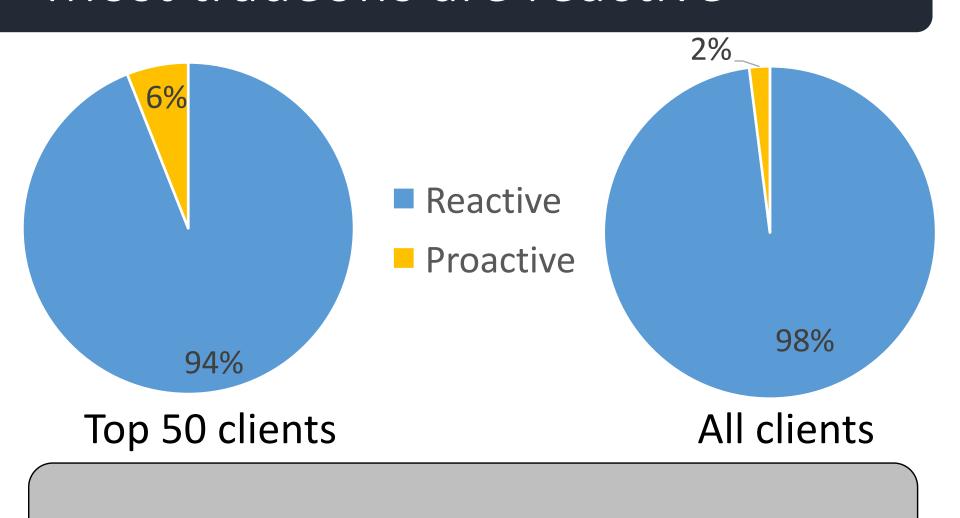
Data-quality tradeoffs are the norm, not the exception

### Most tradeoffs are reactive



- Reactive → occurs on timeout/failure
- Proactive → only request what can be done

### Most tradeoffs are reactive



Reactive tradeoffs waste resources

## Takeaways

- Data-quality tradeoffs are common
- Most are reactive, instead of proactive
- Tradeoffs only consider local information

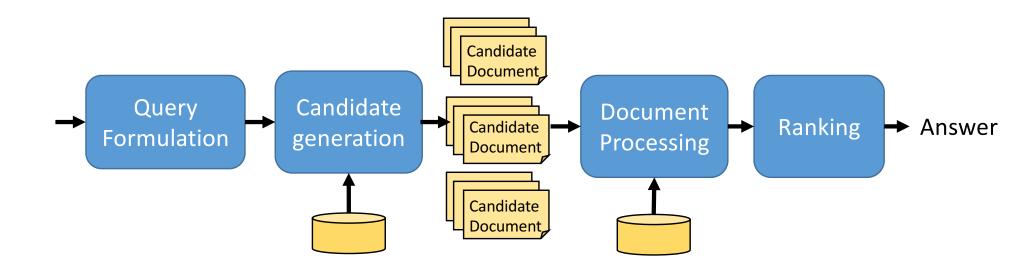
Need global information to enable proactive, better tradeoffs

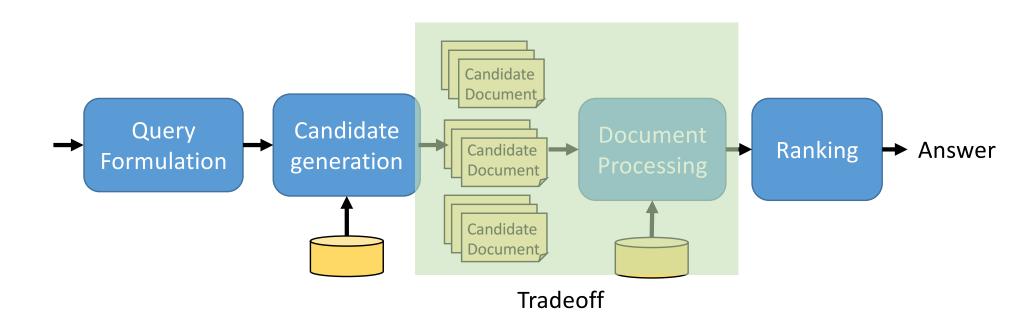
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Library for developers to help make tradeoffs

