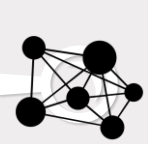


Graph-based Analytics for Decentralized Online Social Networks


Amira Soliman

Researcher @ RISE SICS.

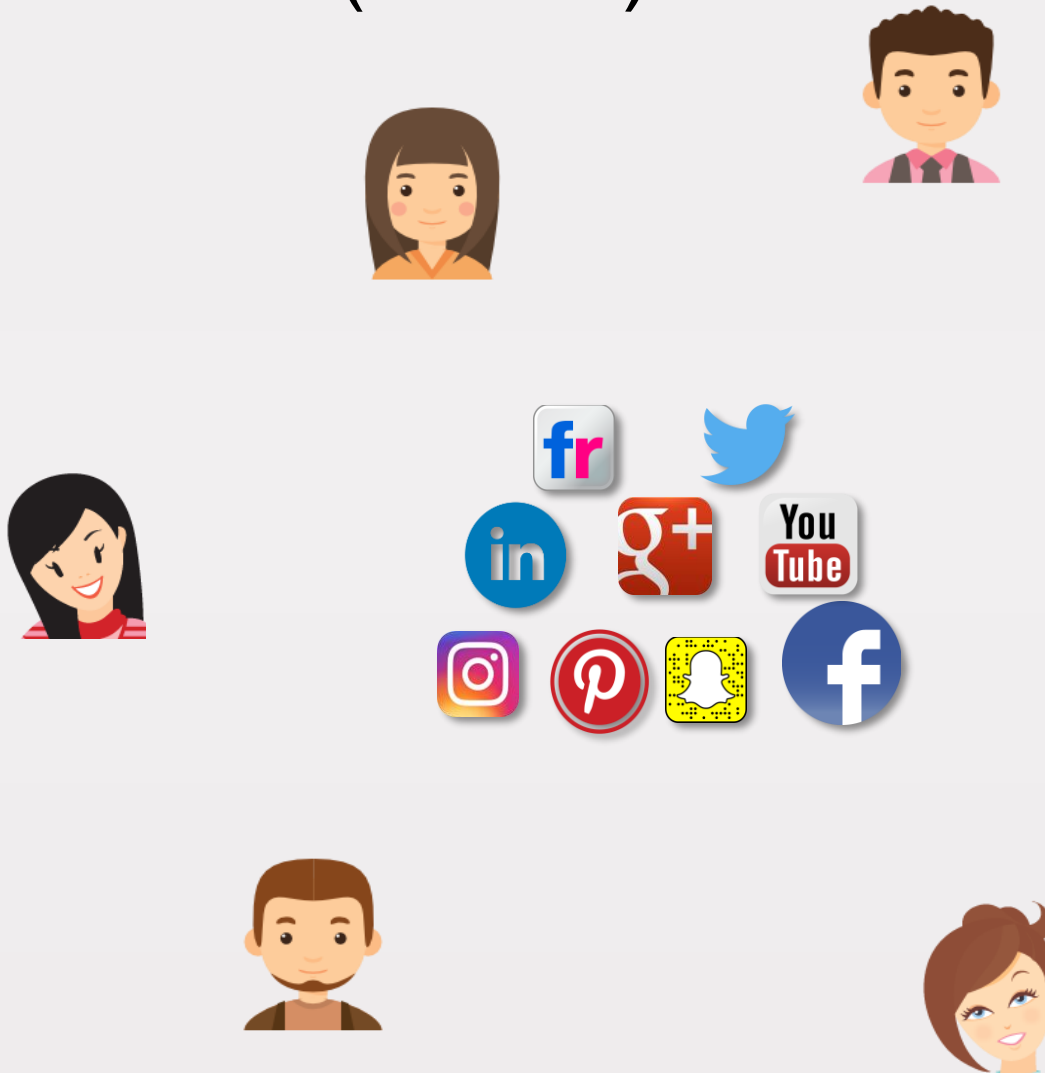


