DECENTRALIZED ALGORITHM FOR RANKING LEARNING

ROSAEC center 2010 Workshop

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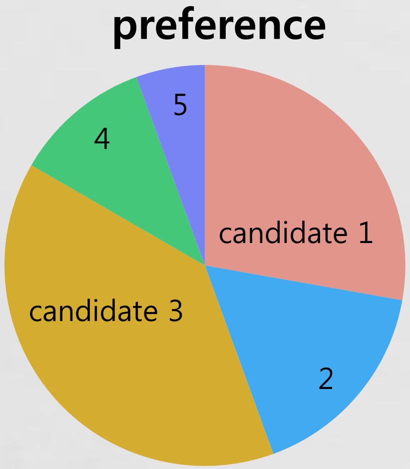
Decentralized Ranking Learning Problem

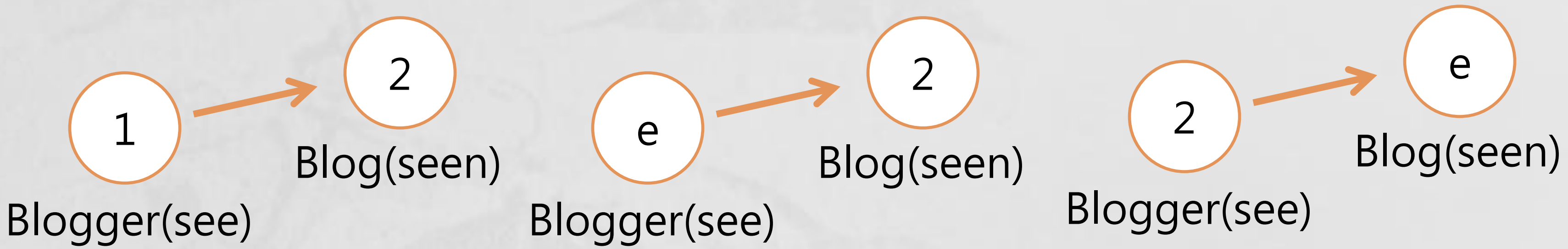
- (Presidential) election (or preference on fashion brands)
- Centralized/decentralized algorithm
- **Problem:** **How to identify *the most frequent item*(candidate) by locally exchanging information between the nodes.**

- **Local message exchange**: Bloger sees Blog around her.
- **Extended (General) version of this problem: How to identify *k most frequent items in order*.**



Previous Works

- Classical voter model – two candidates, {1,2}.
- **Using Three States for Binary Consensus on Complete Graphs**, Infocom 2009 (Perron, Vasudevan, and Vojnovic)
  - Complete graph
  - Comparison between **ternary signaling & state** and **binary signaling & ternary state**
- **Convergence Speed of Binary Interval Consensus**, Infocom 2010 (Draief and Vojnovic)
  - Upper bound on the expected convergence time that holds for arbitrary connected graph e.g. Complete, star-shaped, Erdos-Renyi random graphs



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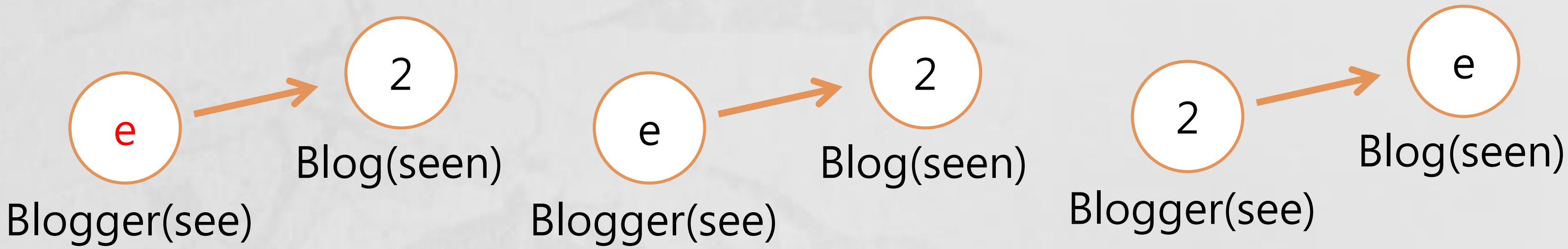