Propagates additional data along causal path



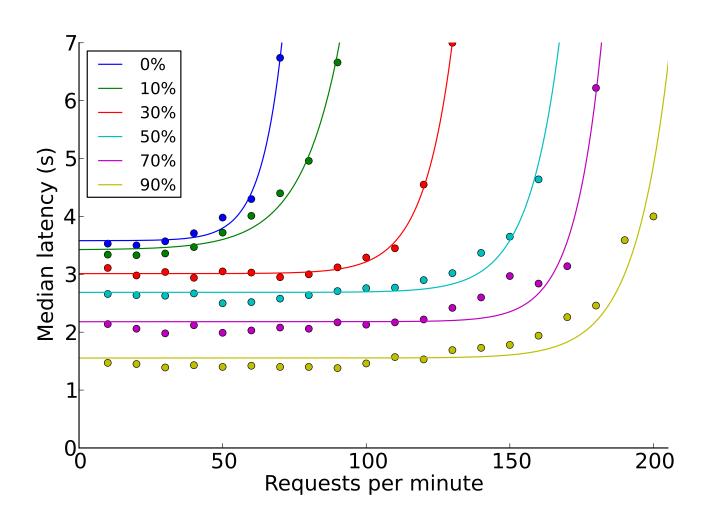


# Phases of operation

• Offline phase: build models

Online phase: use models

# Performance model



#### **Full Quality**

Work/Life

- 1) Facebook
- 2) Google
- 3) Microsoft
- 4) Amazon
- 5) Academia

#### **Full Quality**



- 1) Facebook
- 2) Google
- 3) Microsoft
  - 4) Amazon
  - 5) Academia

#### **Full Quality**



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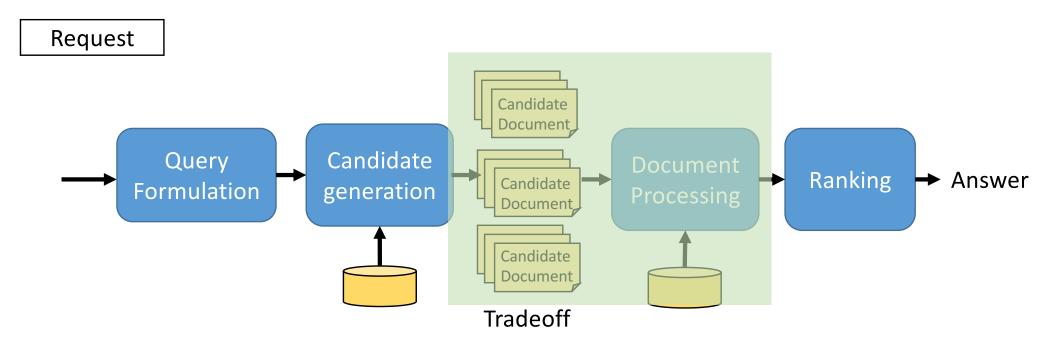


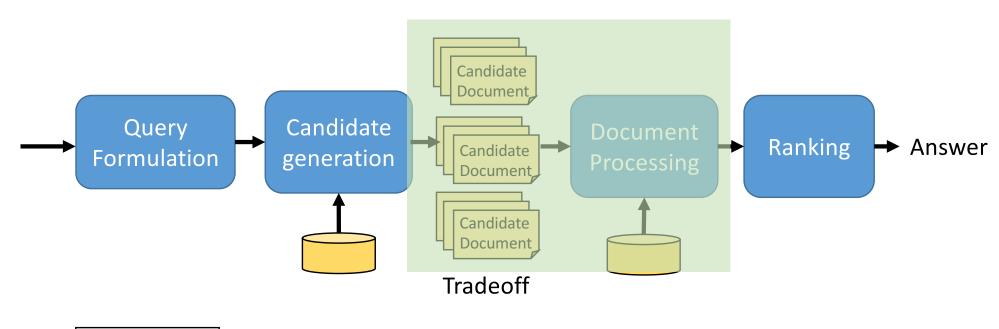
- 1) Academia
- 2) Facebook
- 3) Google
- 4) Microsoft
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# Phases of operation

