#### Optimizing Sampling-based Entity Resolution over Streaming Documents

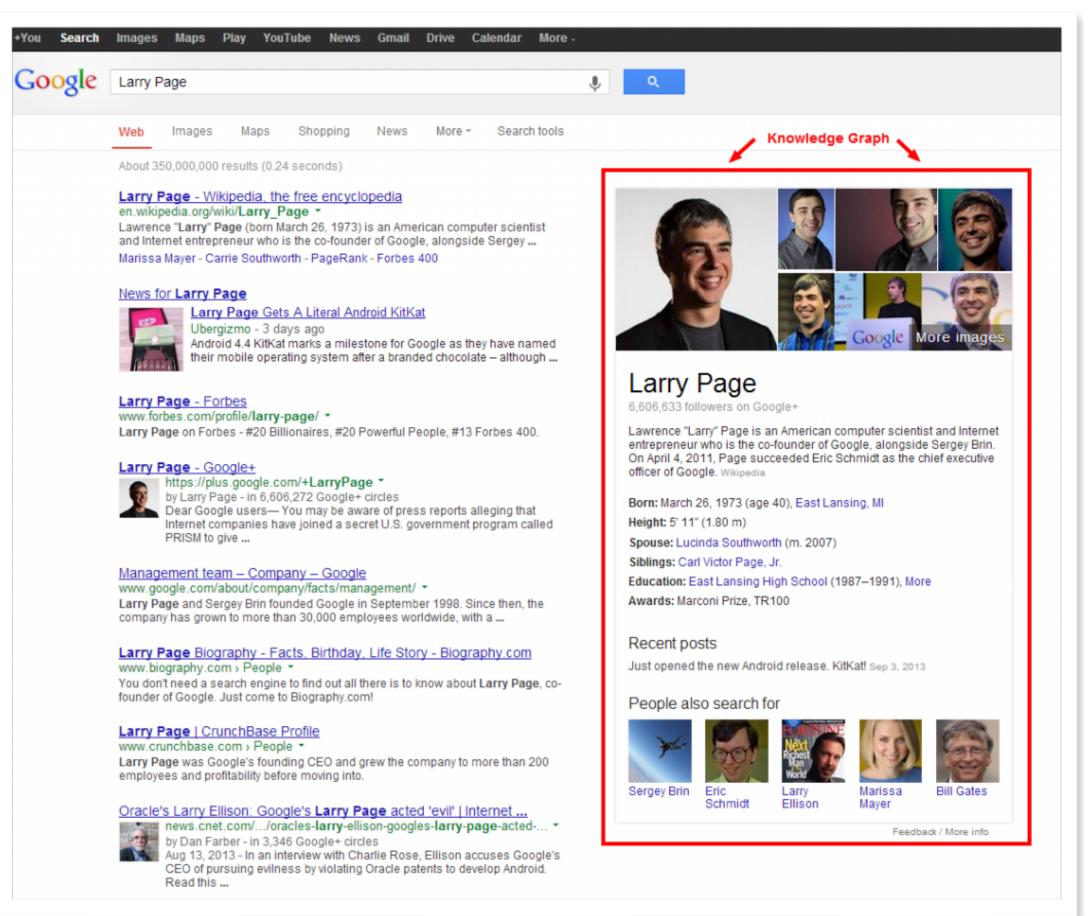
**Christan Grant and Daisy Zhe Wang** University of Florida

**SIAM BSA Workshop 2015** 

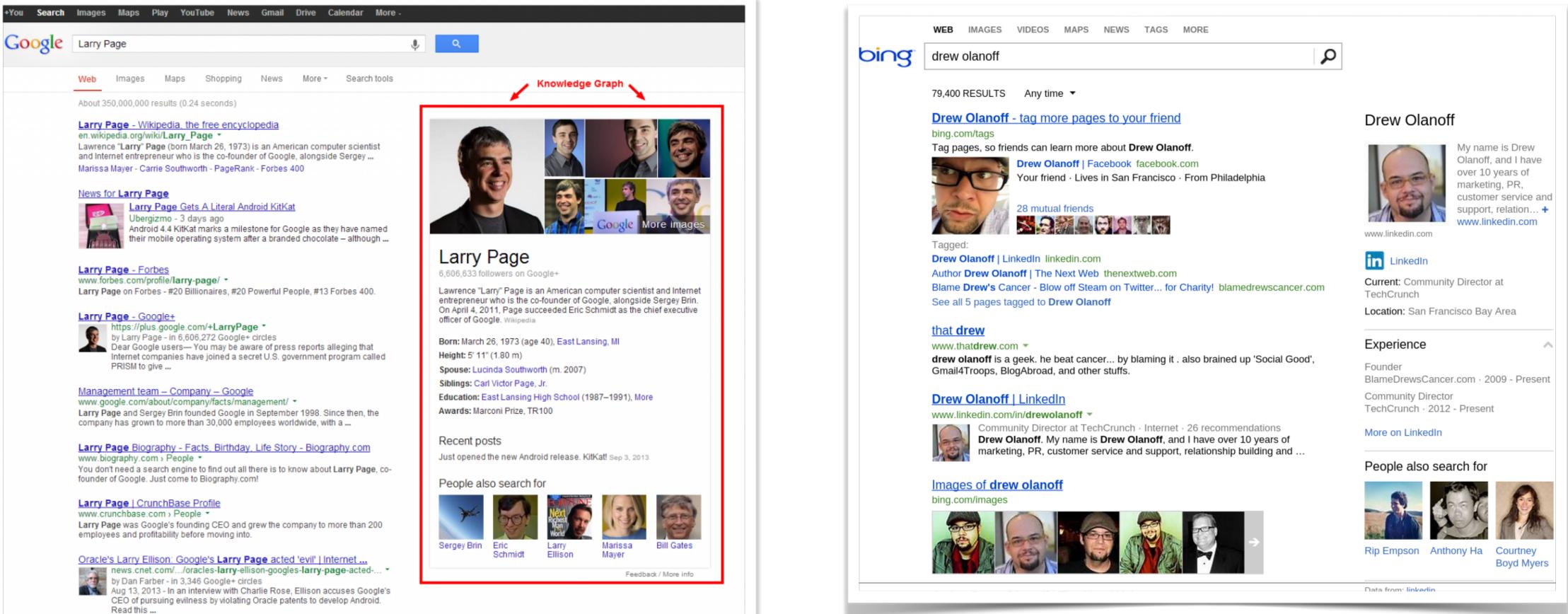
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bootstrapped using Wikipedia/Freebase.

#### Many of these knowledge bases and new knowledge bases are

- bootstrapped using Wikipedia/Freebase.
- sources.

#### Many of these knowledge bases and new knowledge bases are

• All Wikipedia information is based on facts from (reputable?) web

#### Society for Industrial and Applied Mathematics

From Wikipedia, the free encyclopedia

Not to be confused with Société de Mathématiques Appliquées et Industrielles.

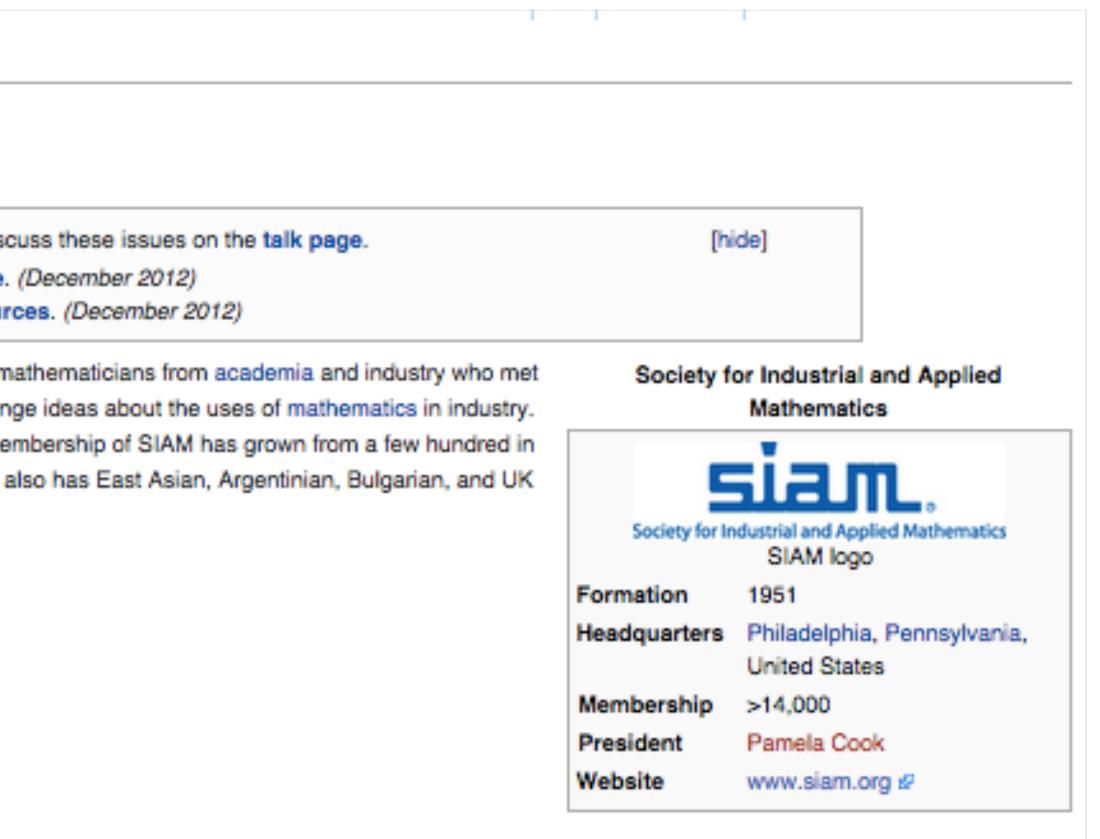


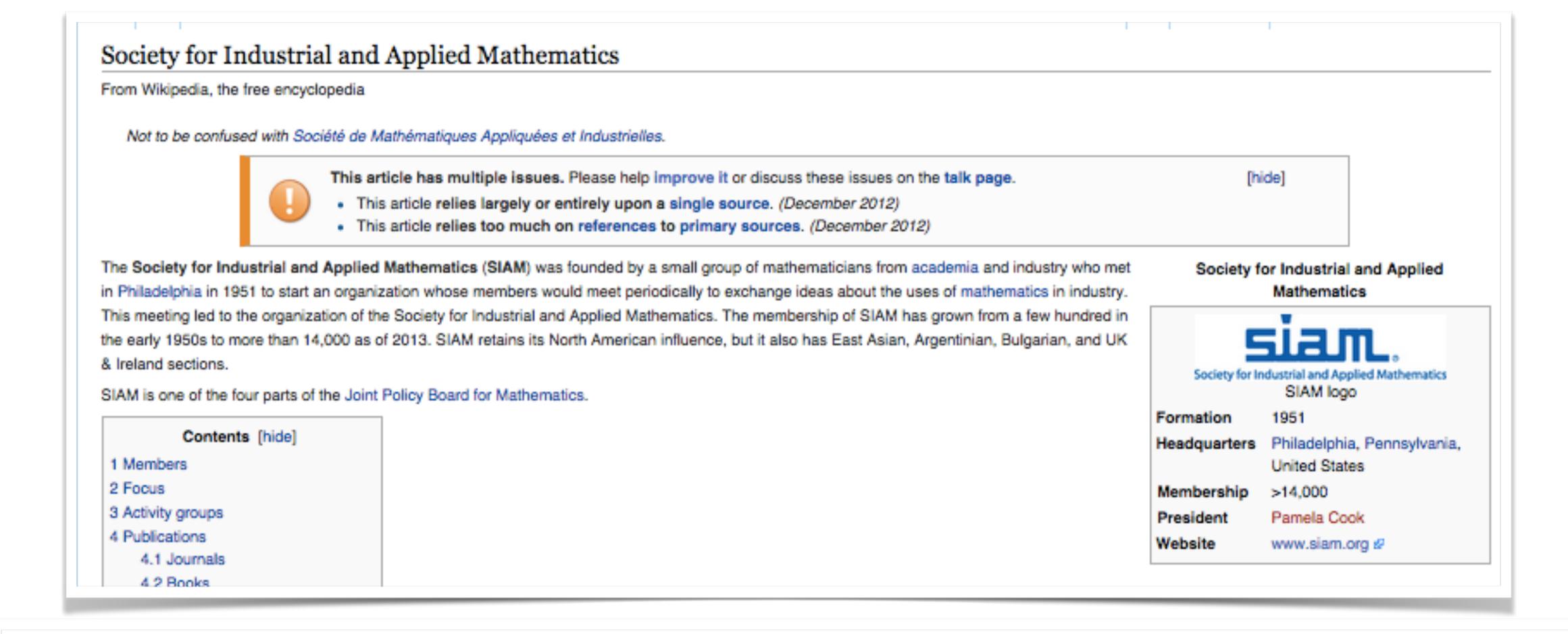
- This article has multiple issues. Please help improve it or discuss these issues on the talk page.
- This article relies largely or entirely upon a single source. (December 2012)
- This article relies too much on references to primary sources. (December 2012)

The Society for Industrial and Applied Mathematics (SIAM) was founded by a small group of mathematicians from academia and industry who met in Philadelphia in 1951 to start an organization whose members would meet periodically to exchange ideas about the uses of mathematics in industry. This meeting led to the organization of the Society for Industrial and Applied Mathematics. The membership of SIAM has grown from a few hundred in the early 1950s to more than 14,000 as of 2013. SIAM retains its North American influence, but it also has East Asian, Argentinian, Bulgarian, and UK & Ireland sections.

SIAM is one of the four parts of the Joint Policy Board for Mathematics.

Contents [hide]
1 Members
2 Focus
3 Activity groups
4 Publications
4.1 Journals
4.2 Books





#### SIAM Fellows [edit]

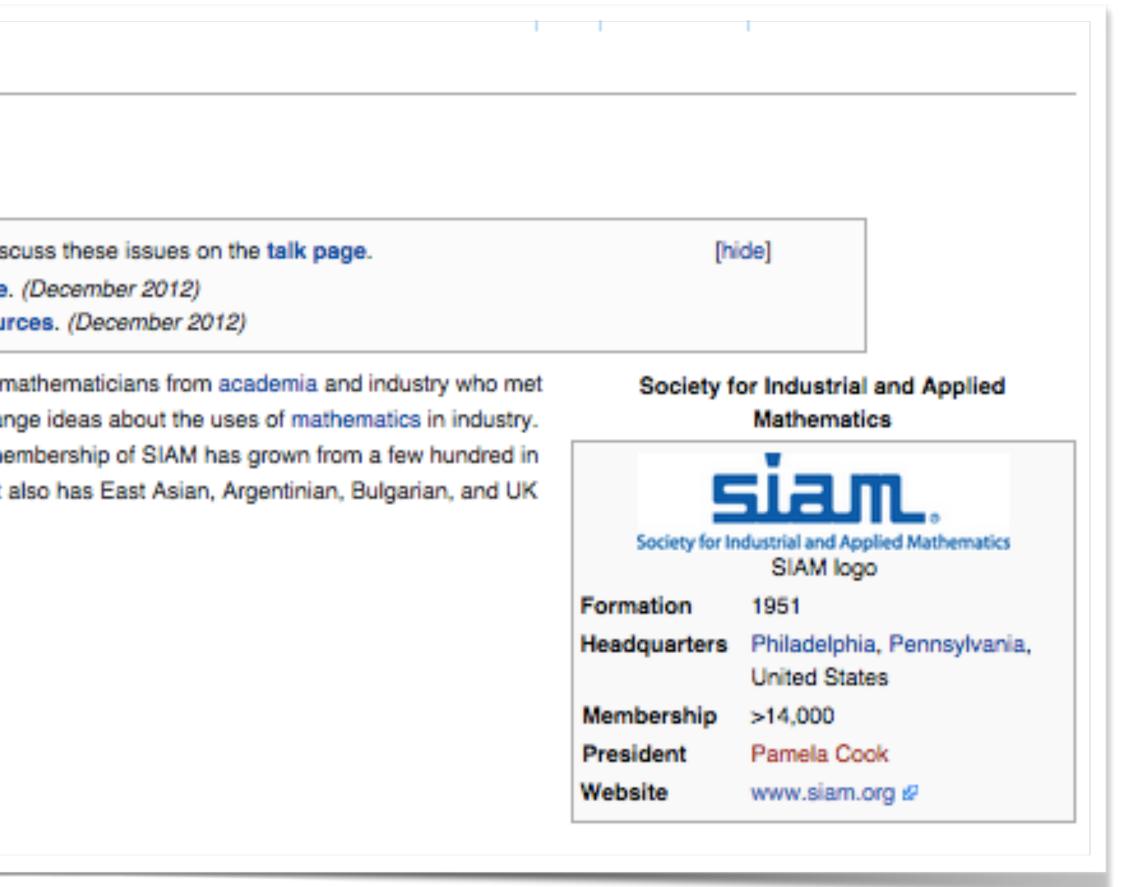
#### In 2009 SIAM instituted a Fellows program to recognize certain members who have made outstanding contributions to the fields SIAM serves<sup>[14]</sup>



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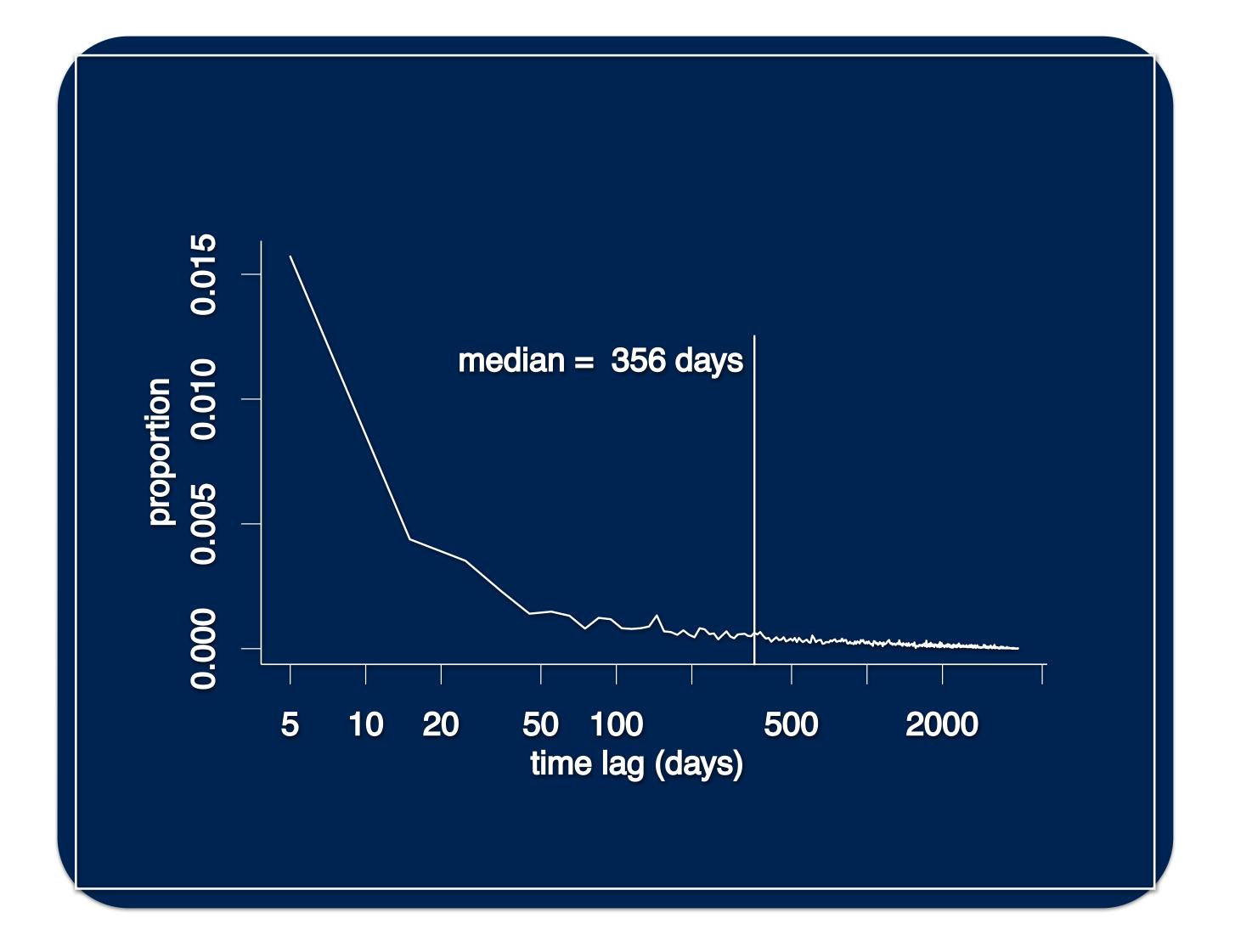




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#### 14. A "Fellows Program" & SIAM. Retrieved 2012-12-04.