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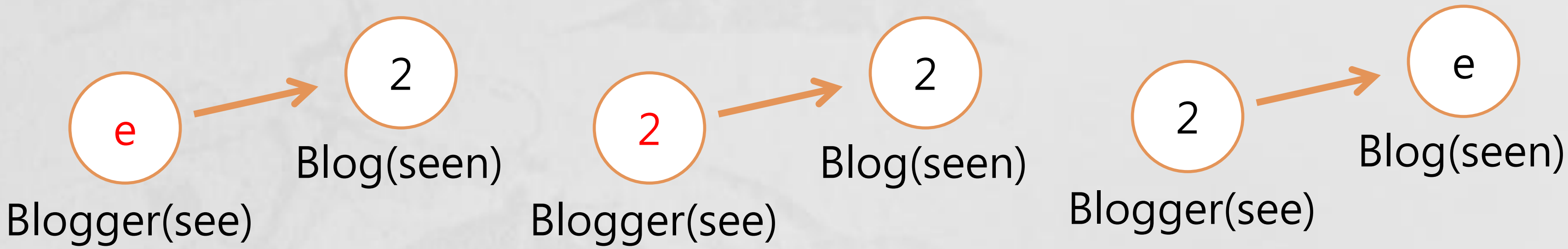

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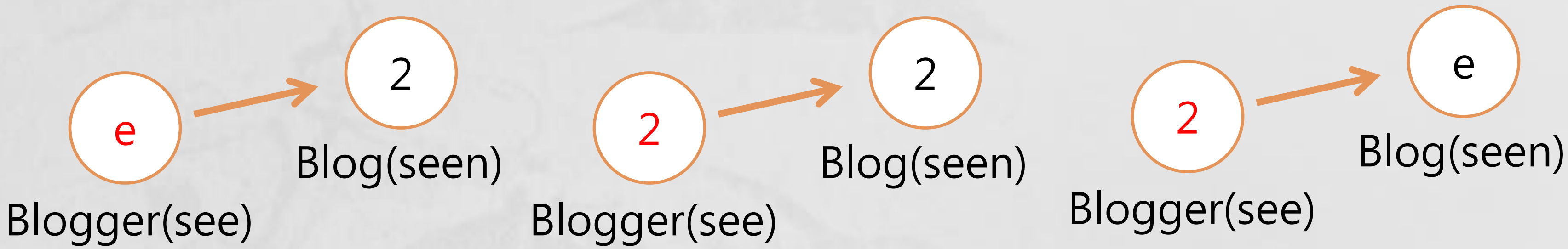
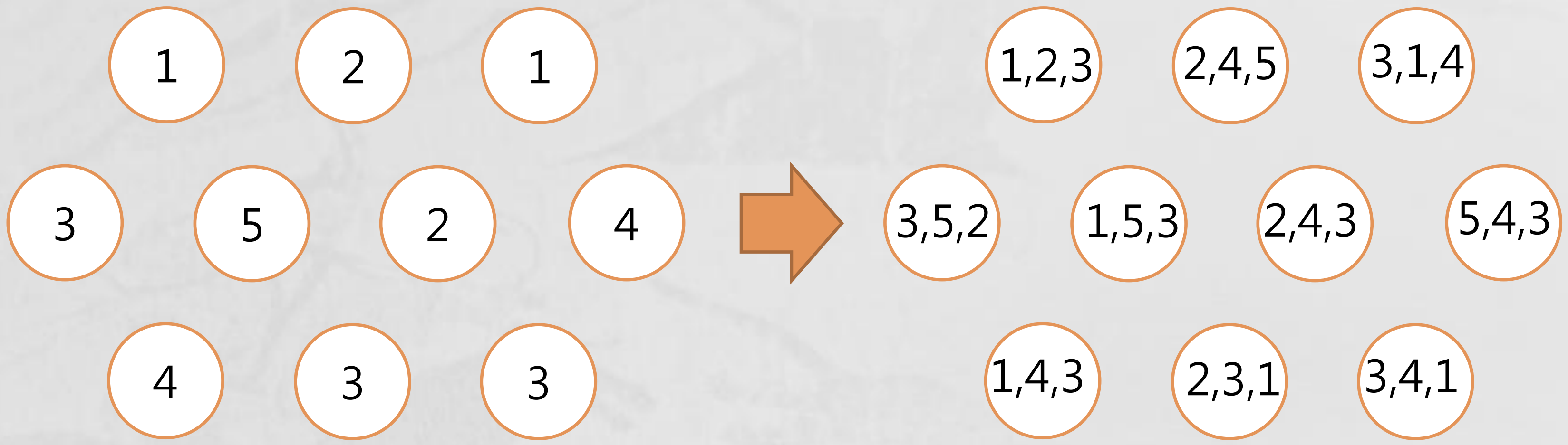