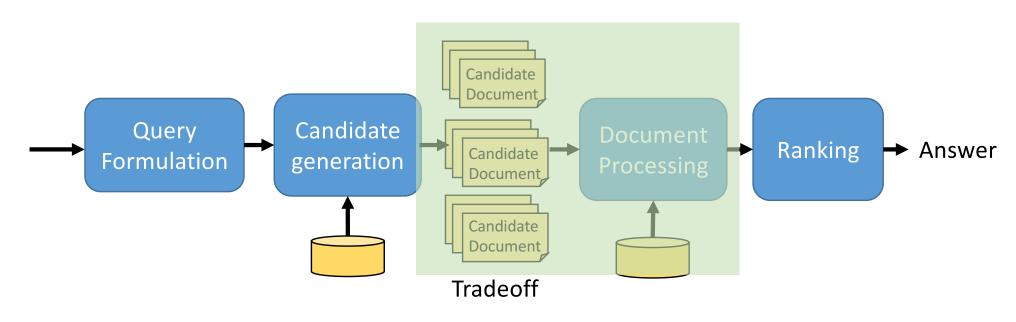
Offline phase: build models

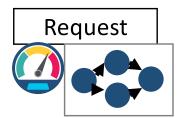
• Online phase: use models

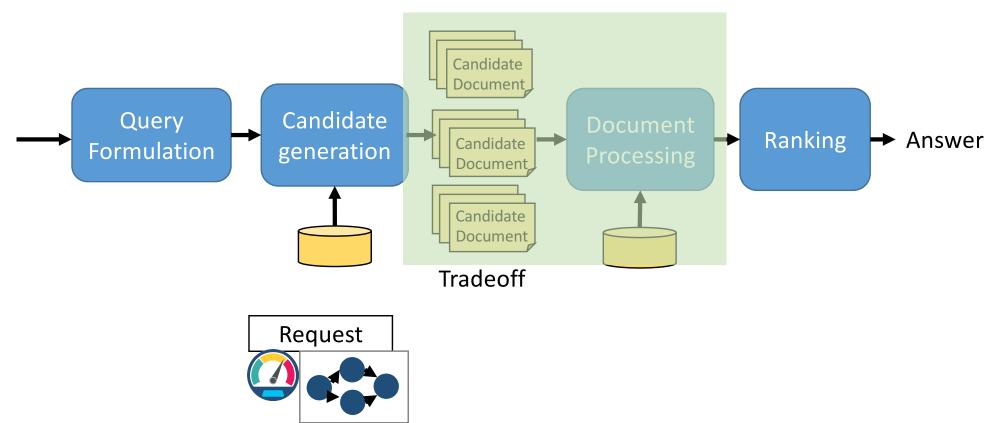