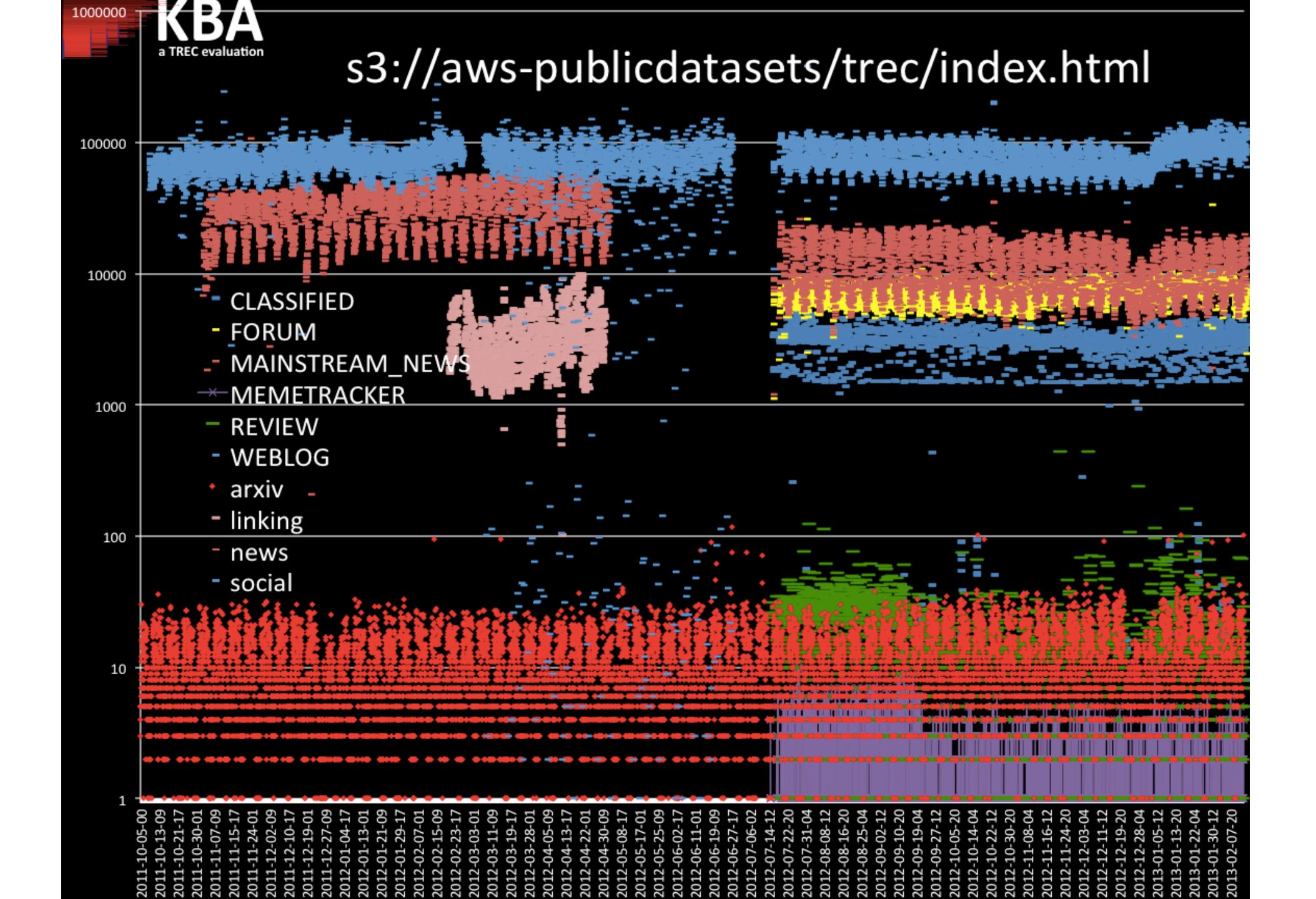




The average time between an event and its appearance on Wikipedia is **356** days.



NIST TREC created a track that reads in streaming documents and a set of entities and suggests citations for wikipedia entities.



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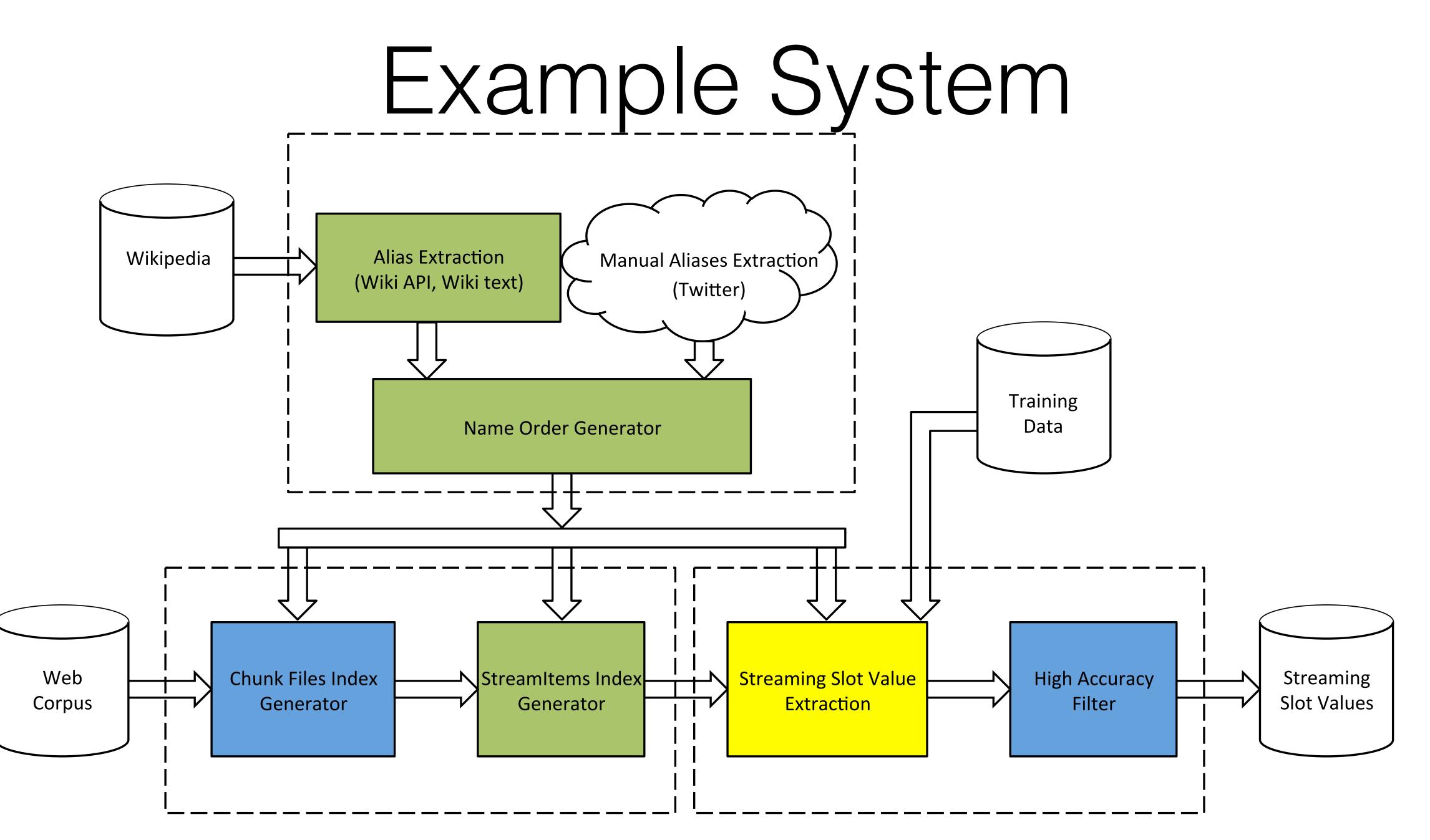
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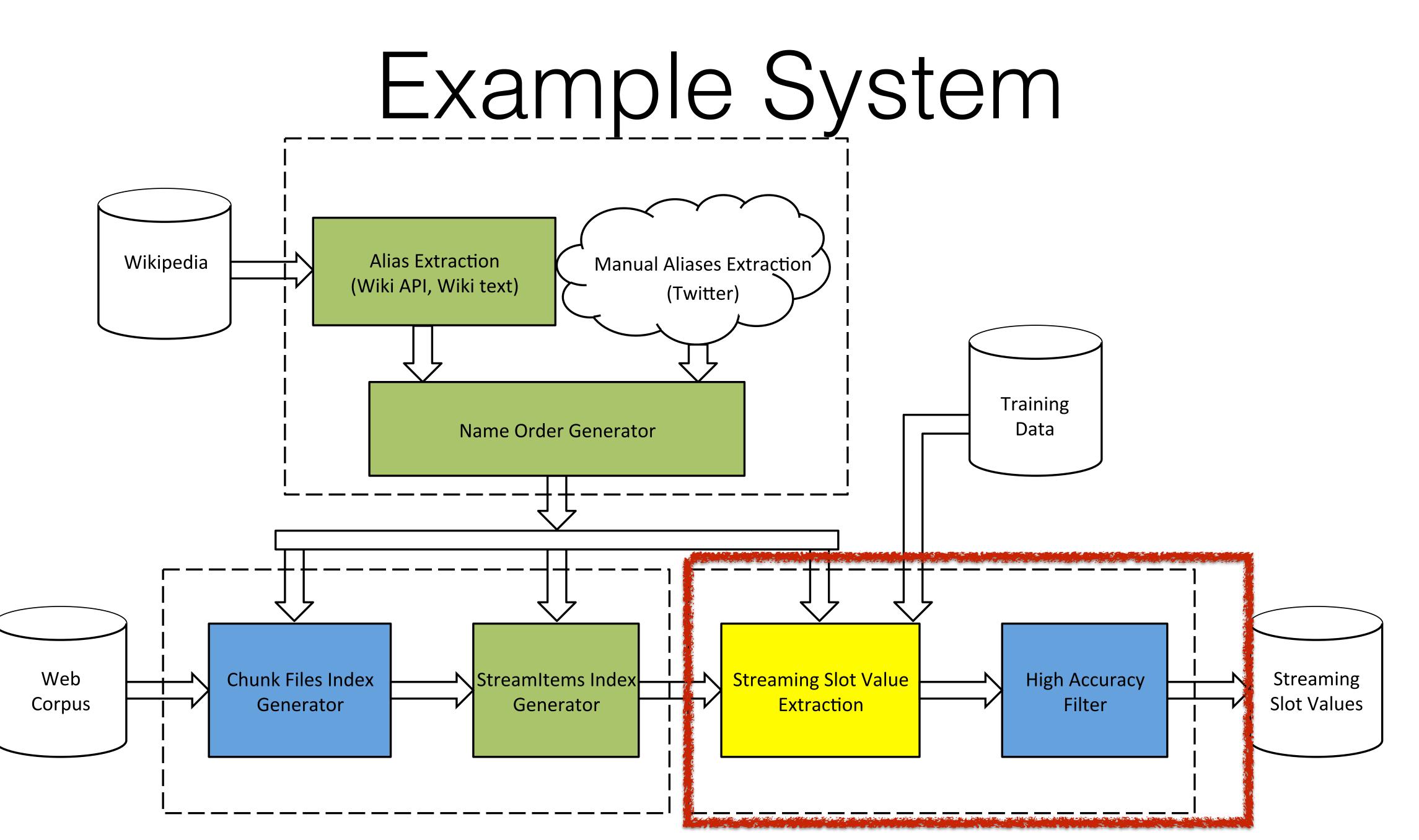
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Challenges:

- 1) A large amount of documents
- 2) Ambiguous text
- 3) Ambiguous Entities
- 4) Finding *relevant* facts





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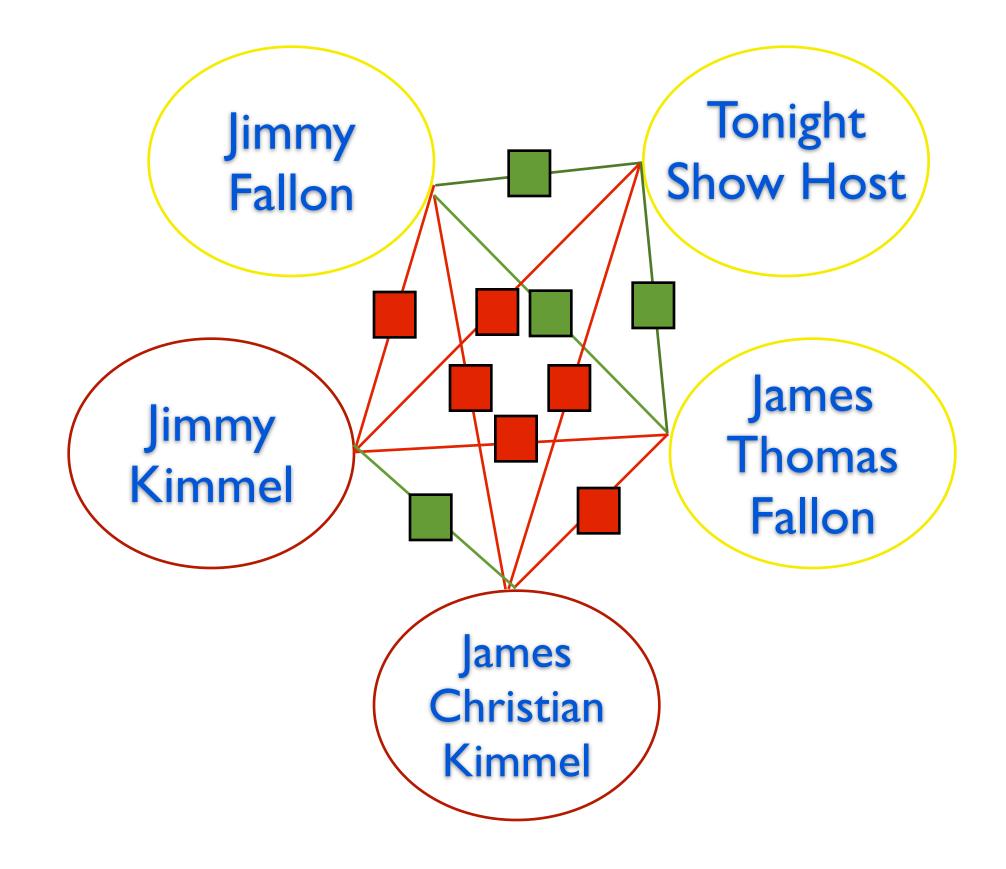
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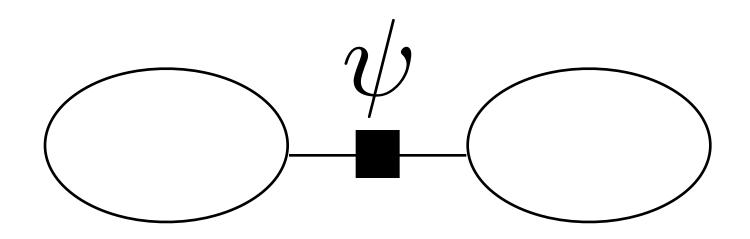
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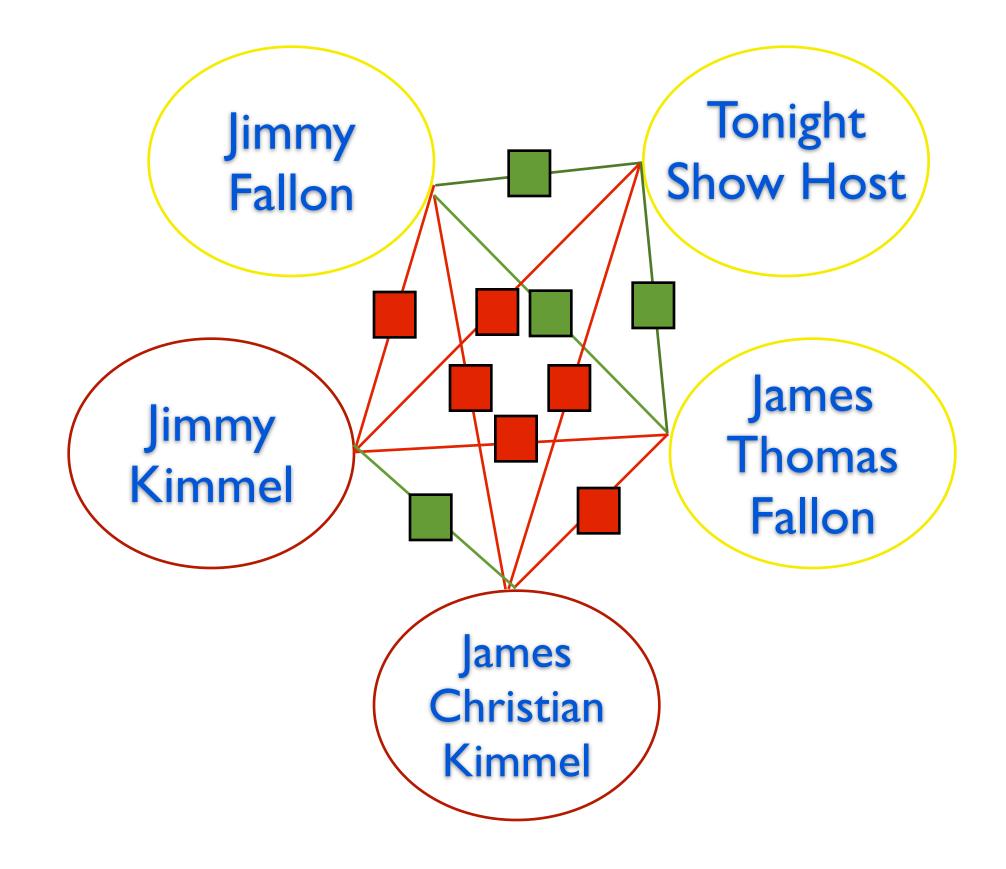
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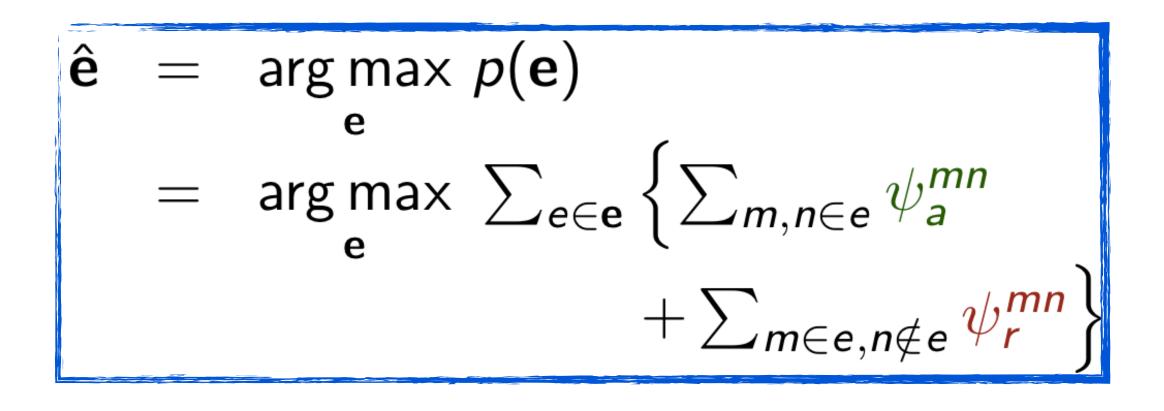
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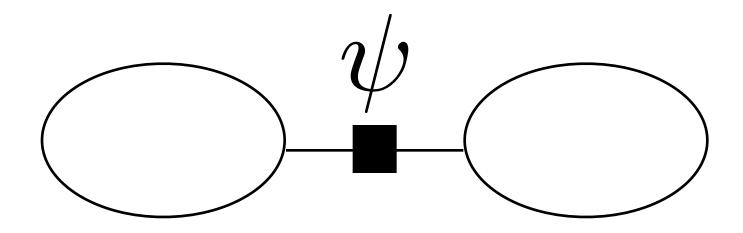