Interactions on top of Online Social Networks (OSNs)



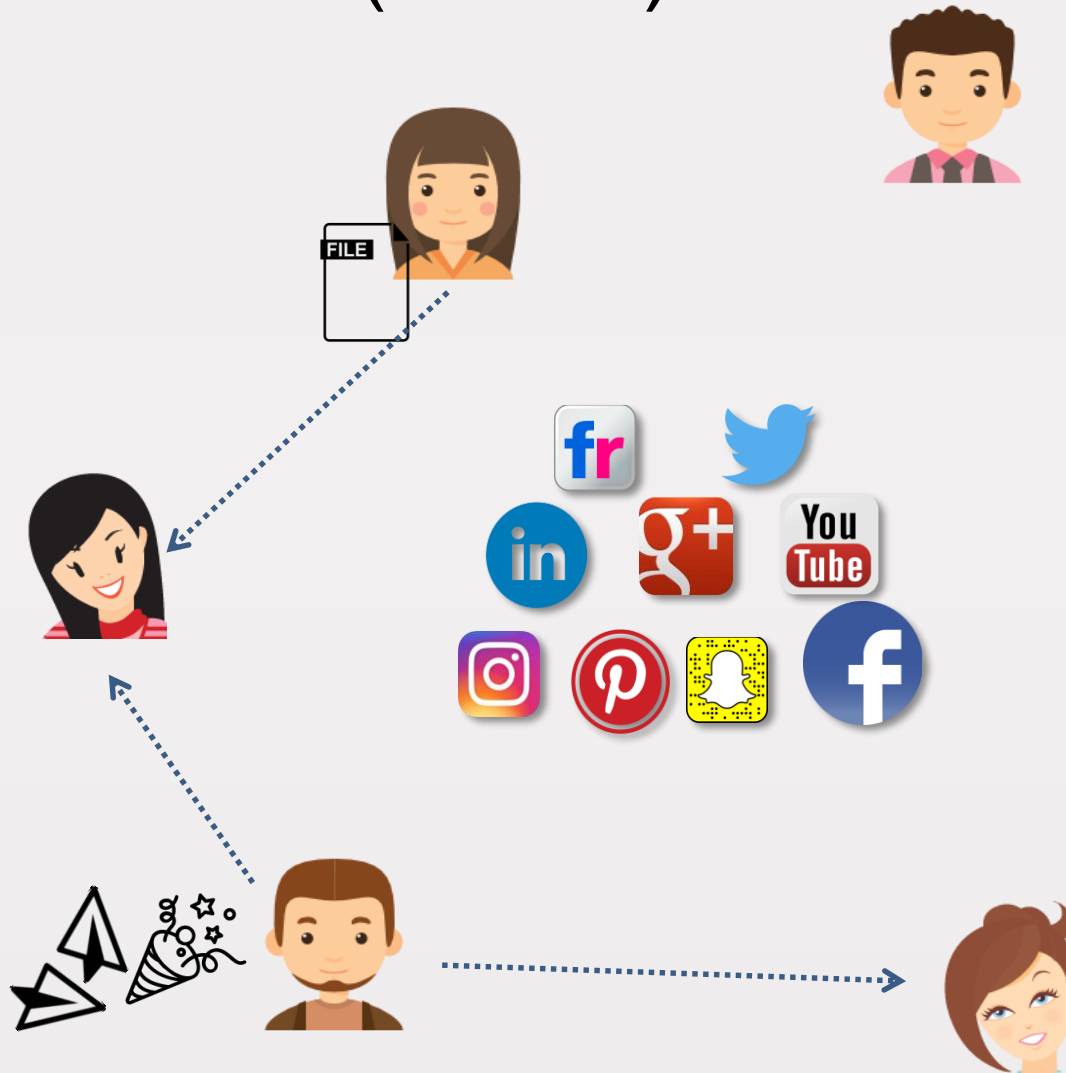



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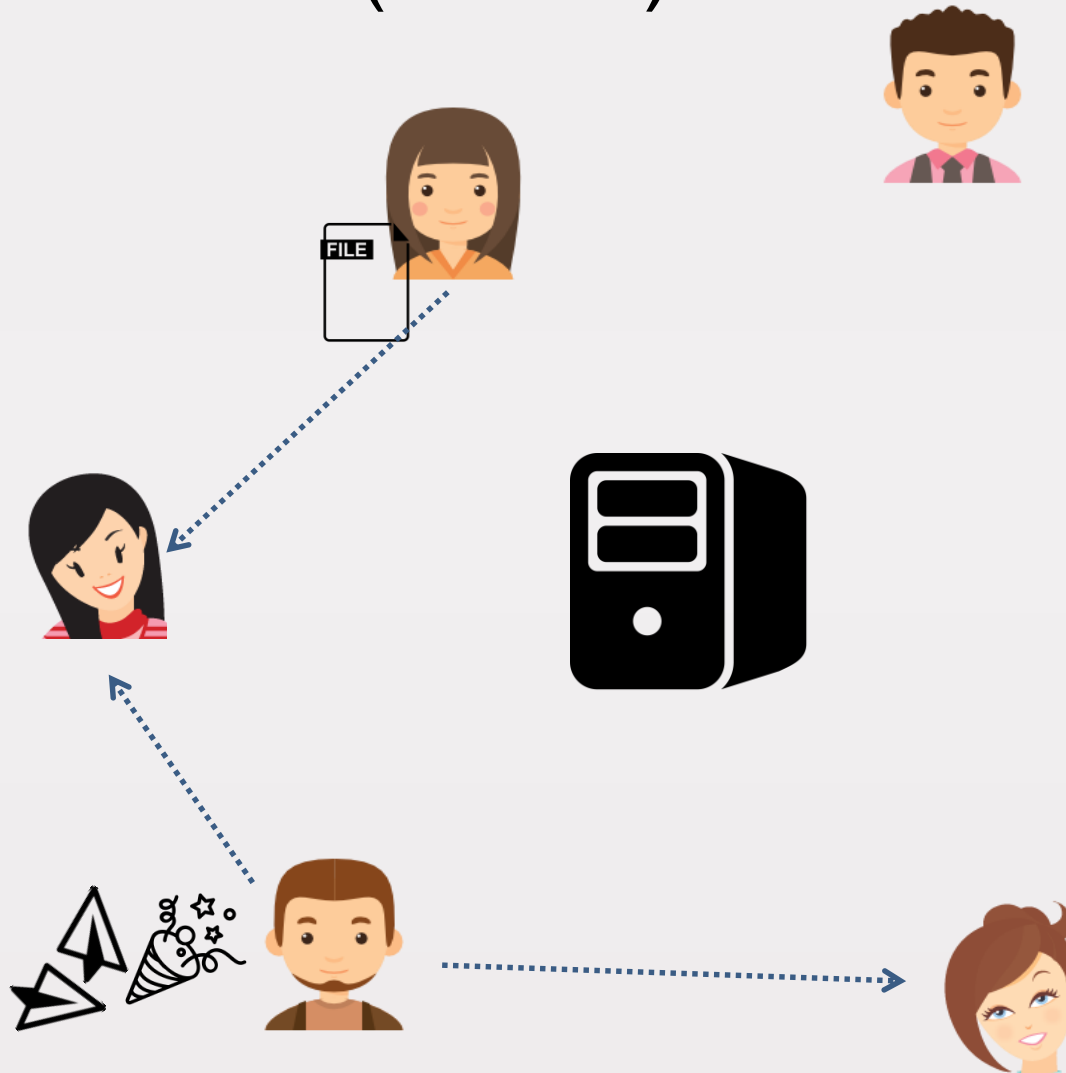



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