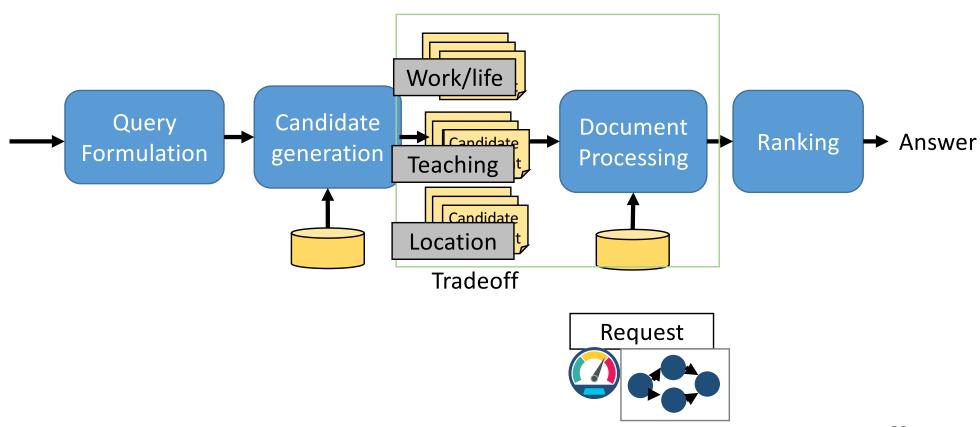


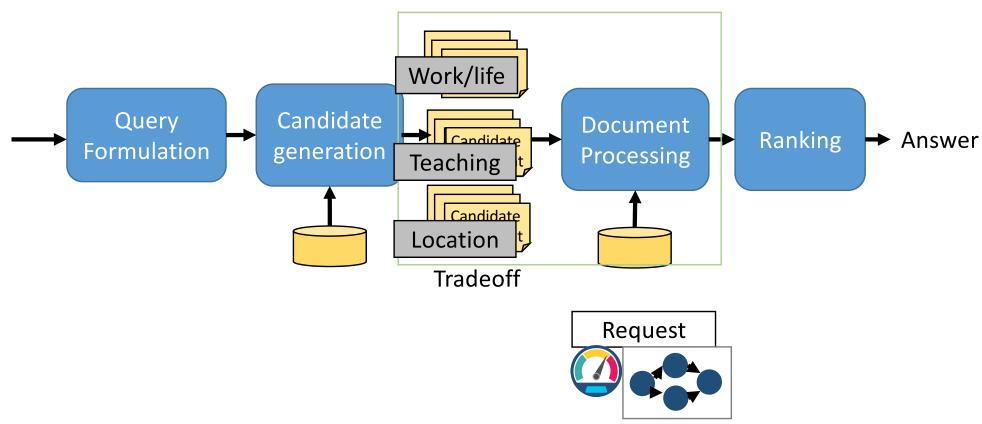


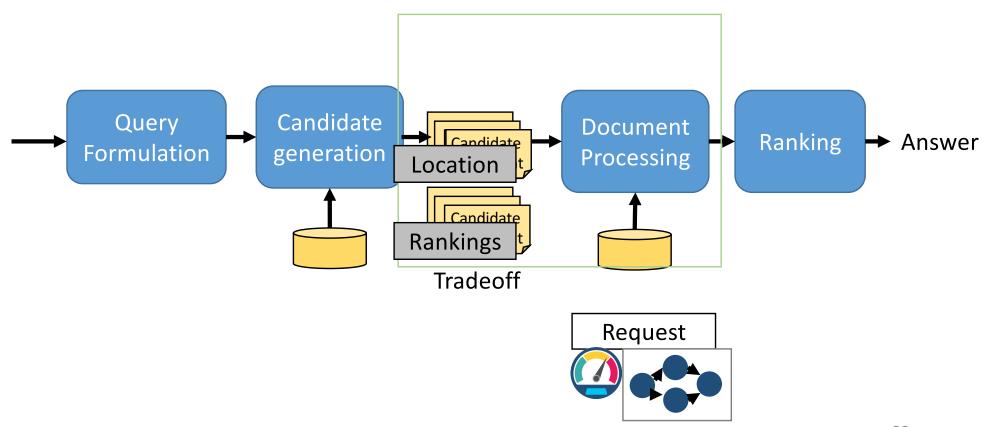


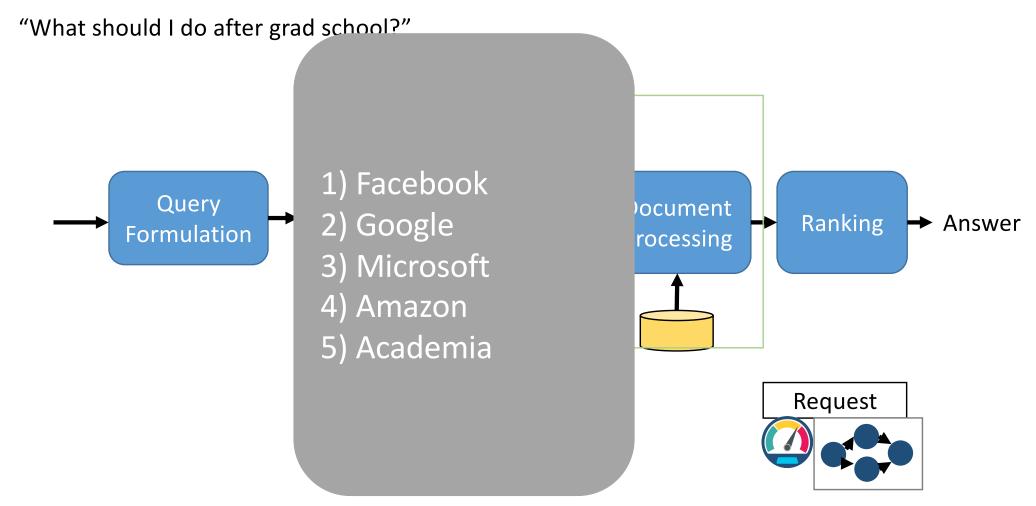