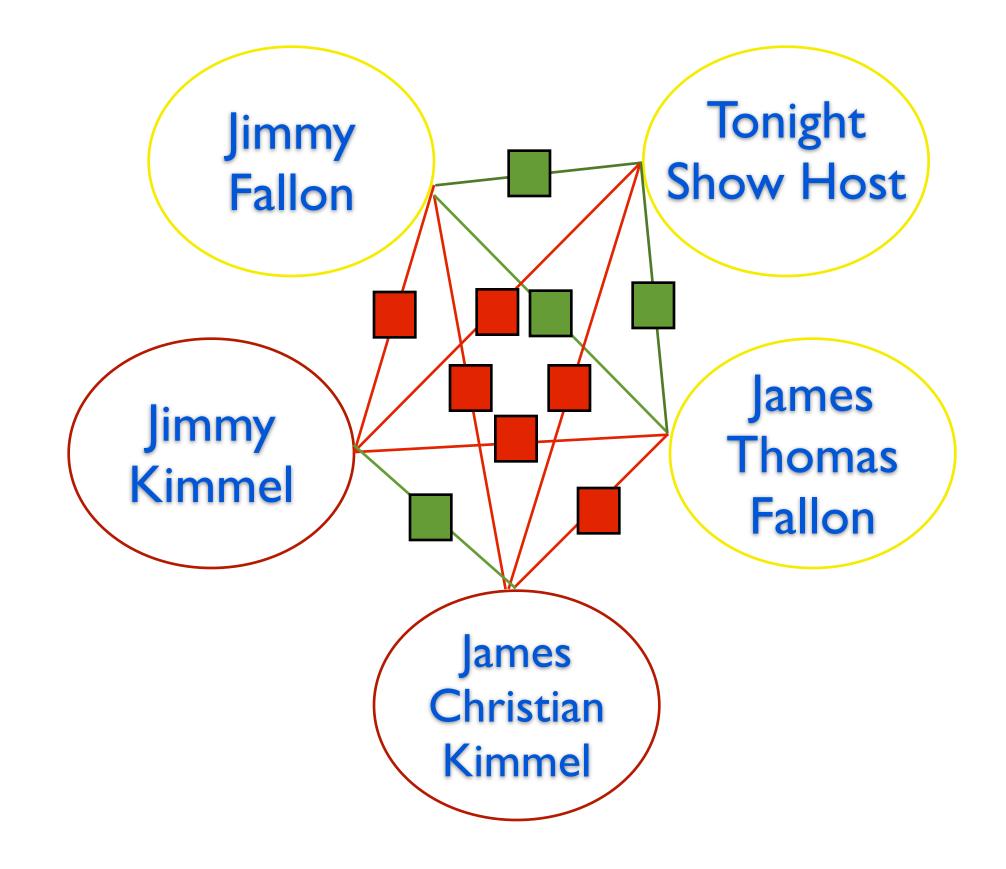




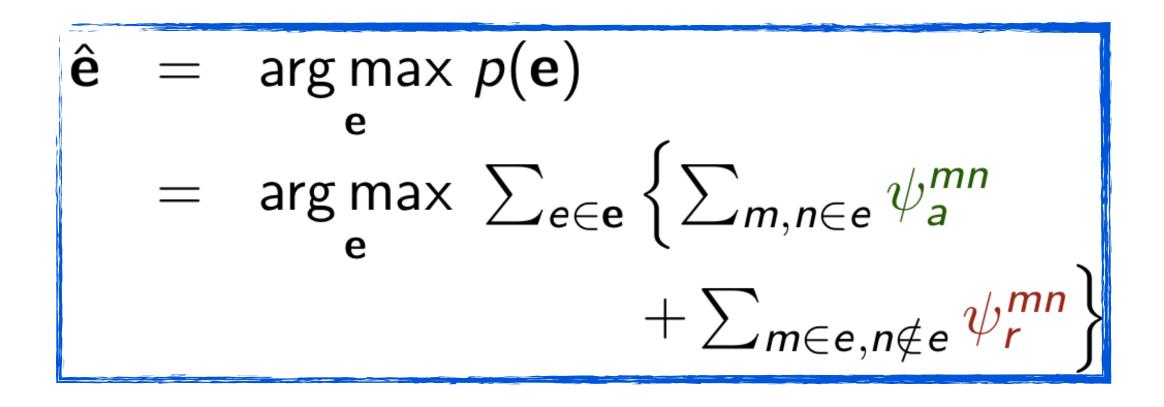


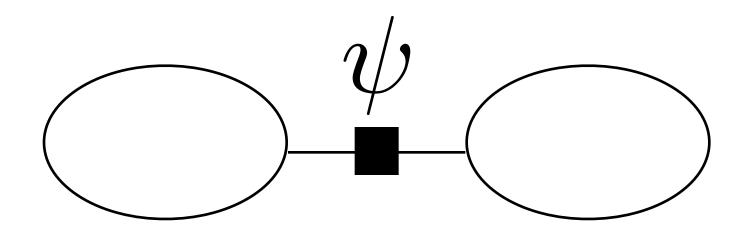


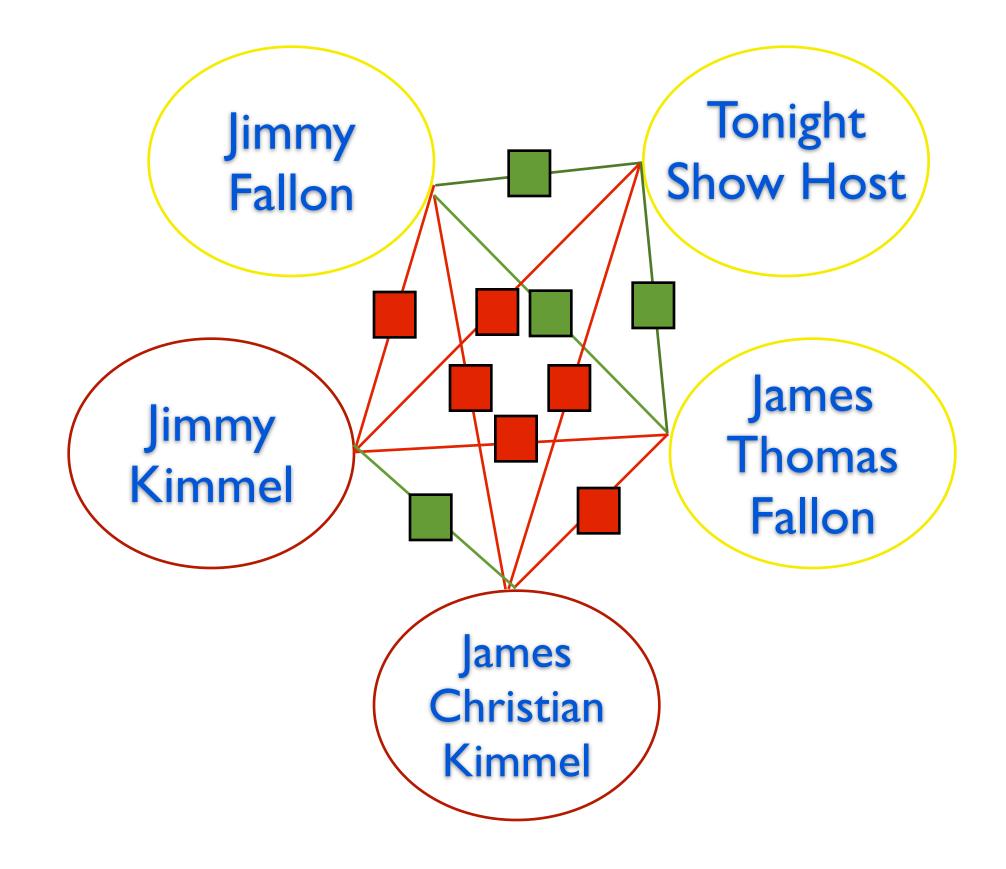




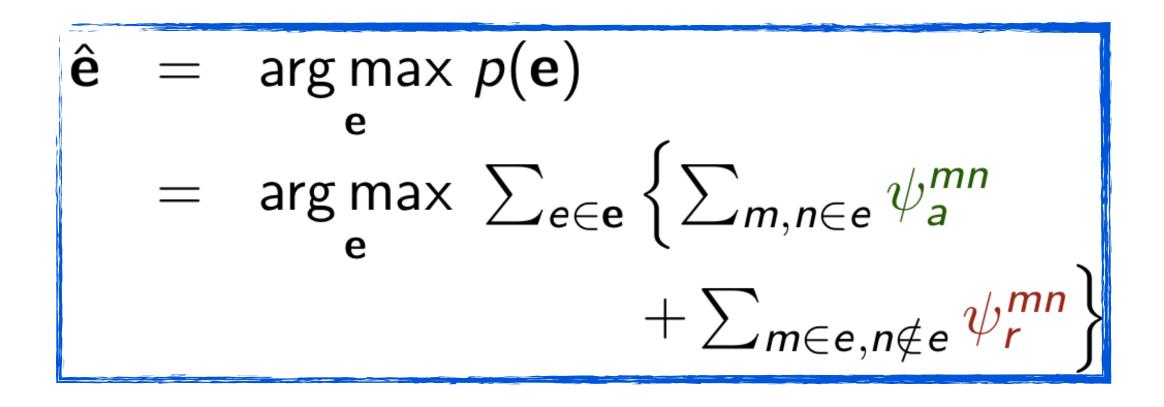
#### Find the best arrangement.

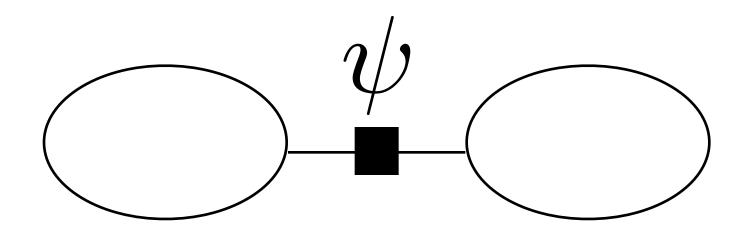


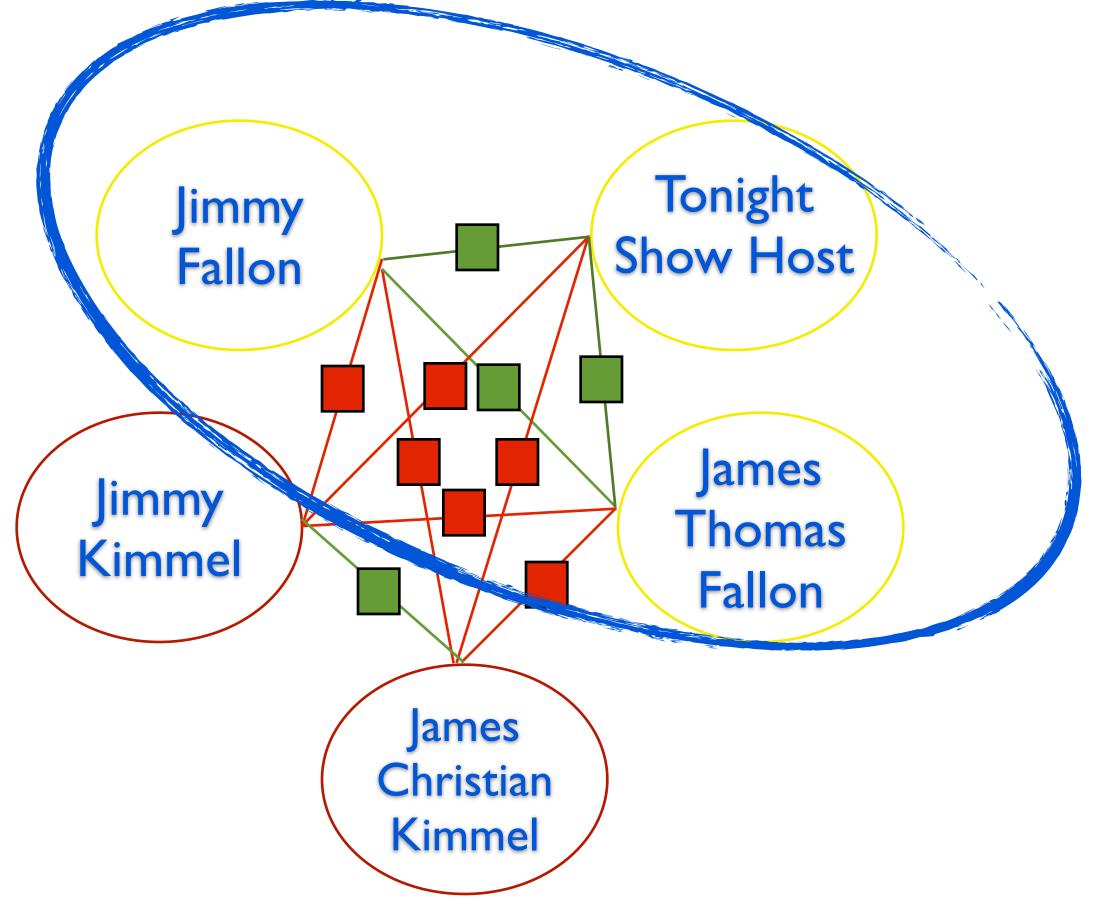




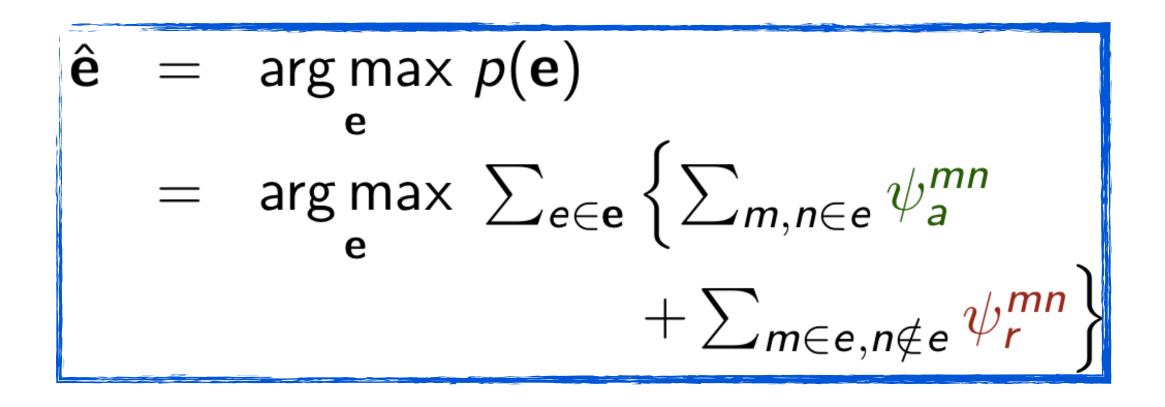
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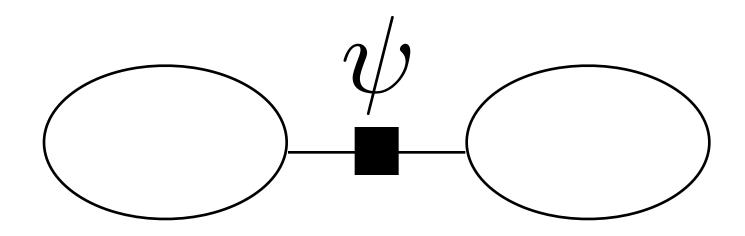


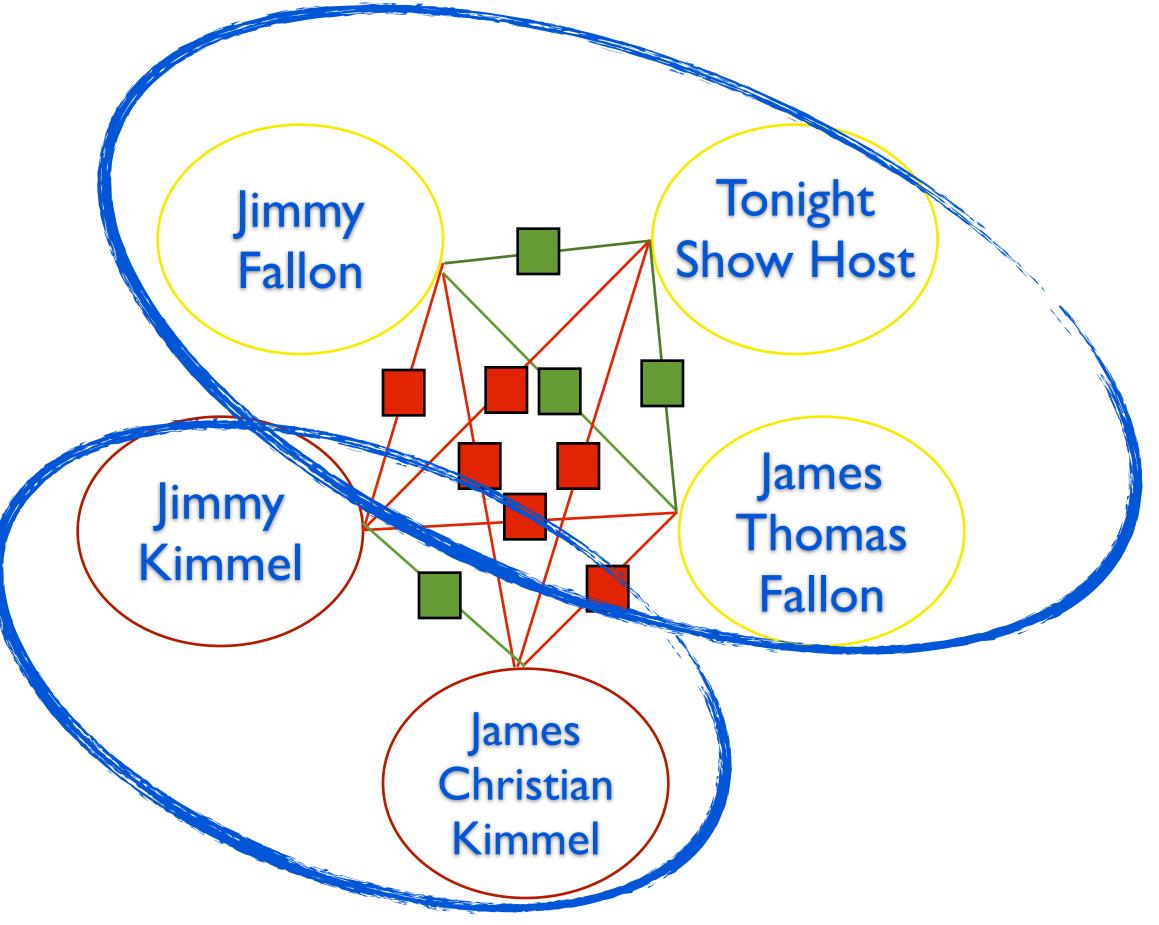




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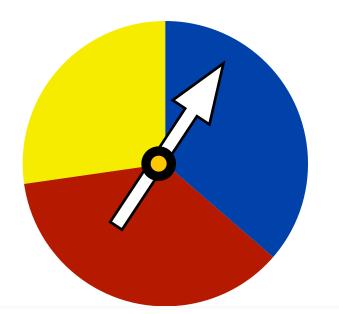


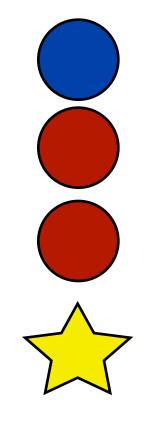
## Entity Resolution Algorithm

The Baseline ER metropolis hastings takes a random mention and adds it to a random entity.