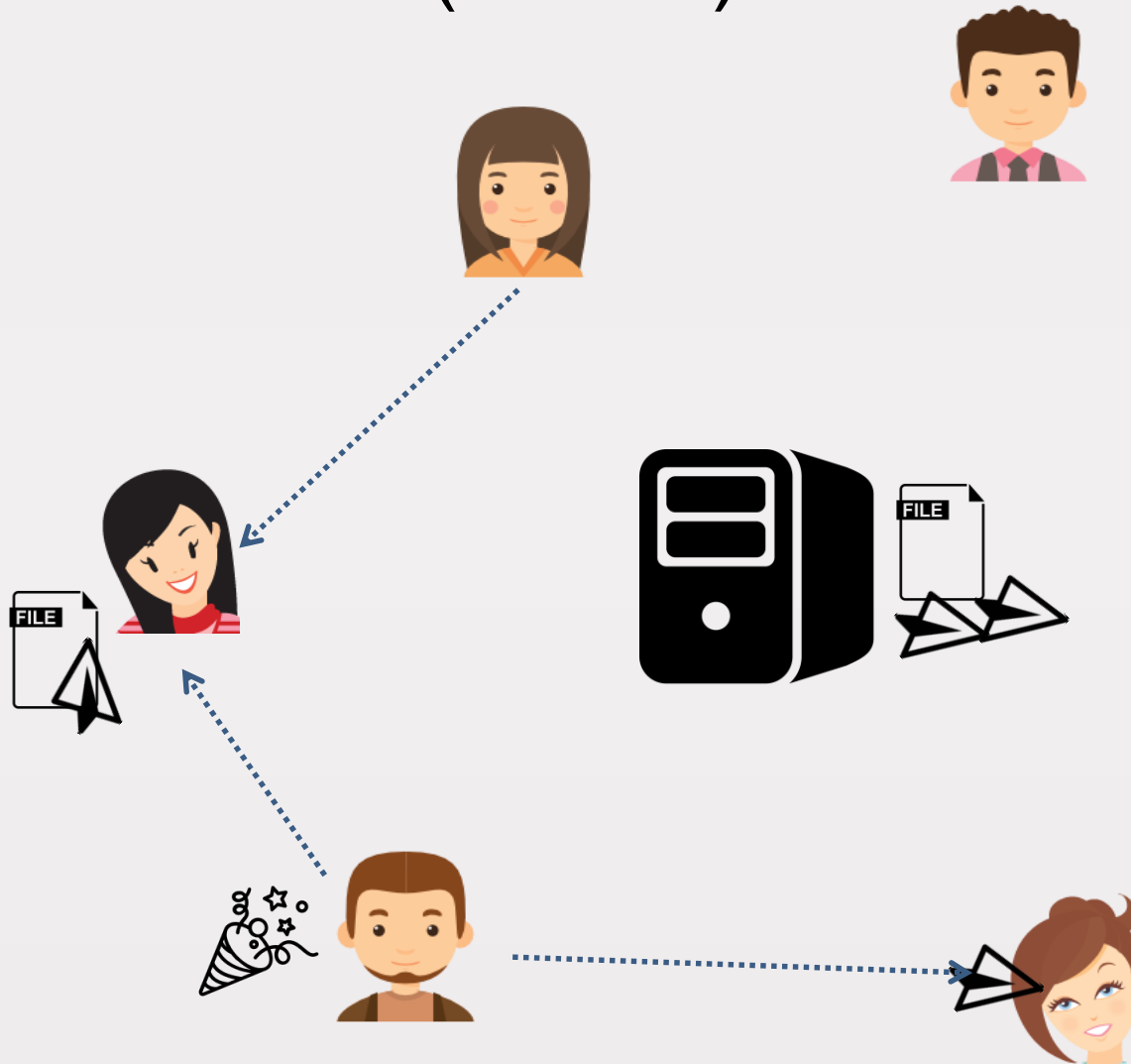



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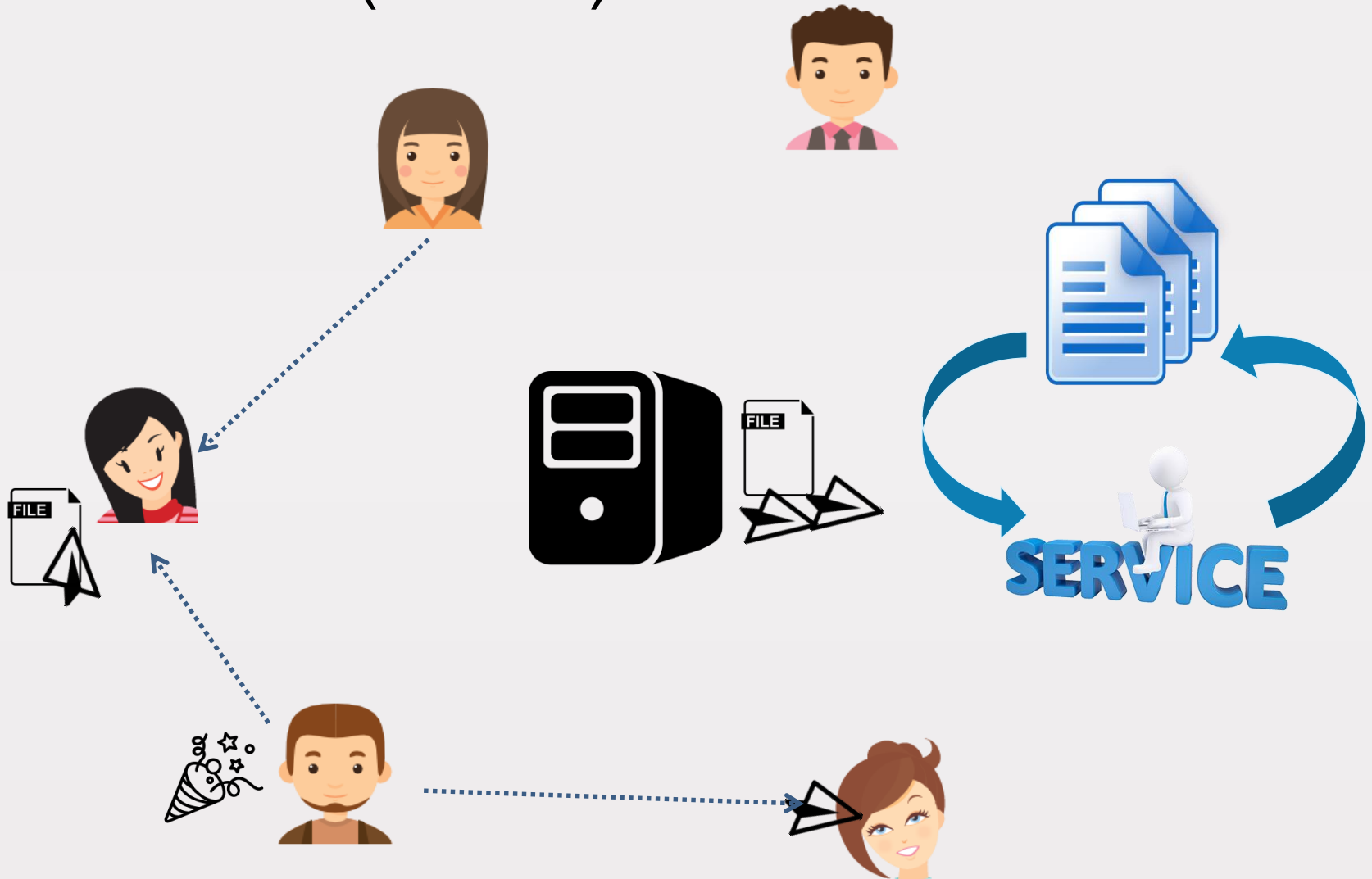


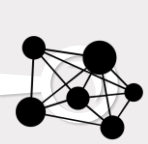
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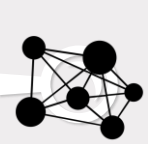
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Data Repurposing: we have no idea about how our data is being used!

- Providers analyze what people share for public, yet they also scan private messages.
- Providers collect personal tastes and navigation from third party applications.
- AI can guess whether a person is gay or straight using profile picture.