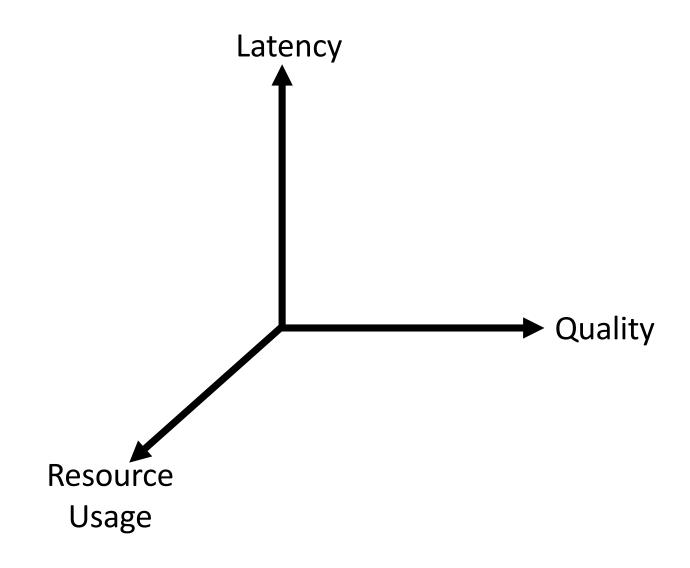


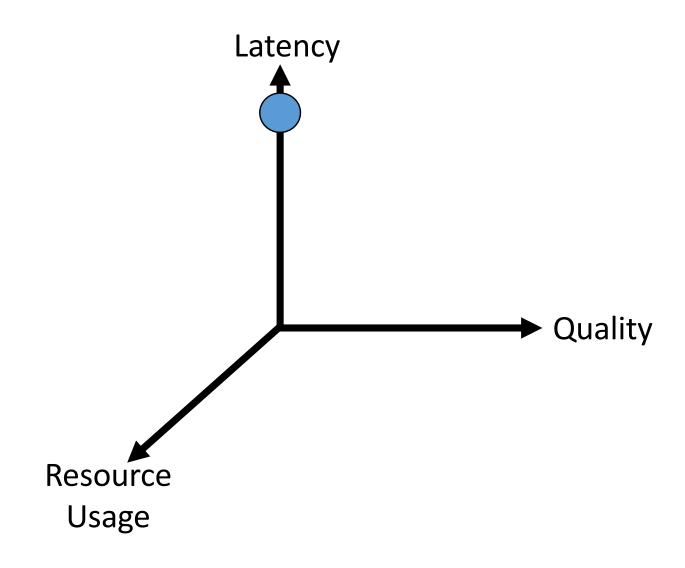


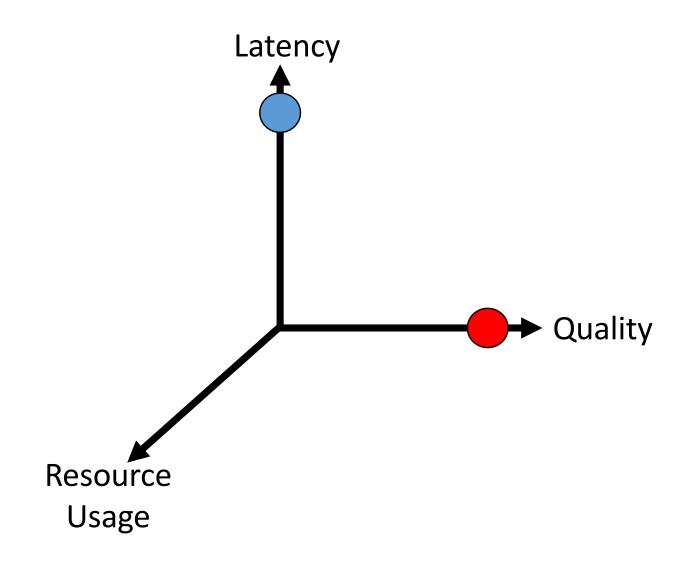


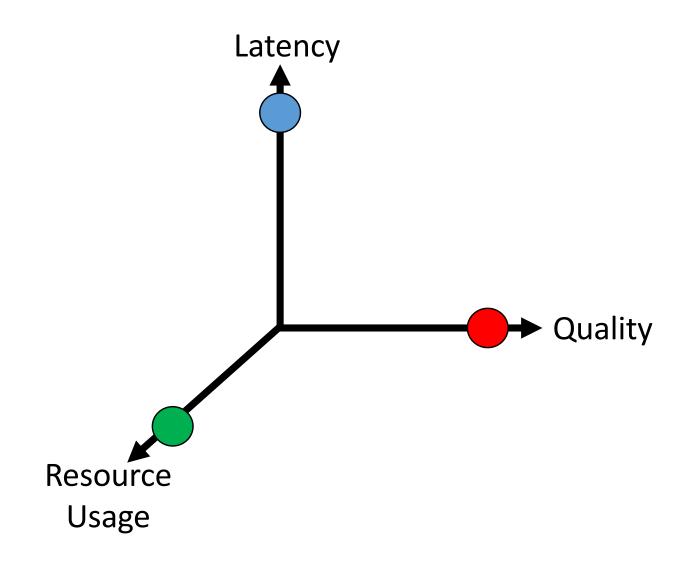












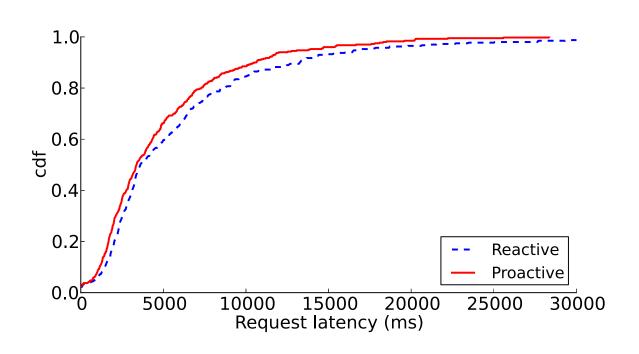
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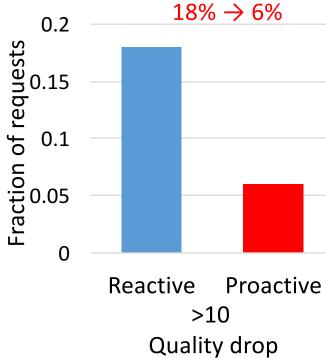
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### Evaluation