# Entity Resolution Algorithm

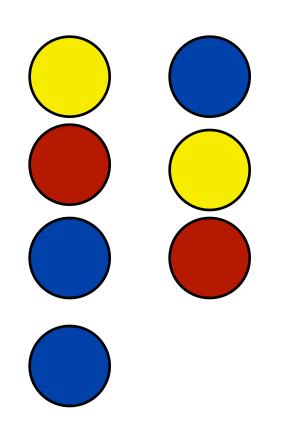
## mention and adds it to a random entity.



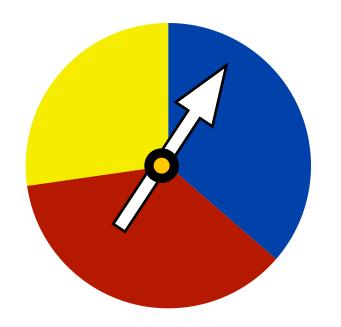


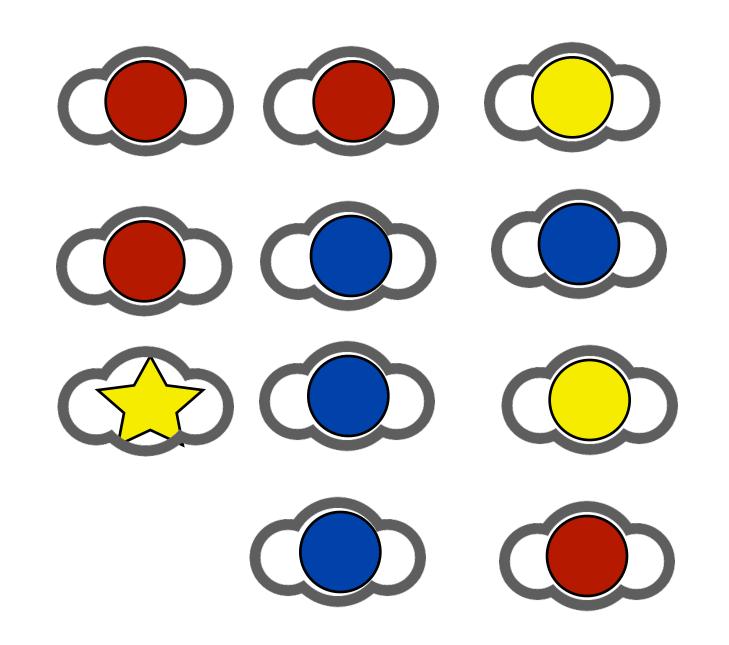
#### Random Number Generator

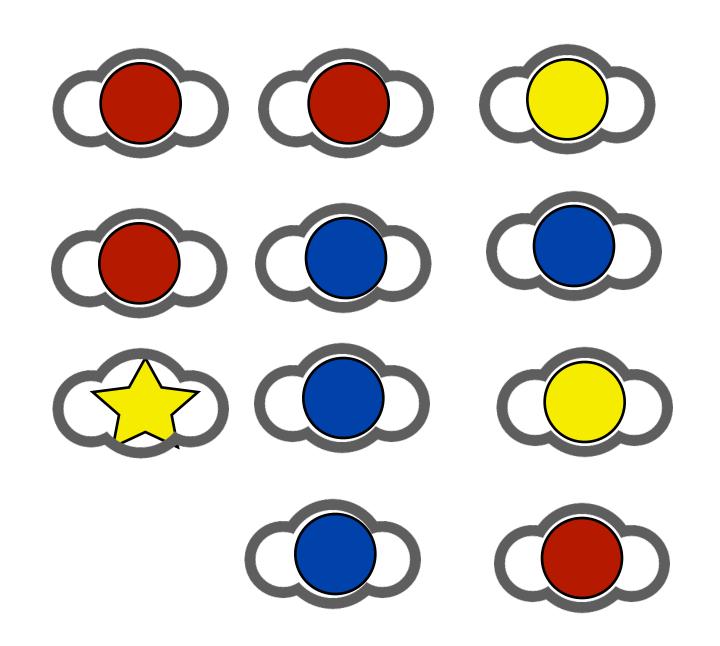
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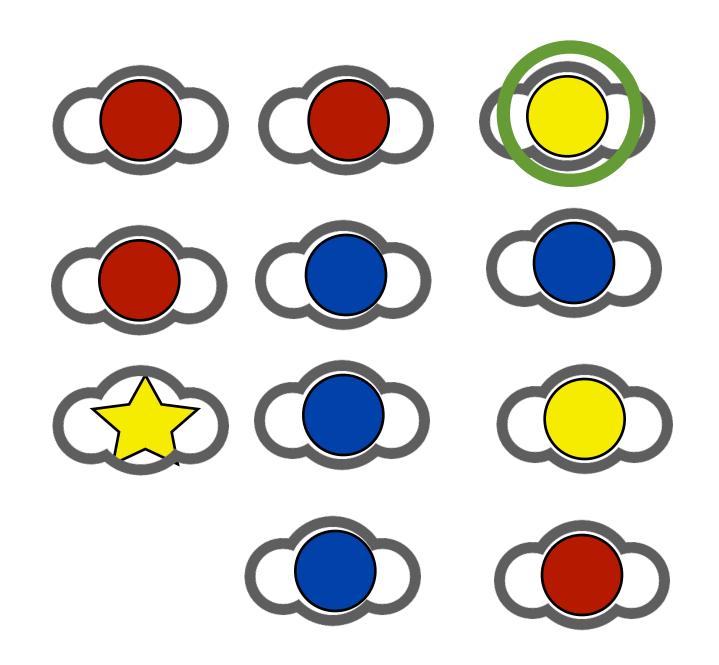






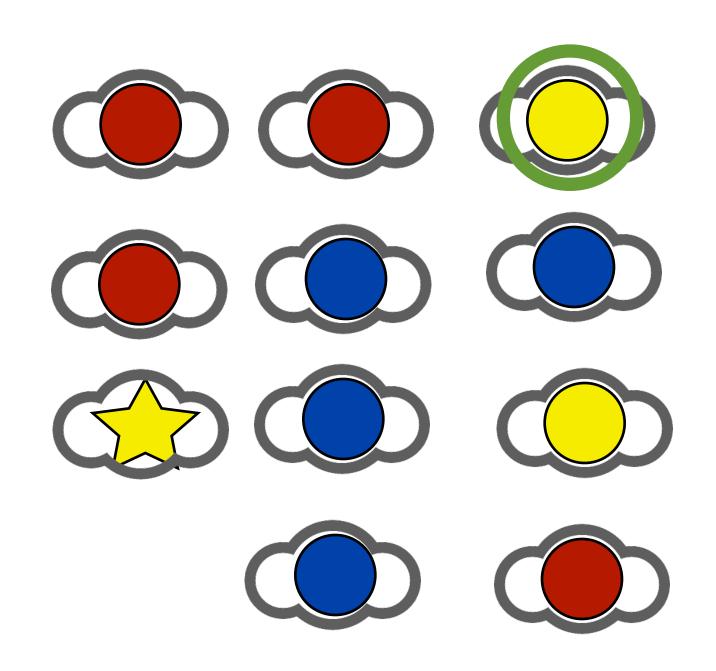


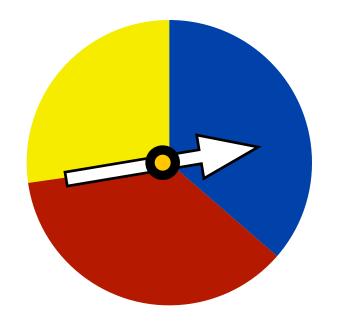
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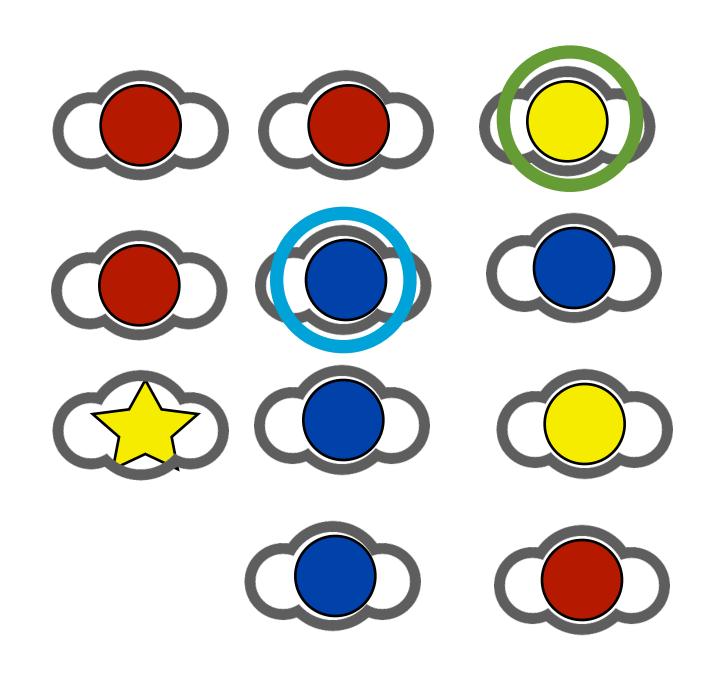


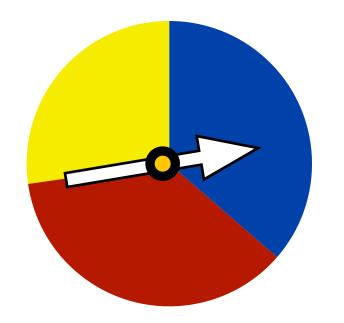
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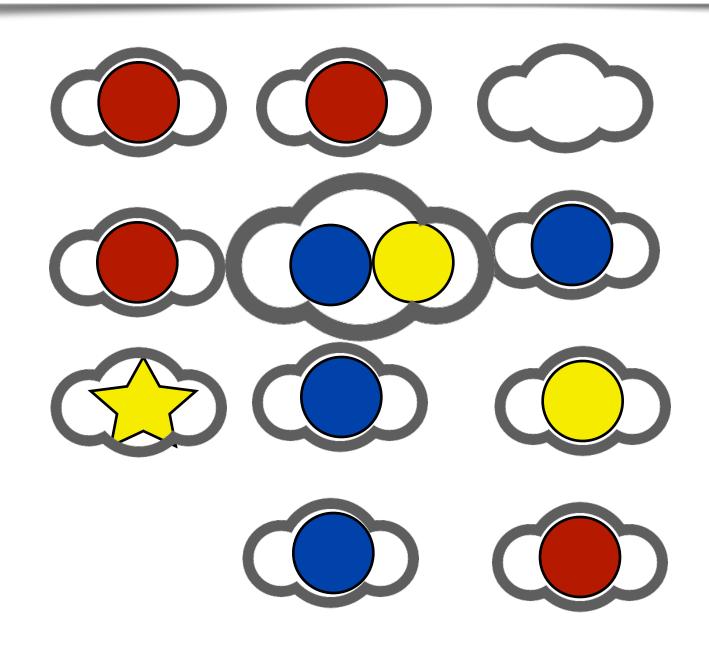


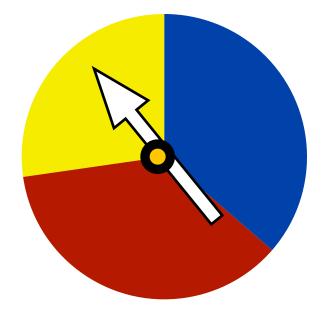
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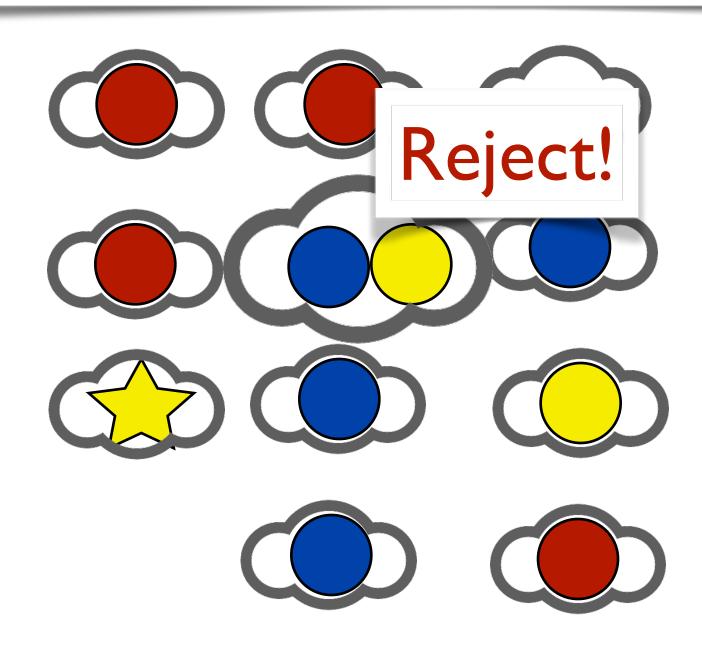


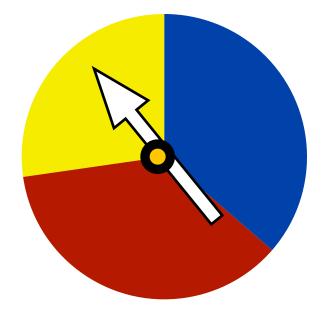


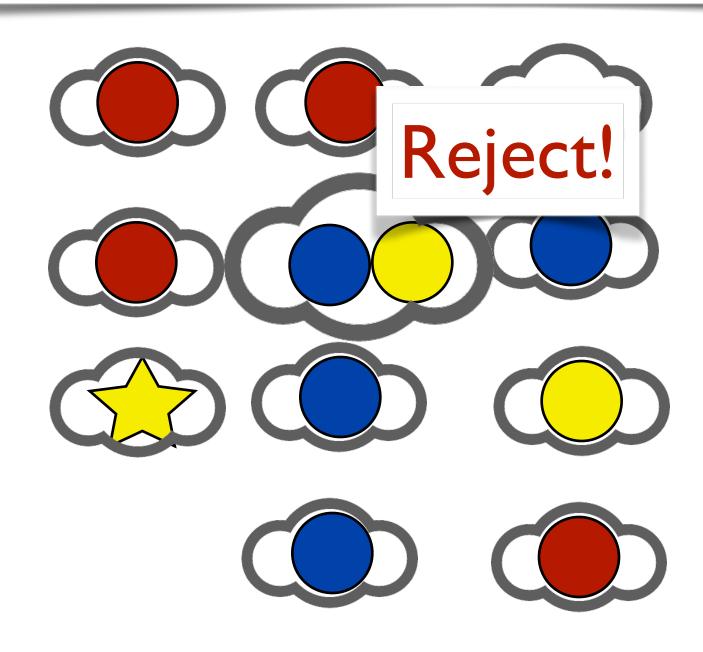
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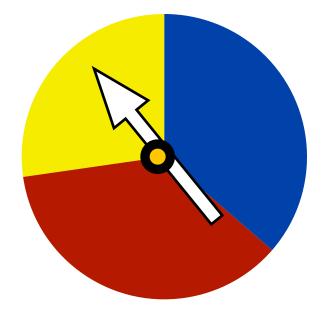




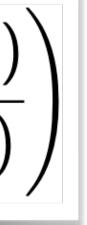


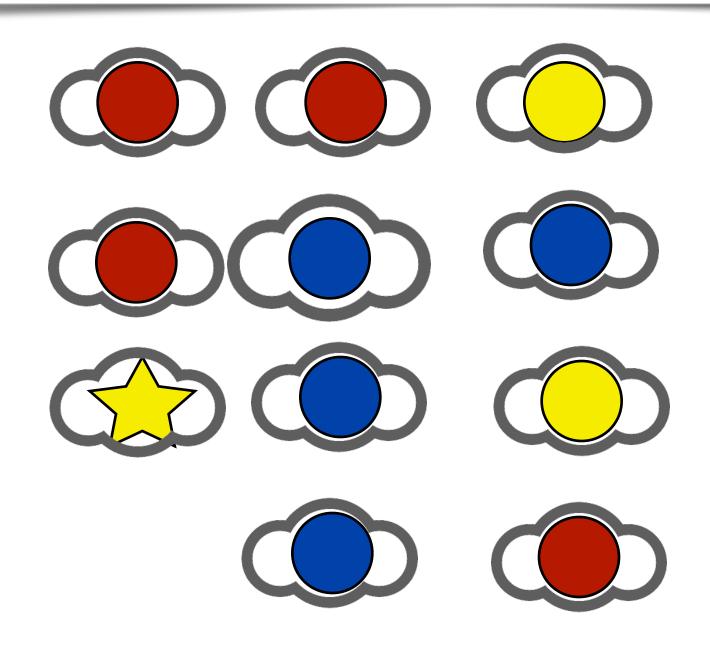


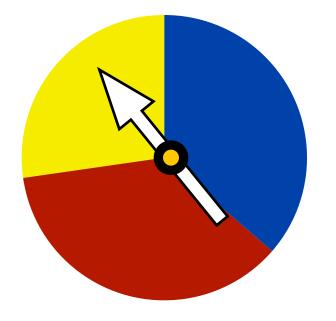


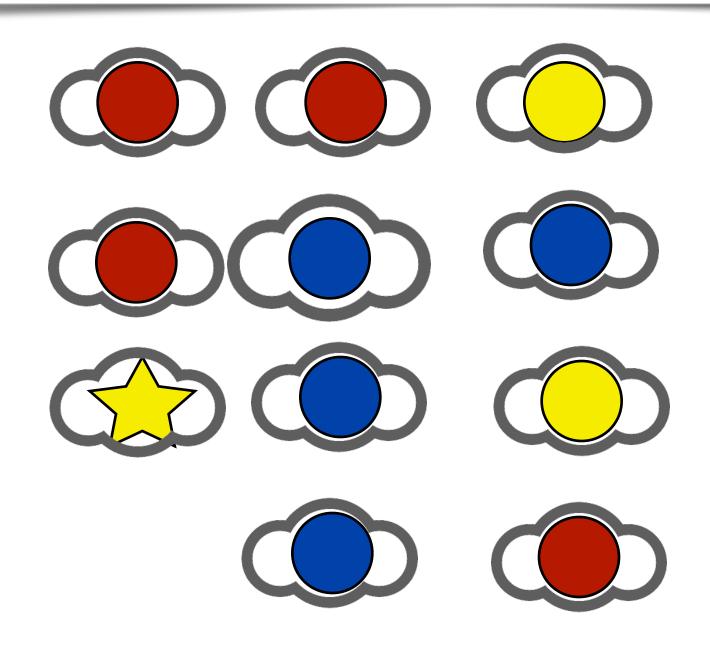


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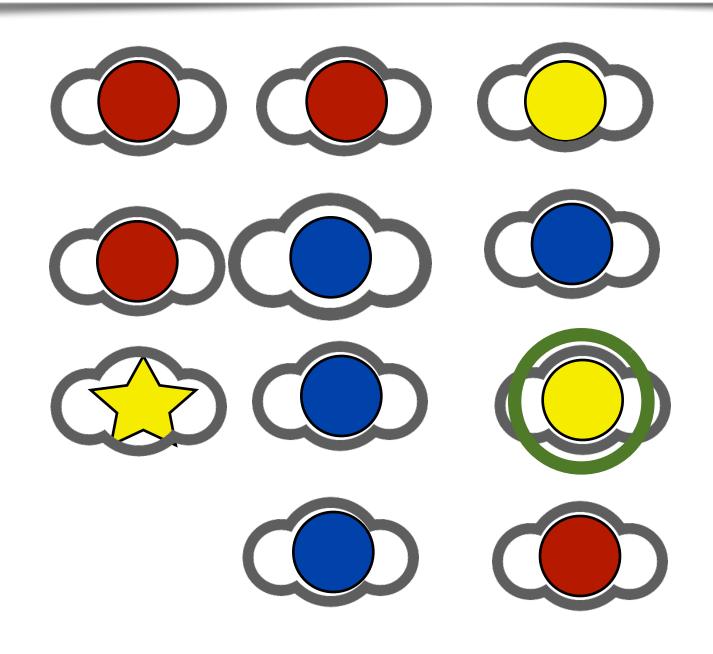