Ranking Learning

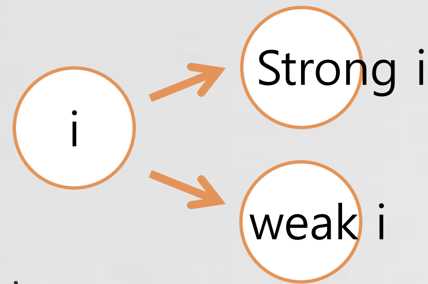
- **Finding the most frequent sorting state = Learning top-k ranking**
- **Sorting state assignment** - Using a rule, we assign a k-tuple as its new state instead of its initial single state for each node. → **Randomized Algorithm**
- **Deviation** between the random number and its expectation **is small.**

e.g. N=10, M=5, k=3



Finding the Most Frequent Item

- Introduction of Strong state, weak state



- Distributed algorithm for the most frequent item
  - If the instigator node is in a strong state, then it switches to the corresponding weak state if the encountered node holds a different strong state.
  - If the instigator node is in a weak state, then it copies the state of the encountered node.

- We proved **convergence for complete graph theoretically.**
- We showed convergence for **random graphs** (Erdos-Renyi and Scale-free) **empirically.**

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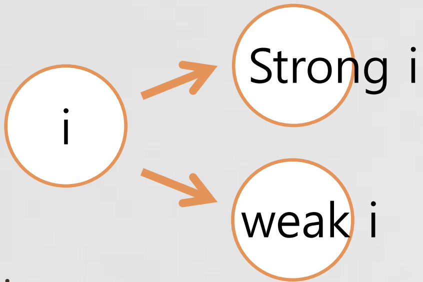

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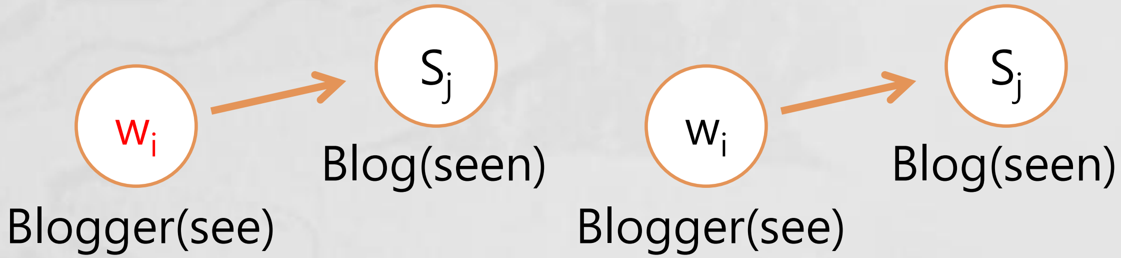

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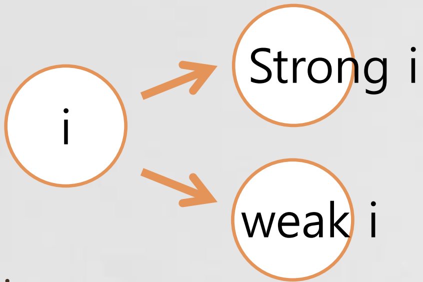

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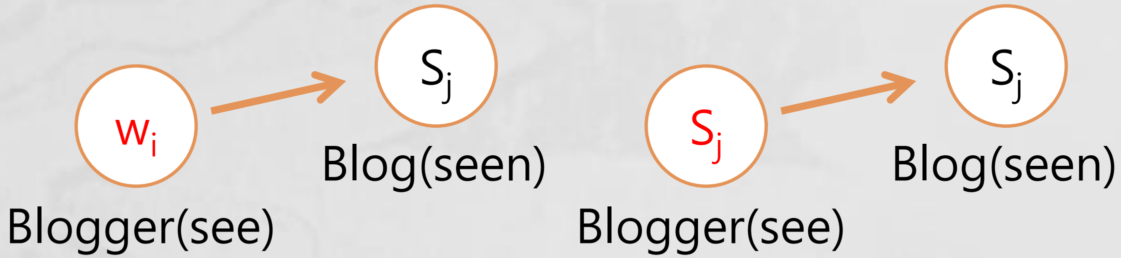

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Future Works and Conclusion

- Conclusion
  - For m-candidate case, we developed a distributed algorithm that is parsimonious w.r.t the memory per node and information exchanged between the nodes for each node to identify the most frequent item.
  - Using the above algorithm, we learn the top-k ranking(in order or w/o order).

- Future work
  - Study on theoretical convergence for other networks of interest, including random graphs (Erdos-Renyi and Scale-free).
  - Improvement on the speed and the probability of error.
  - Suggestion of distributed algorithm two-way communication case.