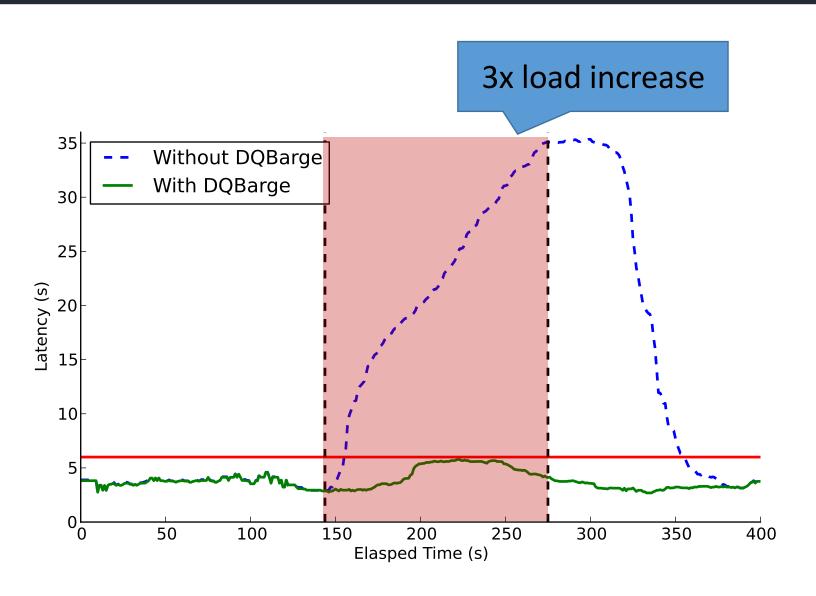
- Do data-quality tradeoffs improve performance?
- How much does provenance improve tradeoffs?
- How much does proactivity improve tradeoffs?
- How does DQBarge help in end-to-end scenarios?
  - Load spike
  - Utilizing spare resources
  - Dynamic capacity planning

# Do proactive tradeoffs help?

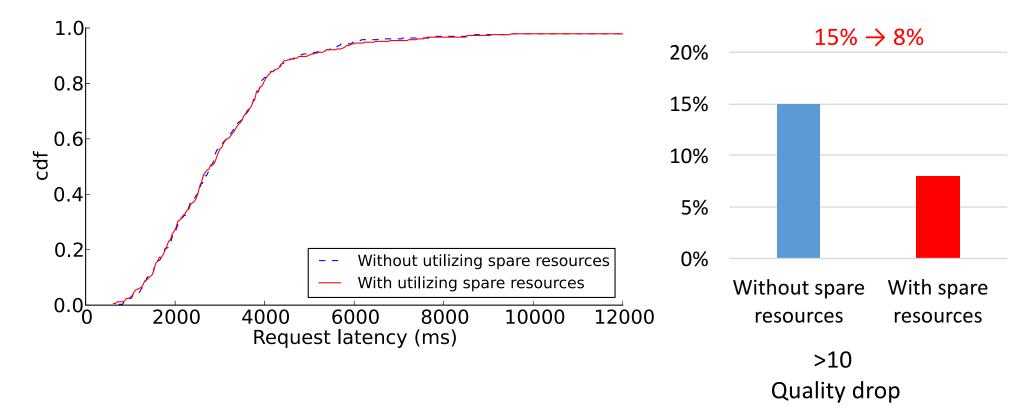




# Load spike scenario



## Utilizing spare resources



### Conclusion

Data-quality tradeoffs are very common

Suboptimal due to reactivity & lack of information

DQBarge improves tradeoffs

### Questions?