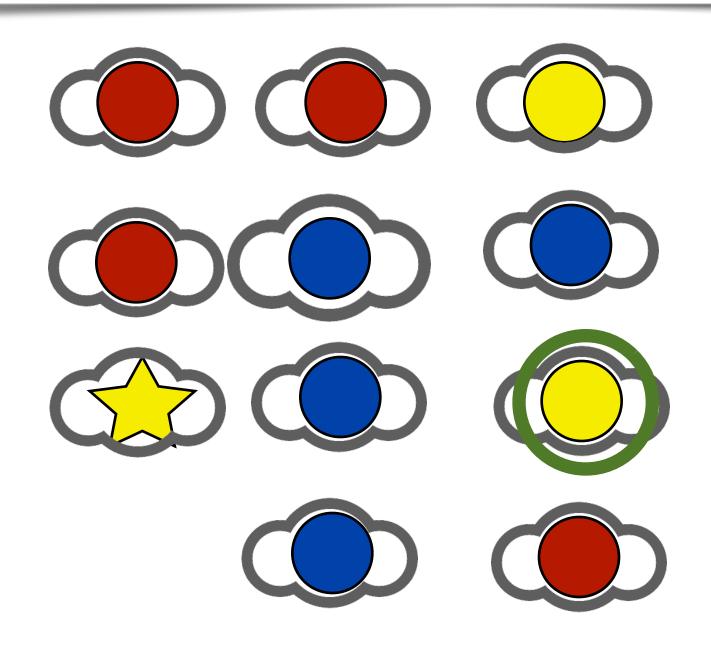


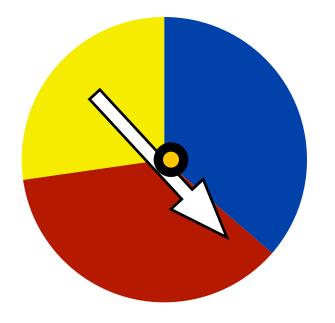


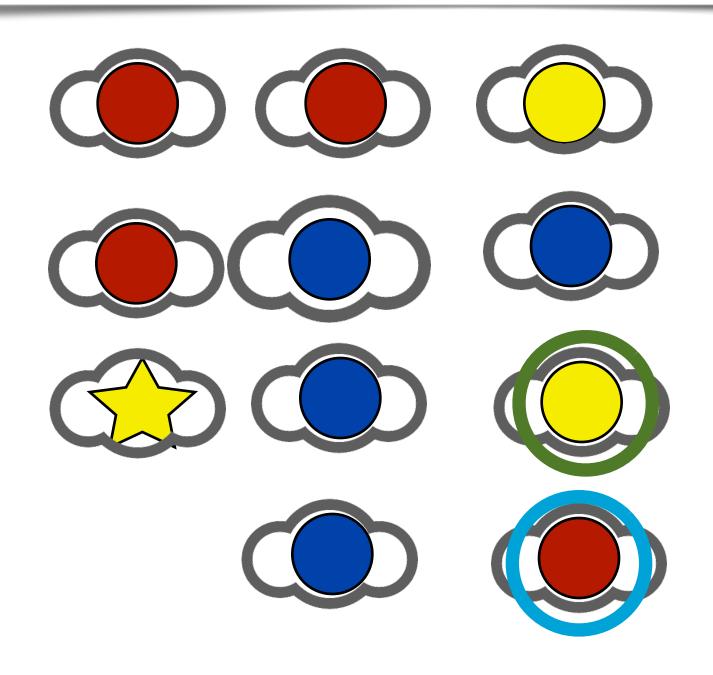


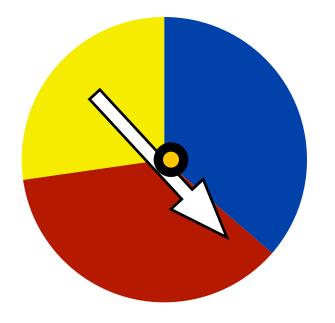


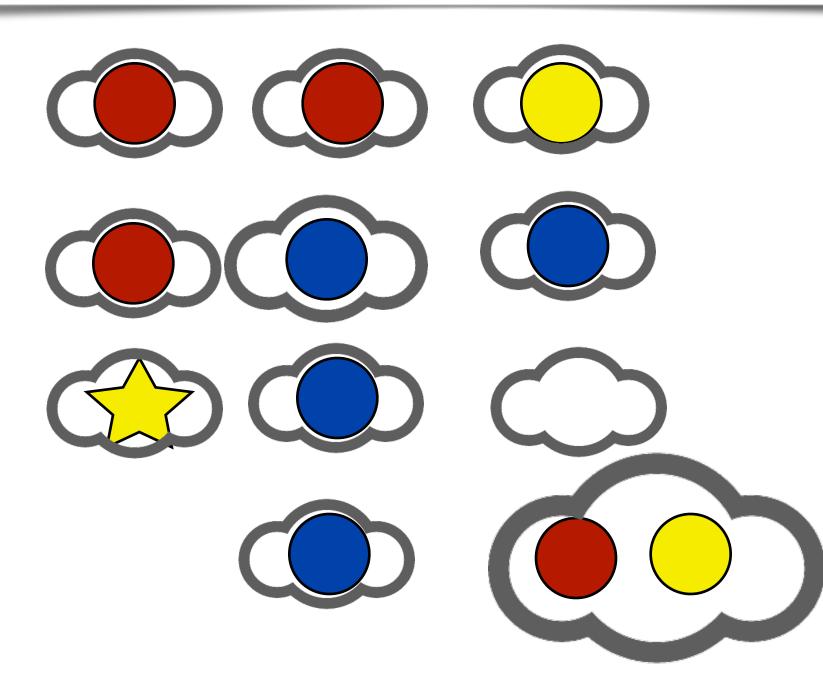


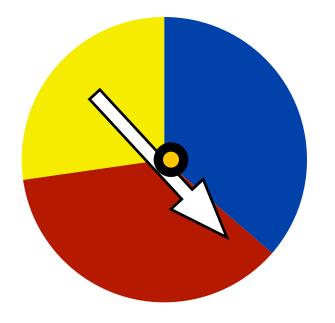


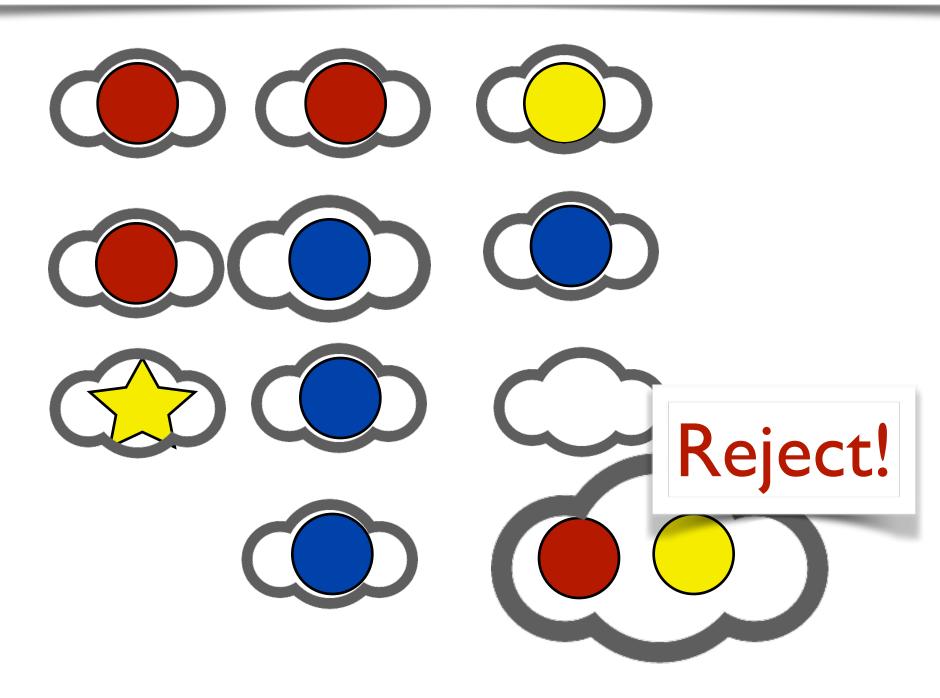


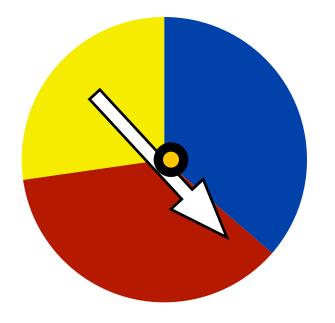


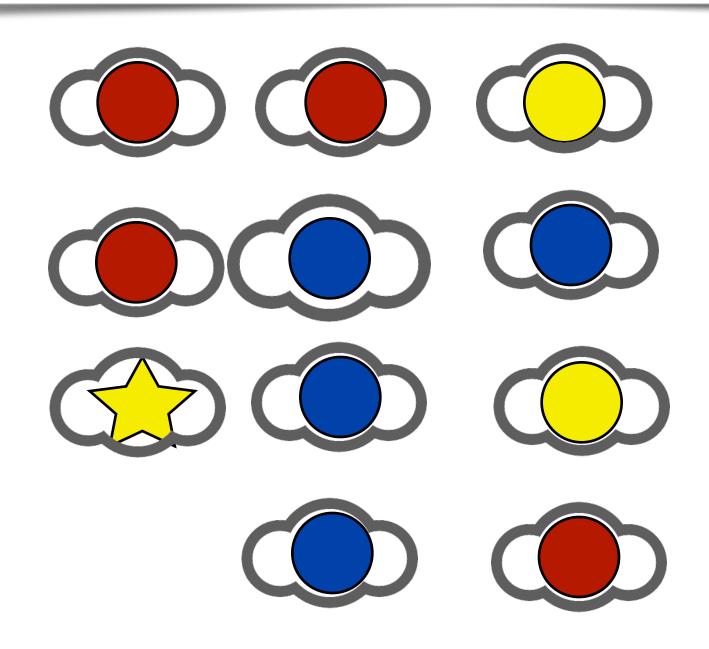


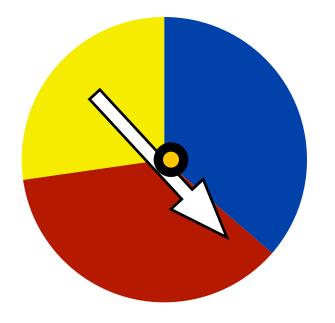


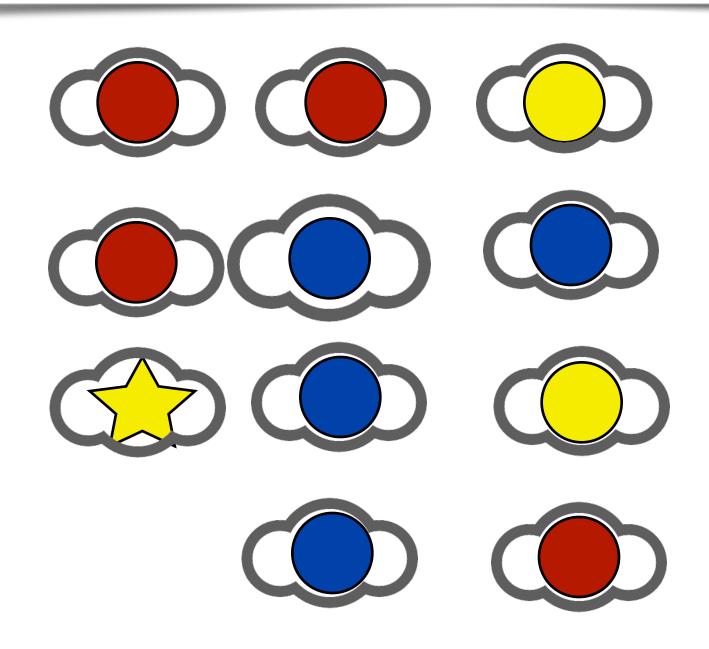


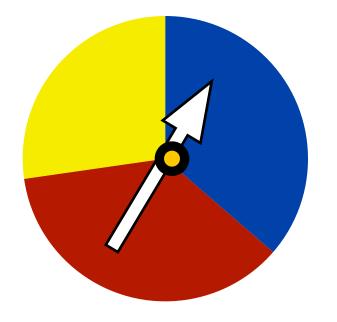


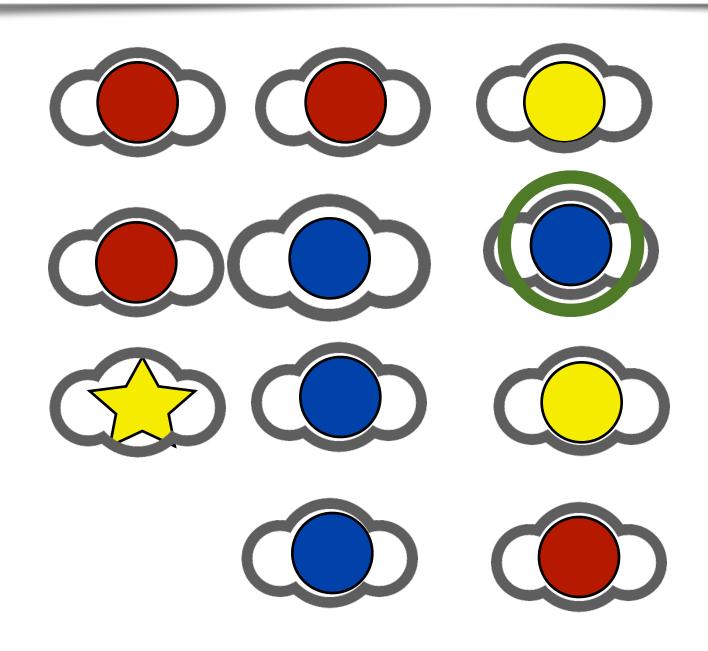


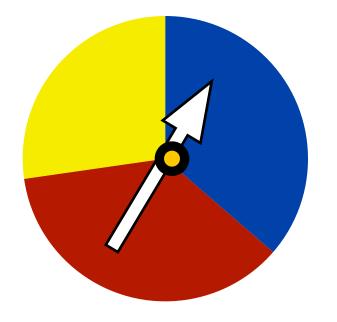


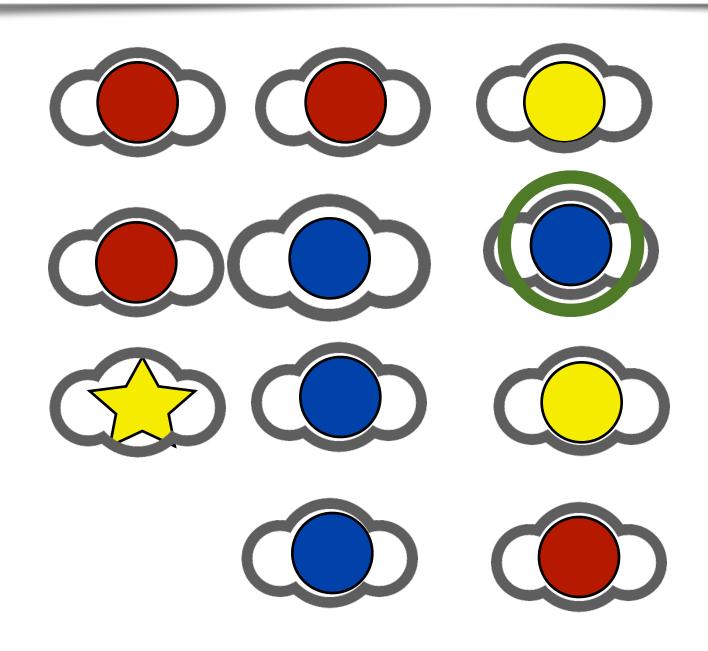


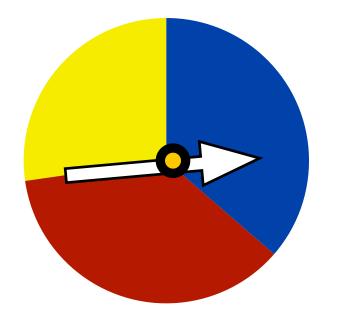


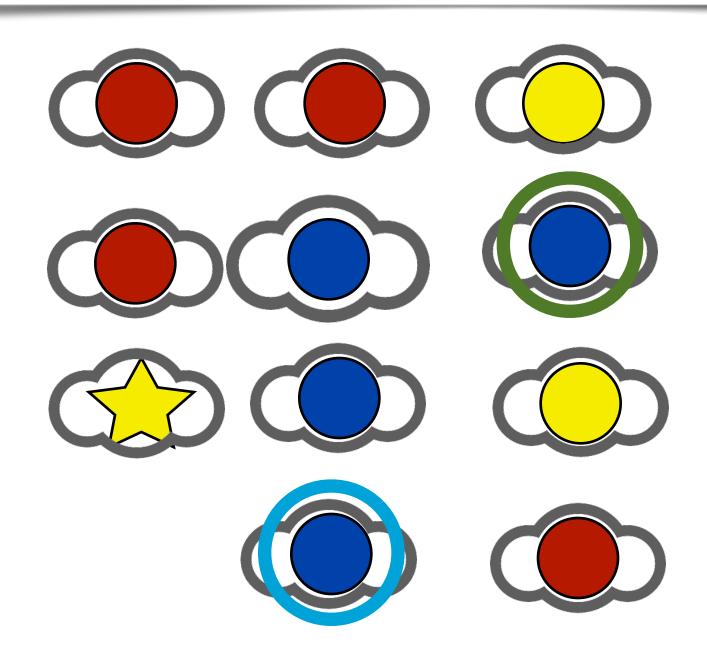


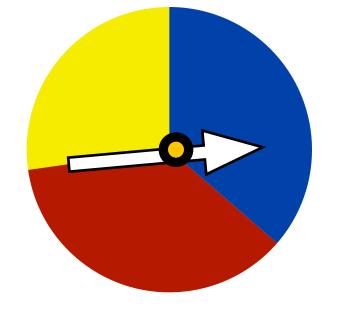




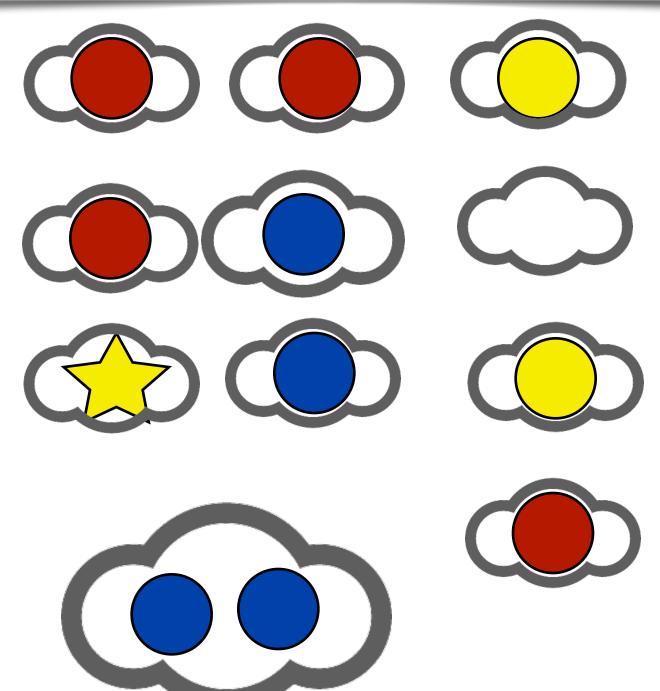


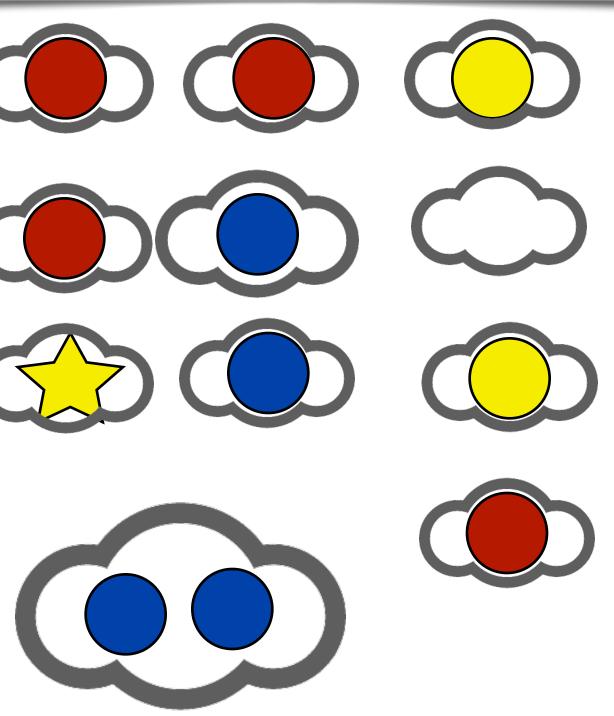


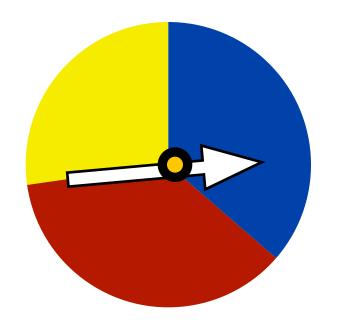




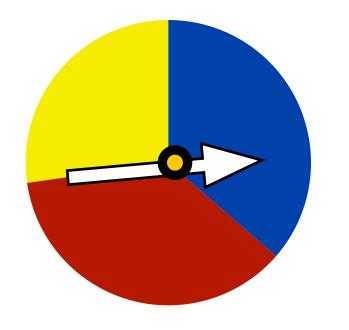
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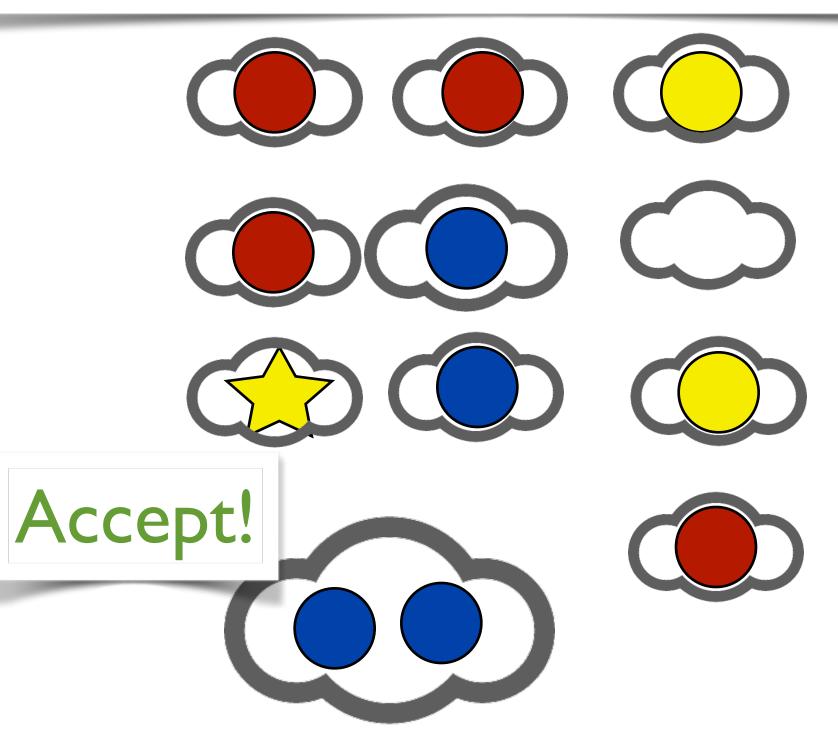




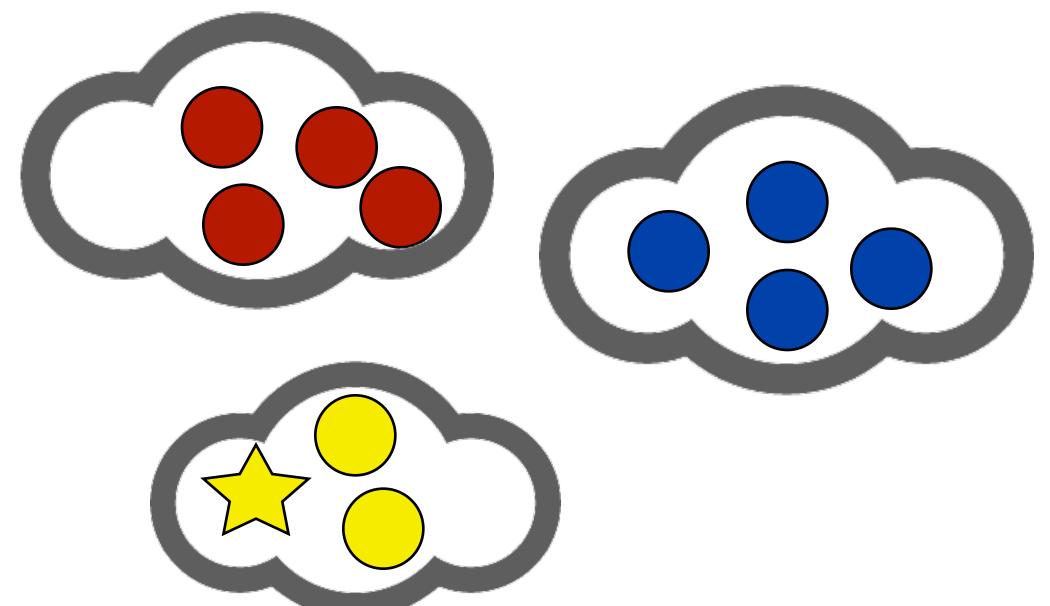


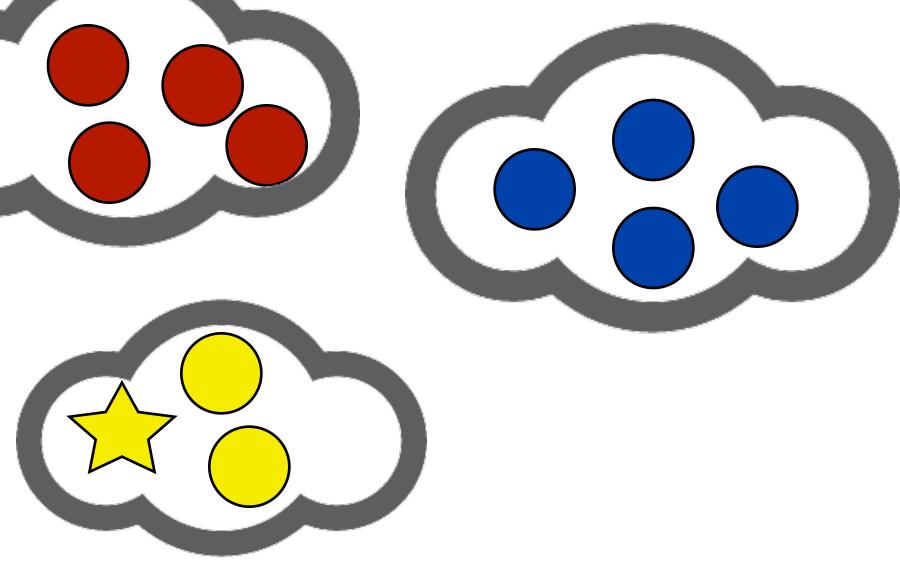
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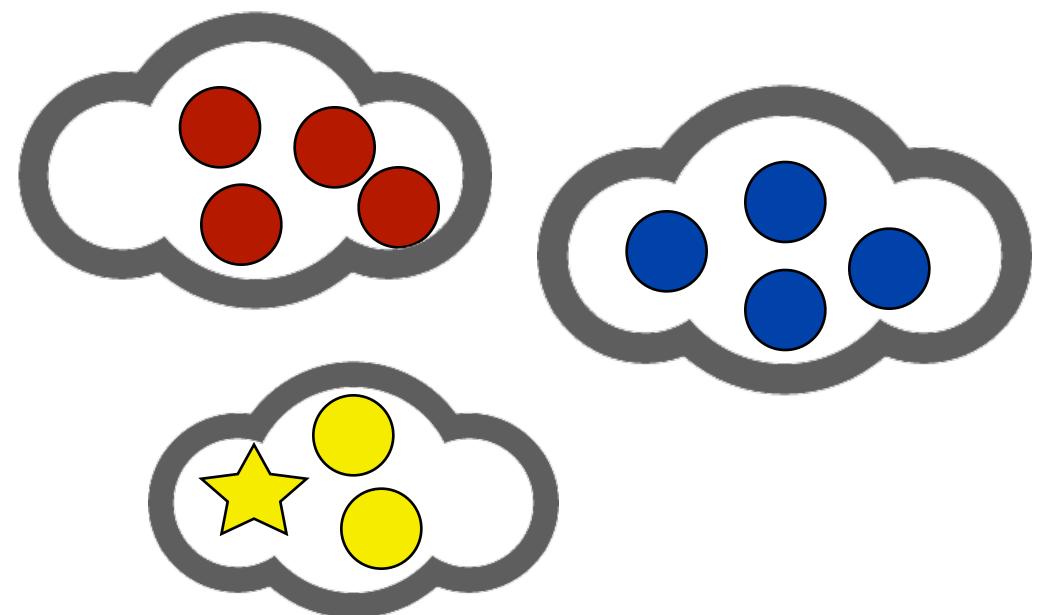


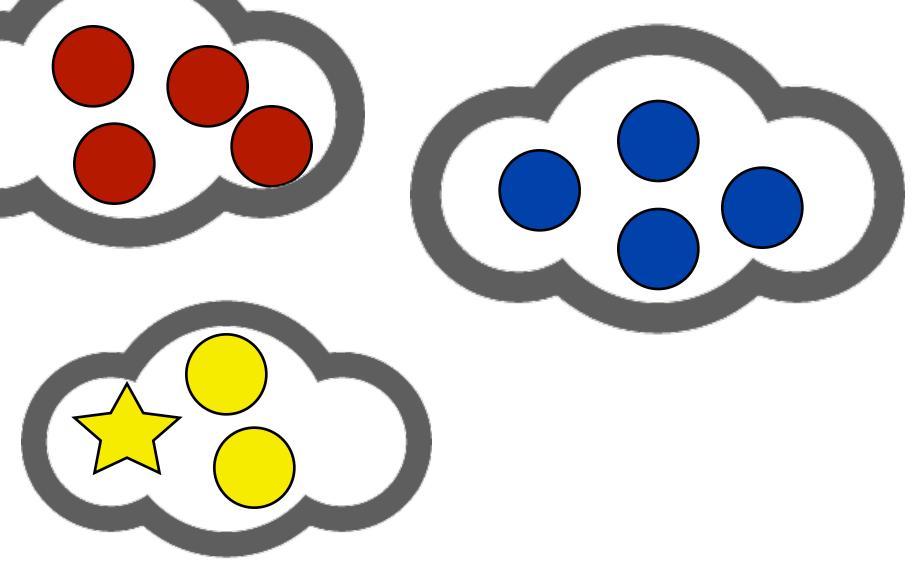
### Eventually **converges**. (State does not oscillate or vary)





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### Markov Chain Monte Carlo Metropolis Hastings!

# Sampling Optimizations

### Distributed Computations (Singh et al. 2011)

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### 1. Large clusters are the slowest.