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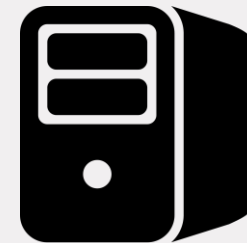
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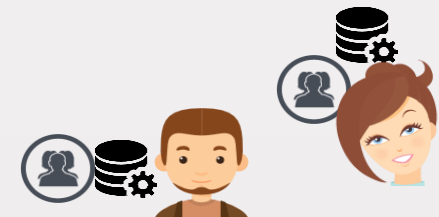
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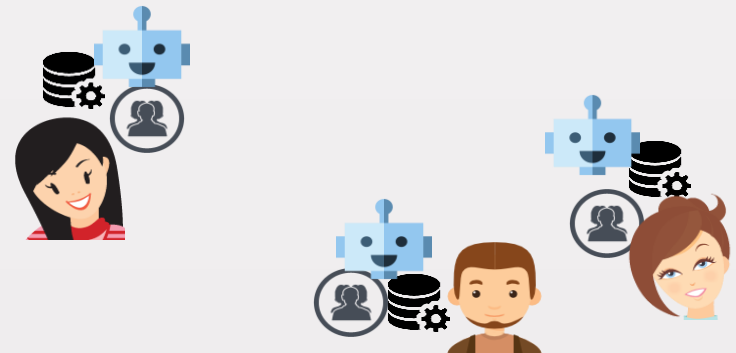
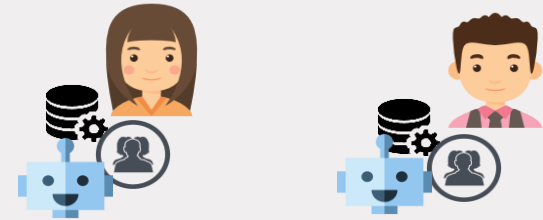
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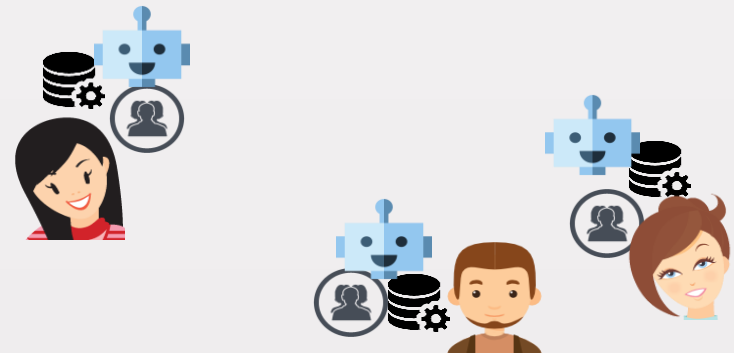