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# Sampling Inefficiencies

 $\Theta(n^2)$ 

Entities such as *Carnegie Mellon* are relatively unambiguous.

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  - Pairwise comparisons are expensive.
- 2. Excessive computation on unambiguous entities

Streaming documents exacerbates these problems.

# Sampling Inefficiencies

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Database style optimizer for streaming MCMC.



Database style optimizer for streaming MCMC.

This optimizer makes two decisions:



Database style optimizer for streaming MCMC. This optimizer makes two decisions: 1. Can I approximate the state score calculation?



Database style optimizer for streaming MCMC. This optimizer makes two decisions: 1. Can I approximate the state score calculation? 2.Should I compress an Entity?



### Experiments

- Wikilink Data Set (Singh, Subramaniya, Pereira, McCallum, 2011)
  - Largest fully-labeled data set
  - 40 Million Mentions
  - 180 GBs of data

http://0009.org/blog/2010/07/31/ profiting-from-stolen-street-art/ Profiting From Stolen Street Art A Missing Wall ... highly collected street artist Banksy

apparently painted a mural...

http://lleven.net/tag/borito/

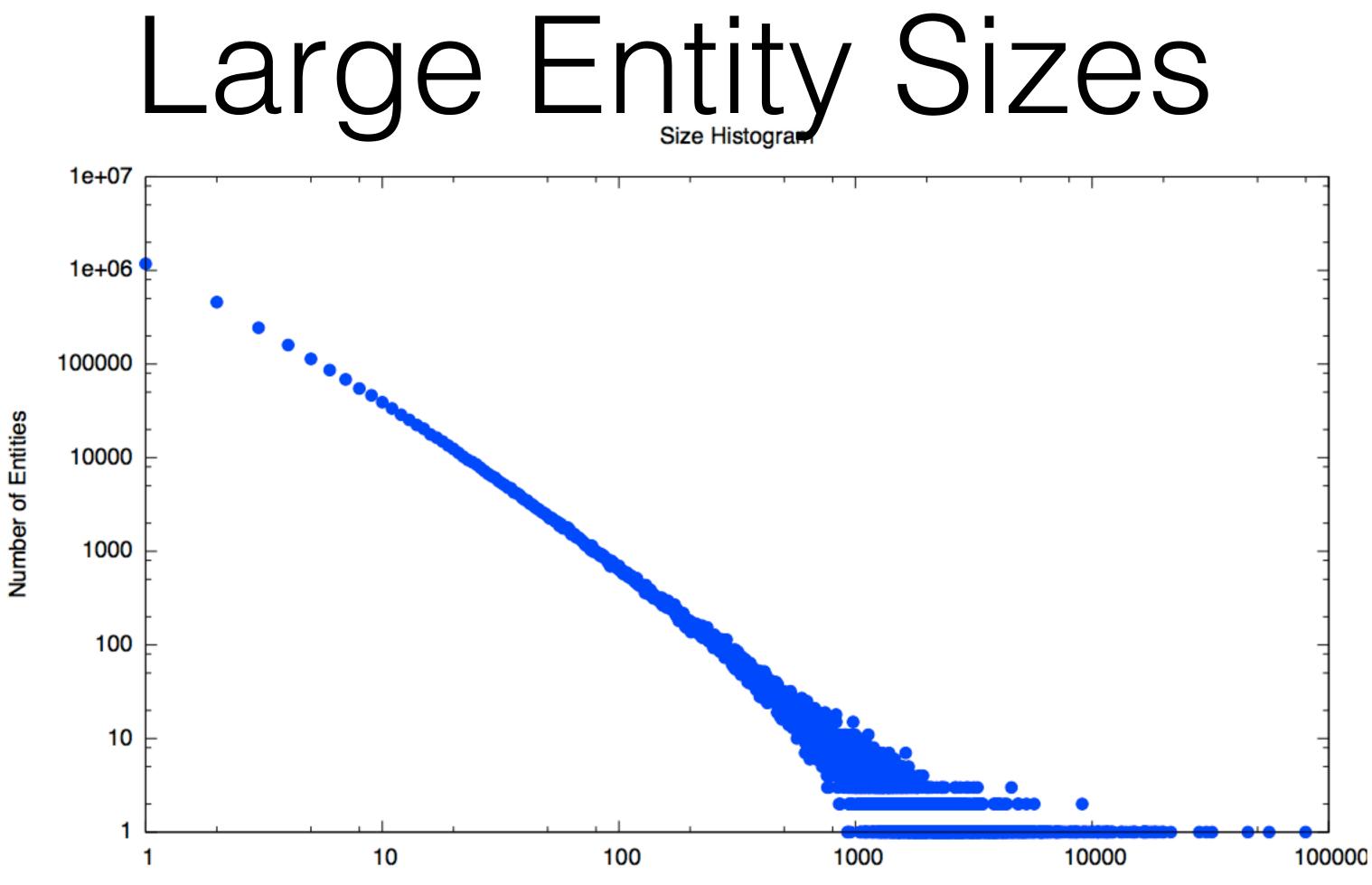
#### The Sunday Times x Banksy Cover March 4, 2010

... of The Sunday Times, artist Banksy did not only create the cover art, but ...

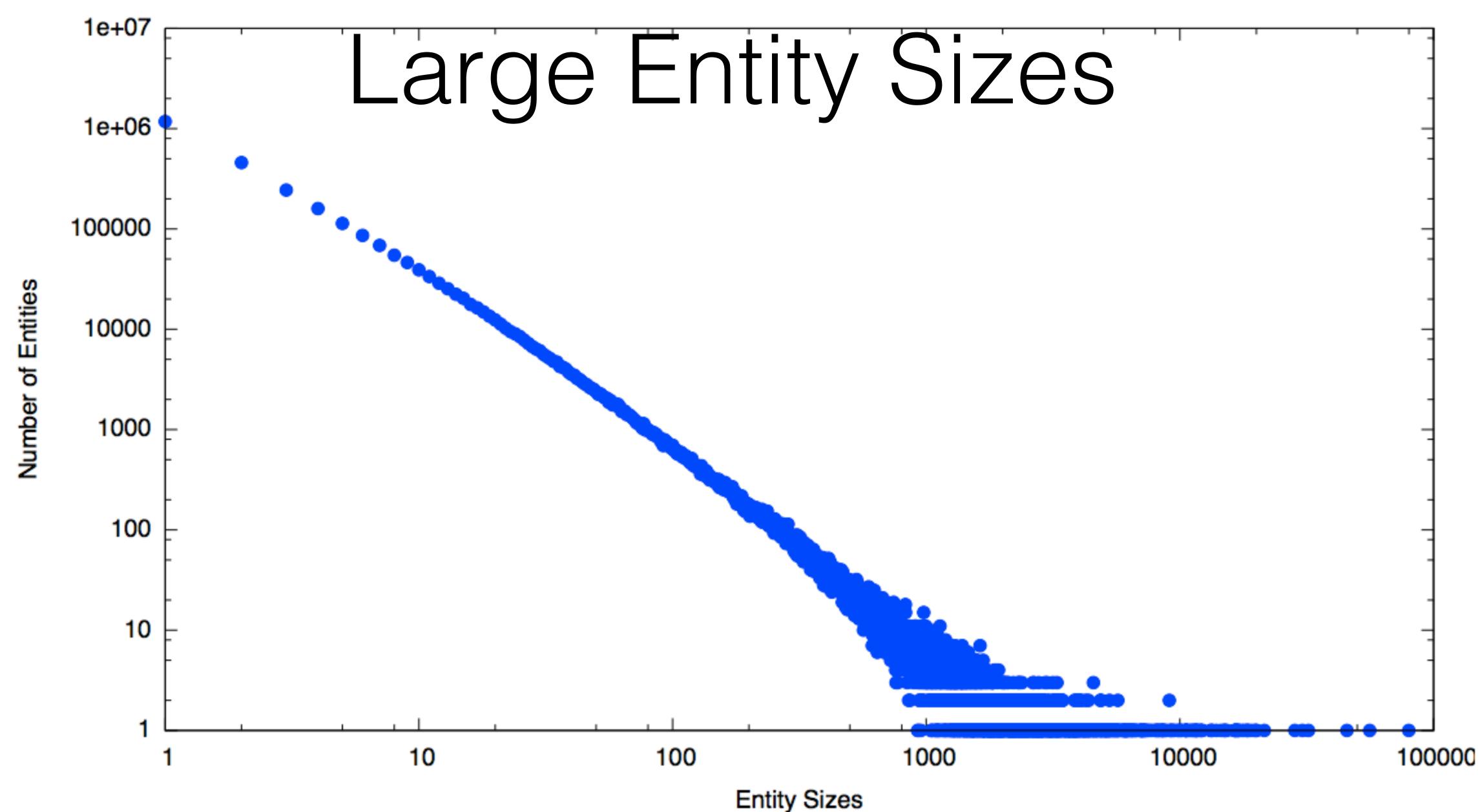
WIKIPEDIA The Free Encyclopedia

Figure 1: Links to Wikipedia as Entity Labels





**Entity Sizes** 



Size Histogram



Known matches can be compressed into a representative mention.

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- Entity compression can reduce the number of mentions (*n*).

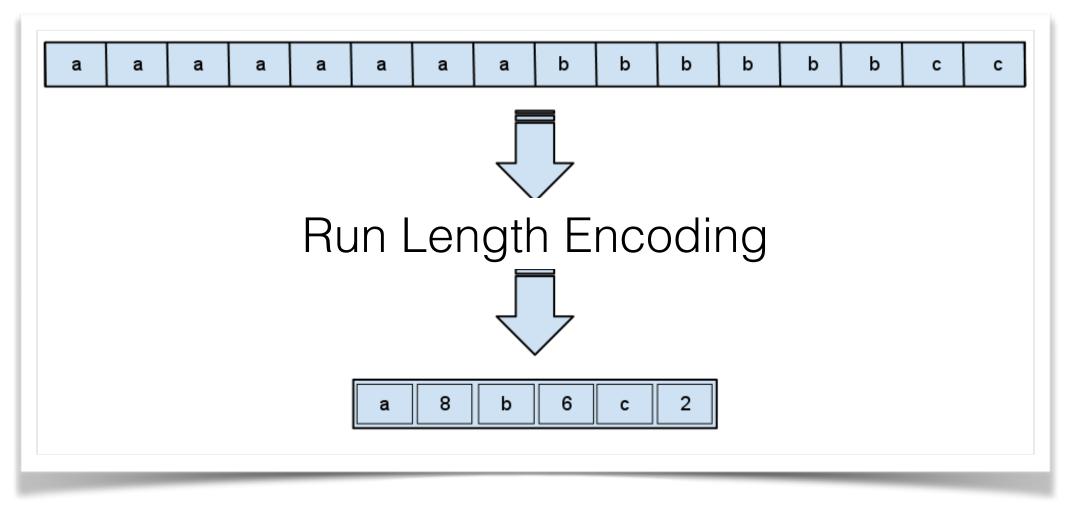
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- Entity compression can reduce the number of mentions (*n*).
- Compression of large and *popular* entities is costly.
- Compression errors are permanent.

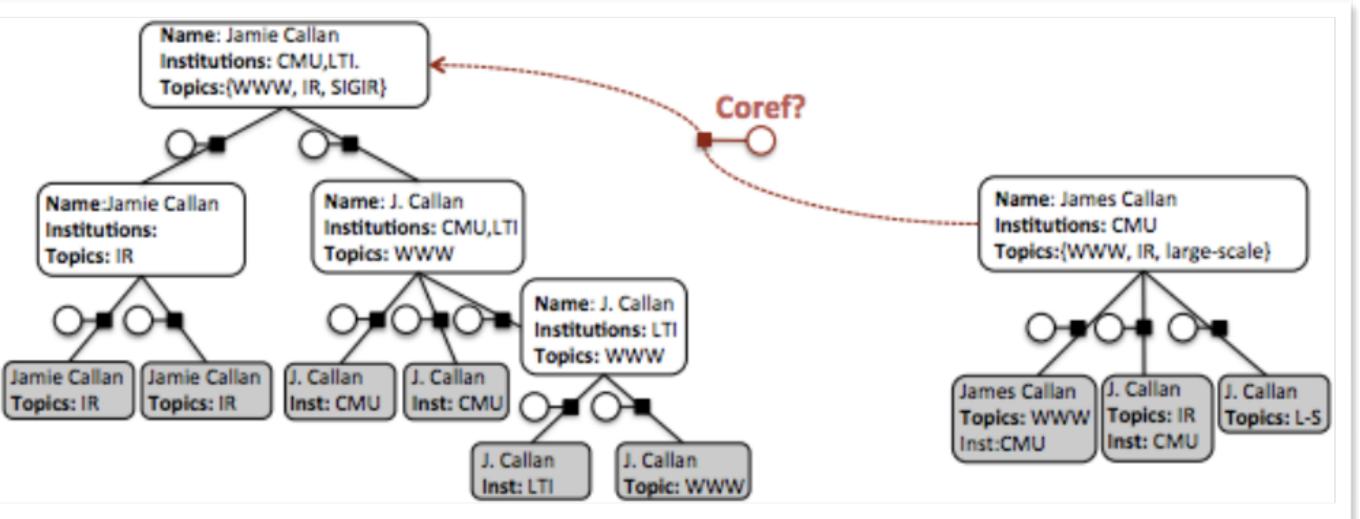
# Compression Types

- Run-Length Encoding
- Hierarchical Compression (Wick et al.)



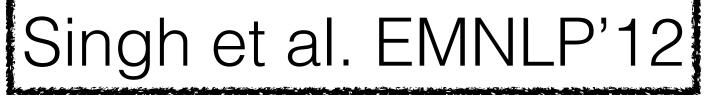






# Early Stopping

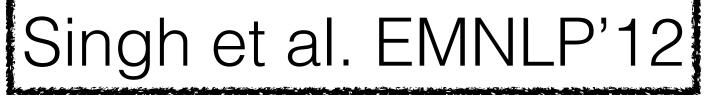
 Can we estimate the computation of the features?





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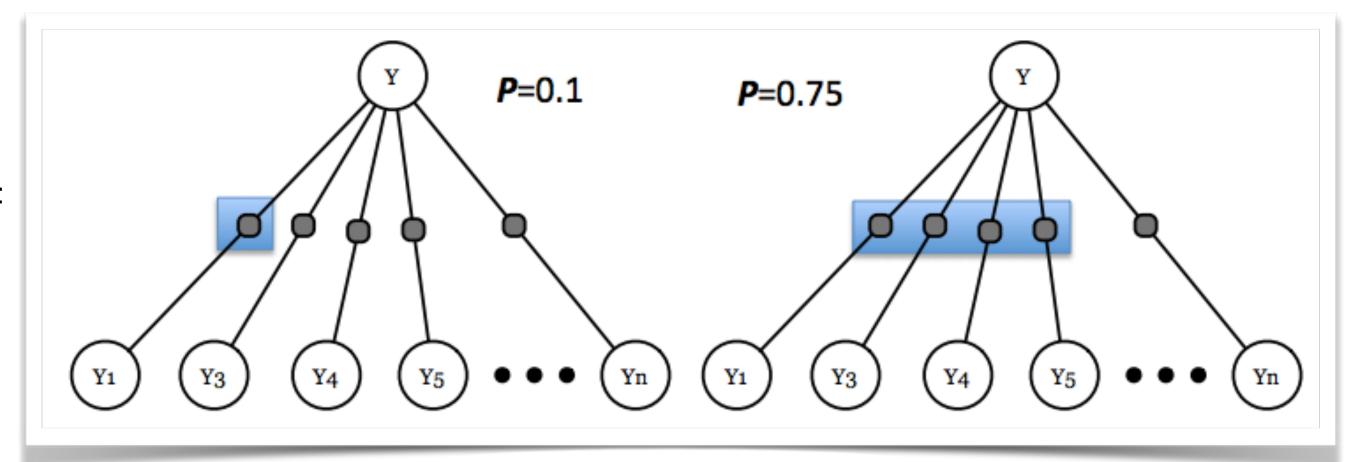
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- Given a *p* value, randomly select less values.





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- Given a *p* value, randomly select less values.



Singh et al. EMNLP'12



#### Optimizer

#### Current work

- 1. Classifier for deciding when to perform *early stopping*.
- 2. Classifier for the decision to *compress*.

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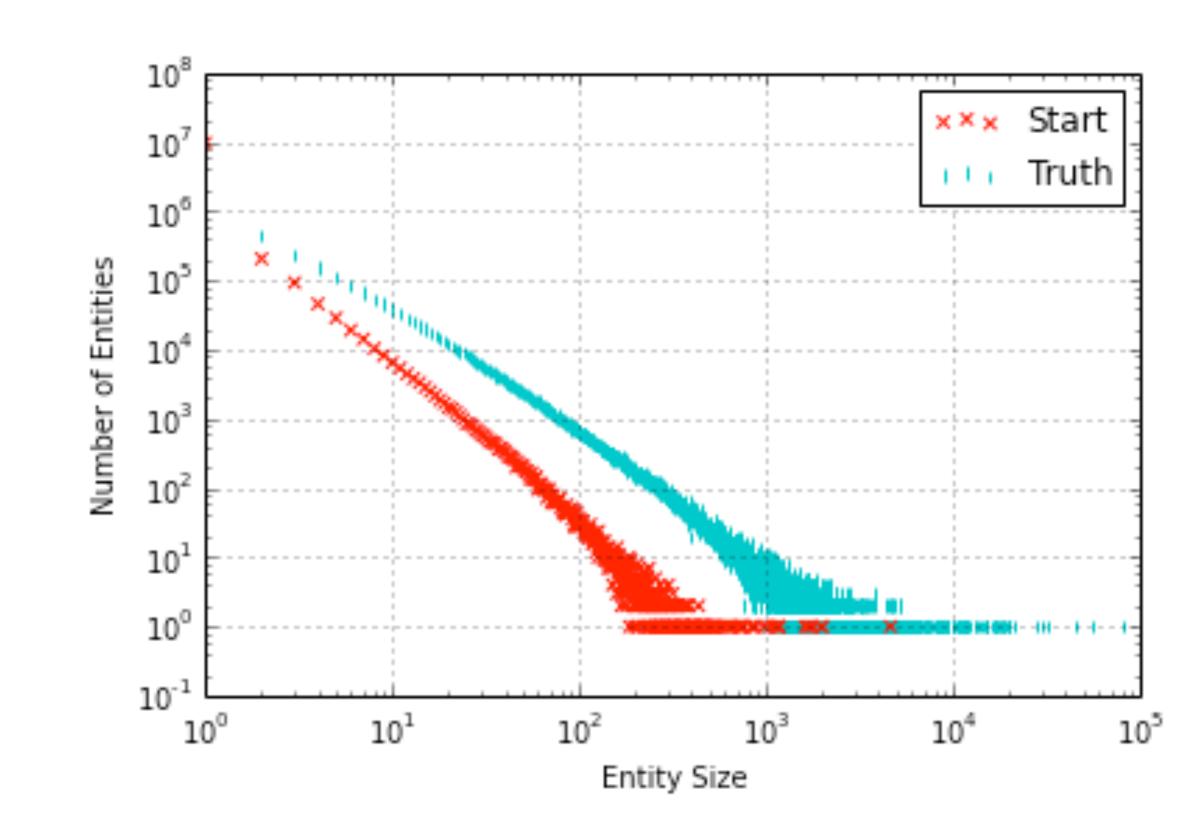
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Examining the Wiki Link data set.

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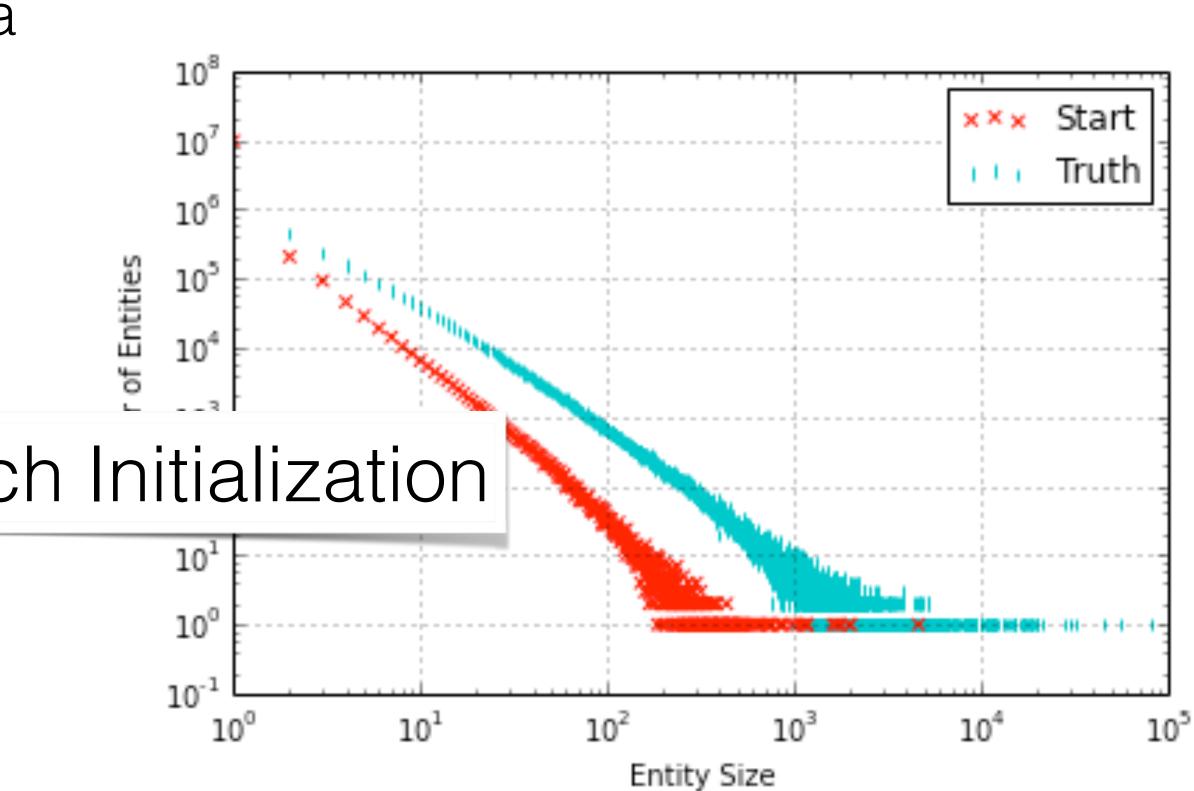
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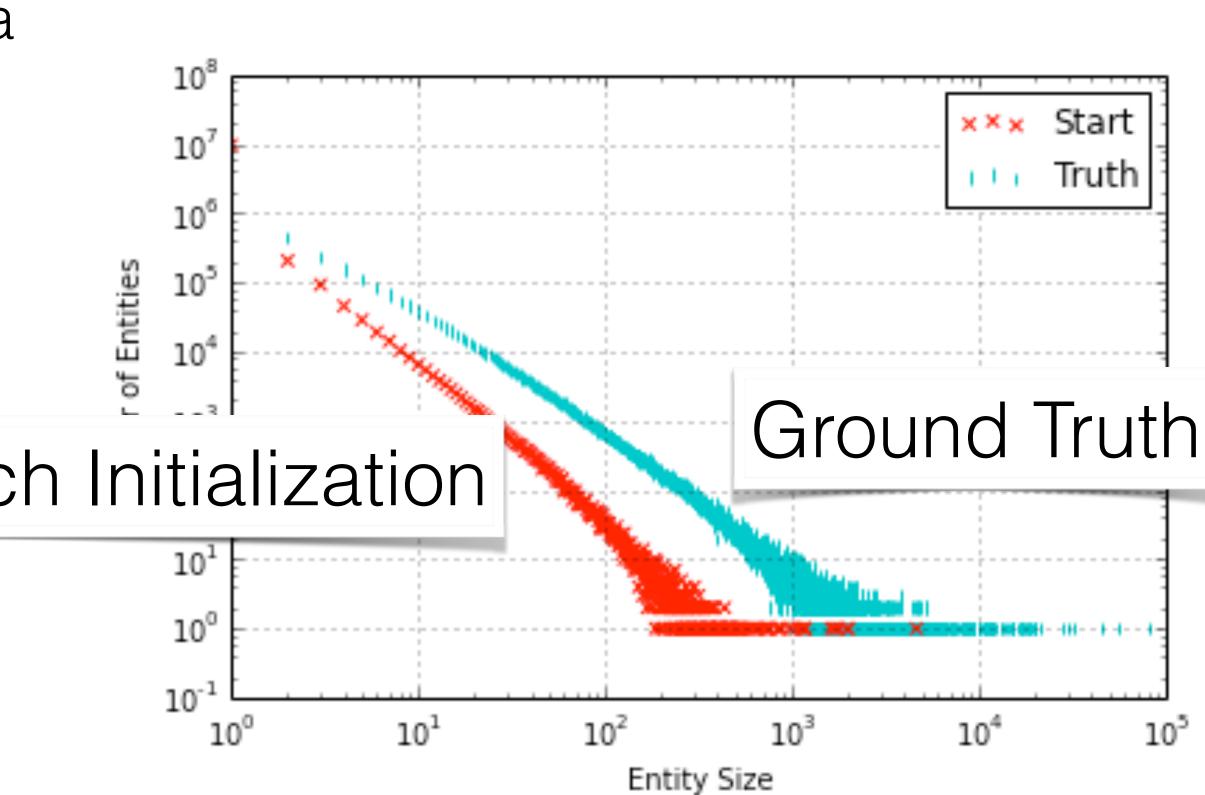
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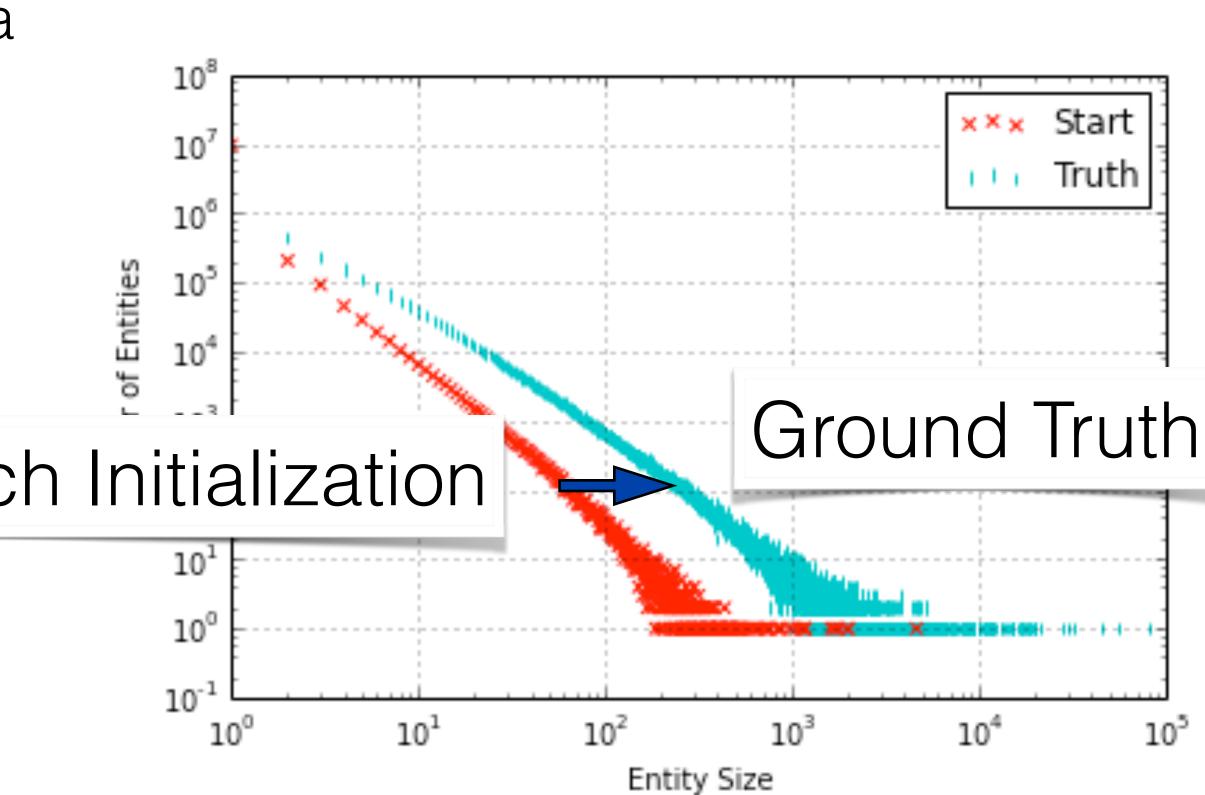
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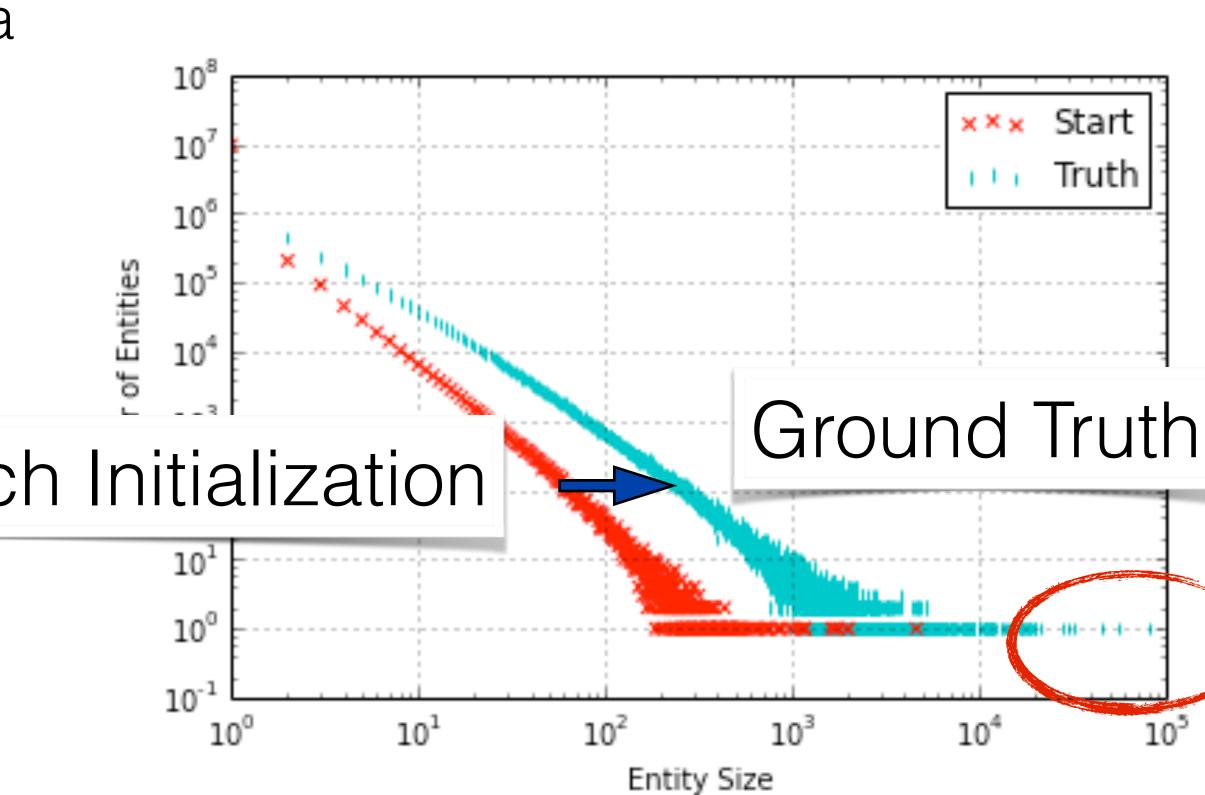
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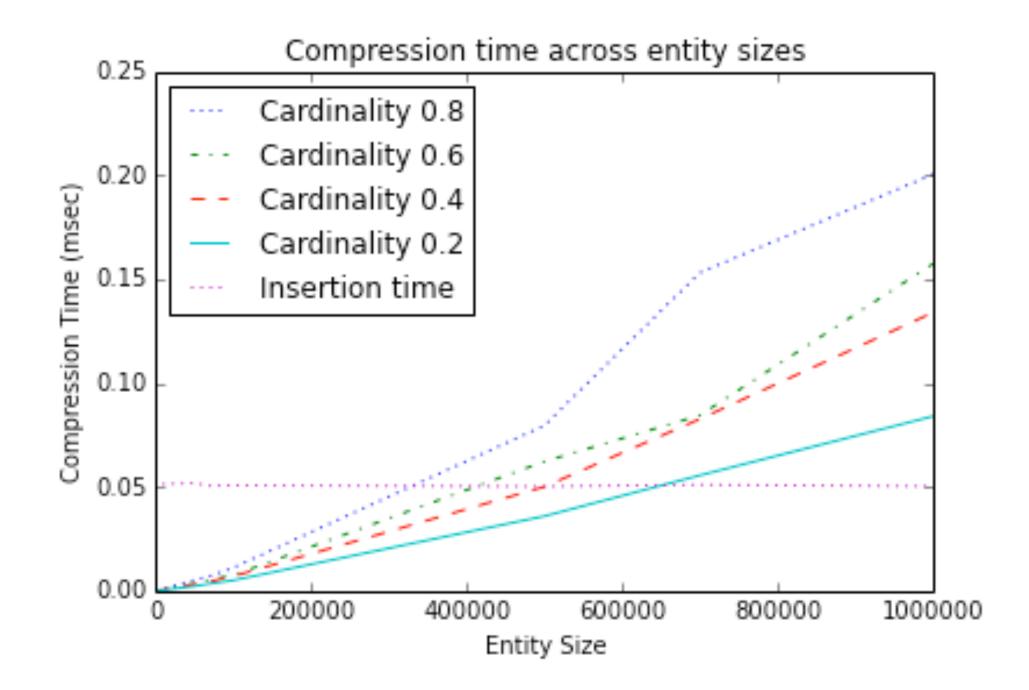
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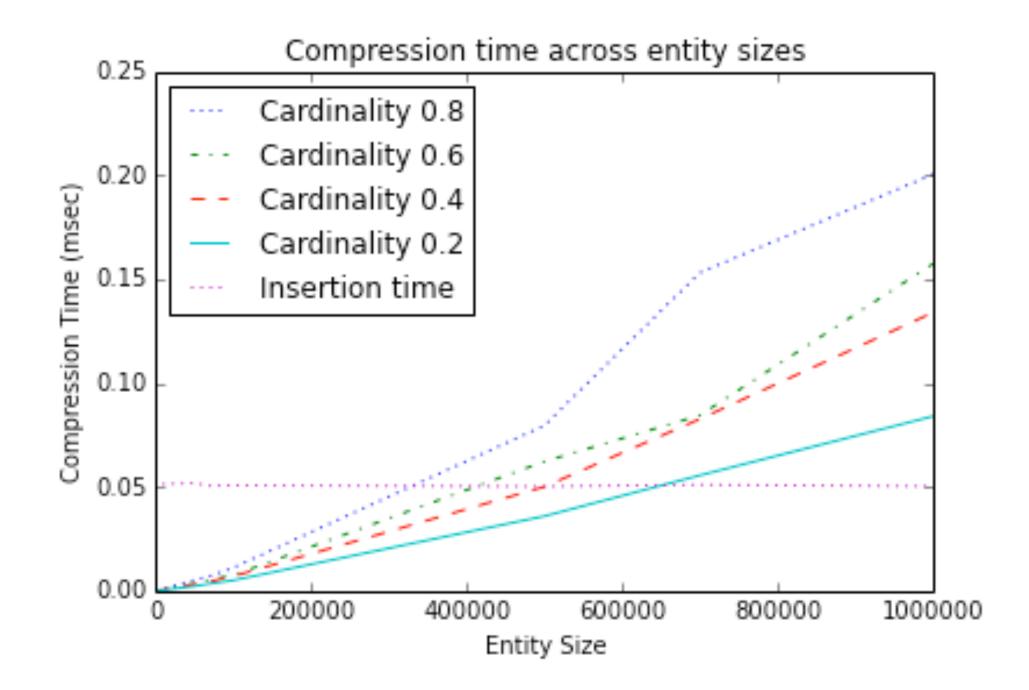


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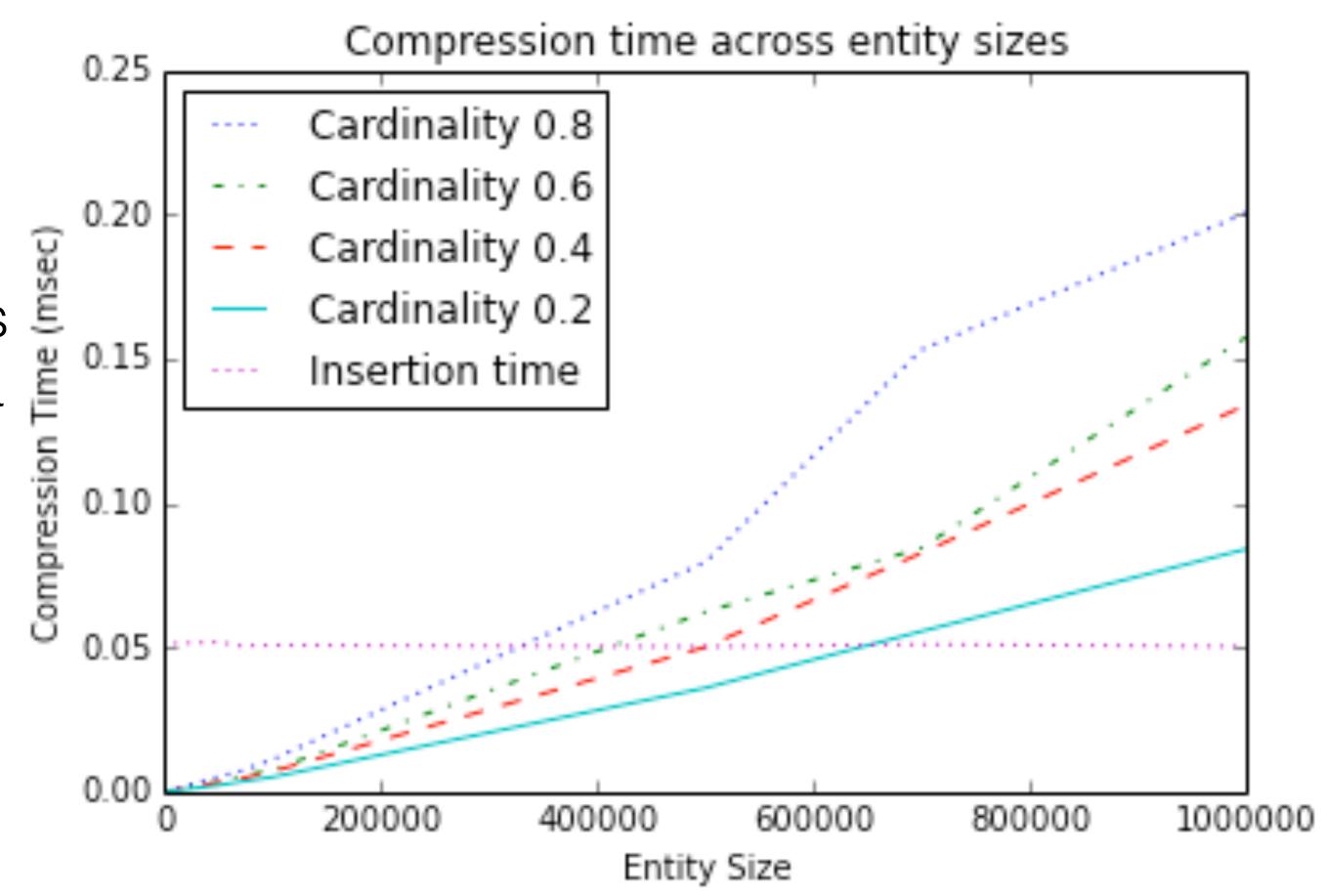
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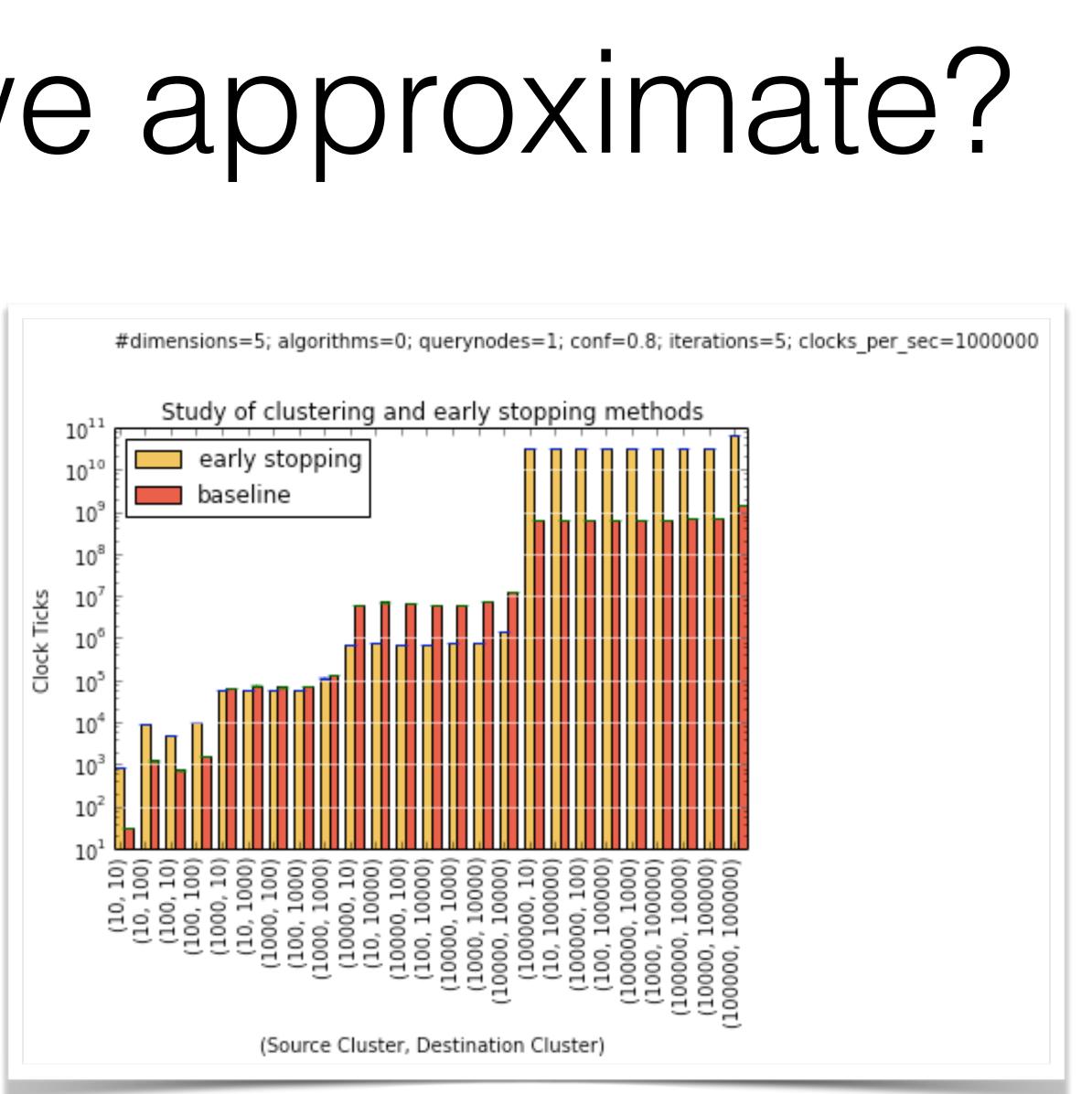




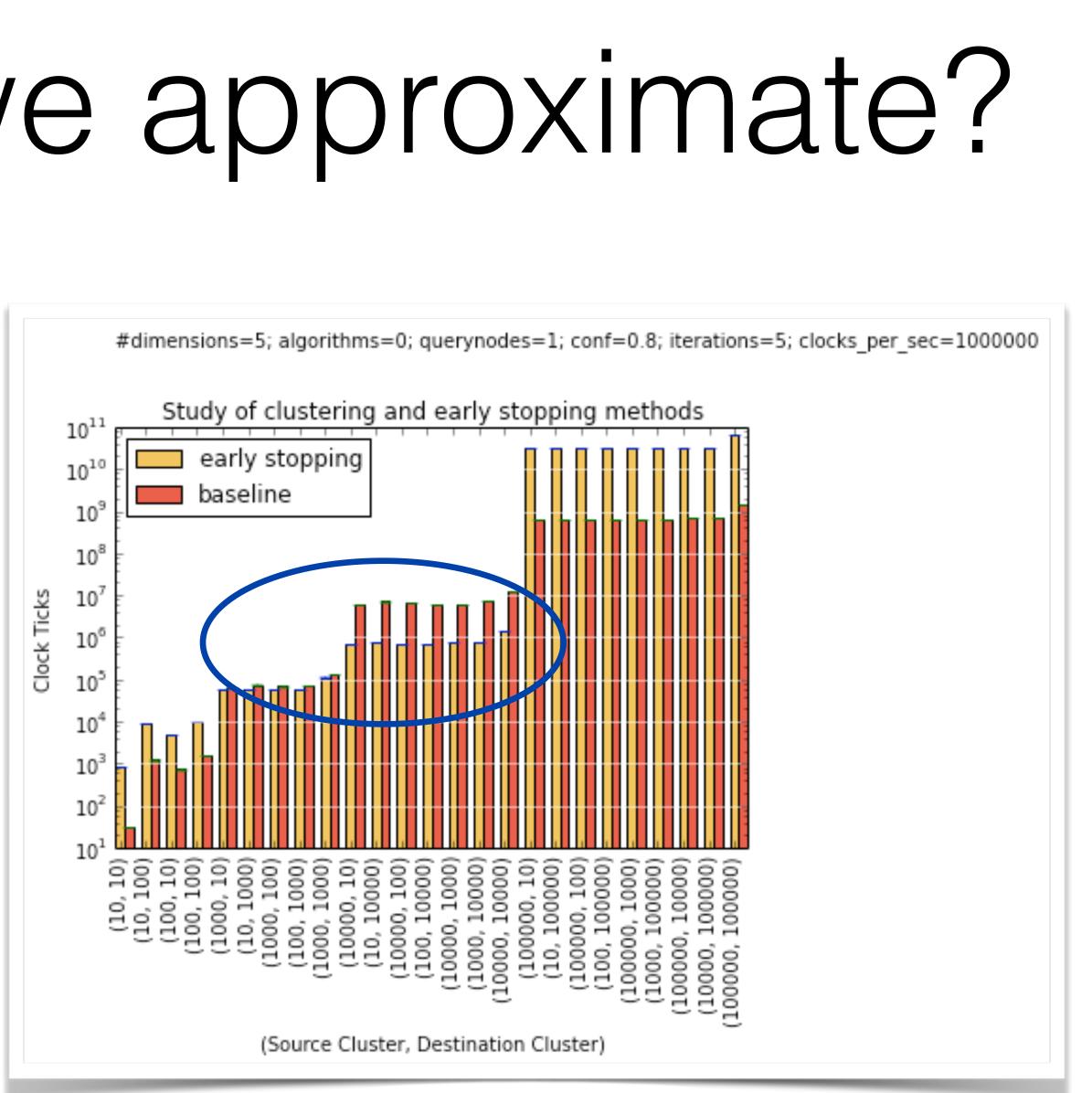
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- It is better to do full comparison for small and large cluster sizes.



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# Optimizer for Query-Driven Sampling

Optimizer needs to know:

- Current Cardinality of Items in each entity.
- Memory/CPU configuration for estimating baseline time

while samples-- > 0: m ~ Mentions e ~ Entities state' = move(state, m, e) o = Optimize(state, state', m, e) if (!score(state', state, o)): state = state' doCompress(state, m, e, o)



#### Summary

- We motivated the need and discussed the open space for optimization of MCMC sampling methods.
- Want to collaborate?!

• We plan to use the newly released labeled TREC stream corpus.

• Lets talk if you want to do a Ph.D. at the University of Oklahoma!

# Thank you!