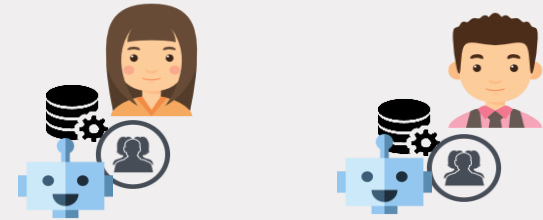
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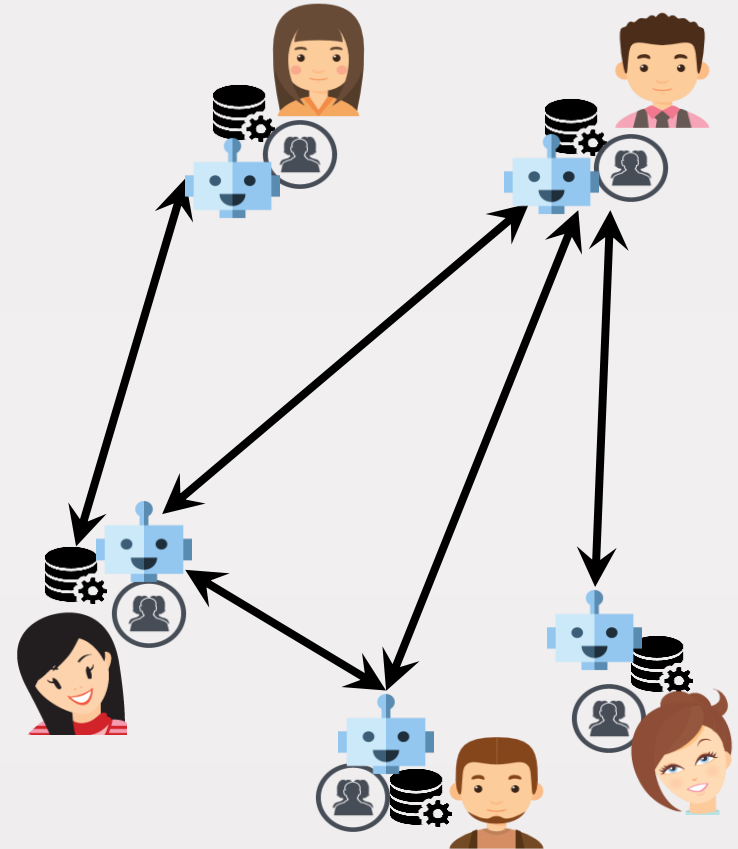
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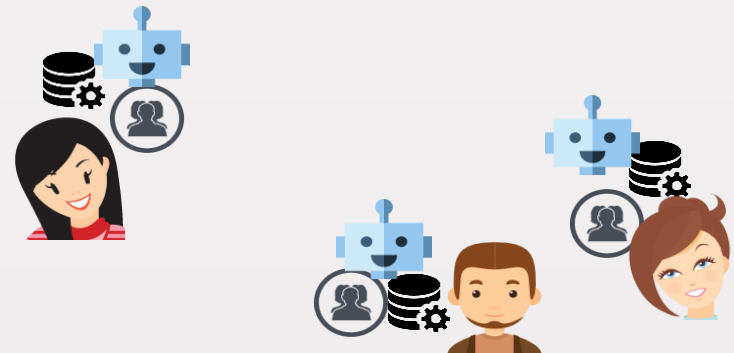
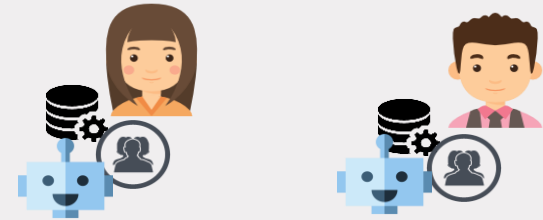
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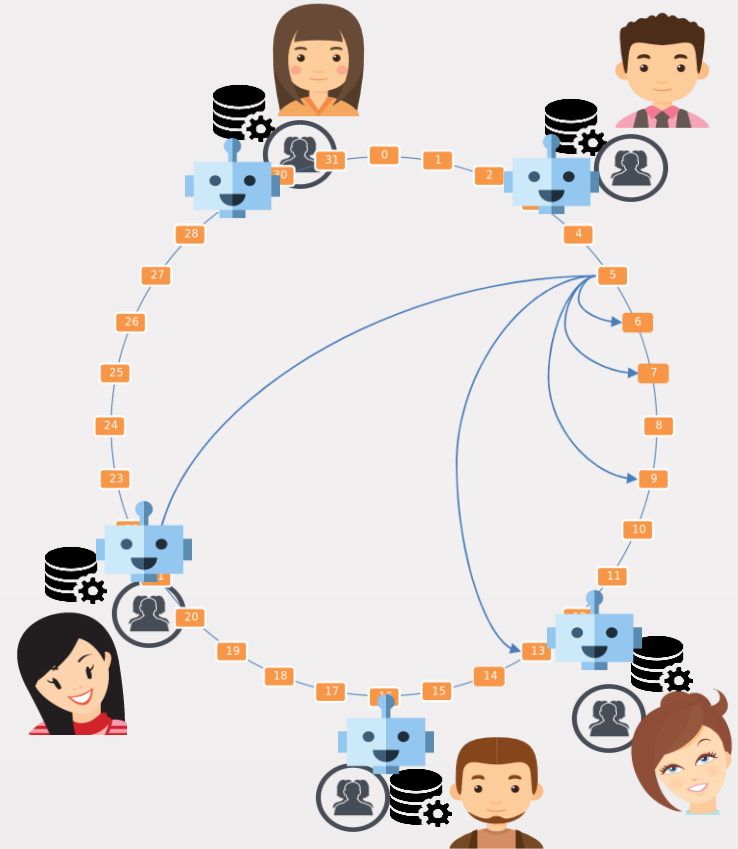
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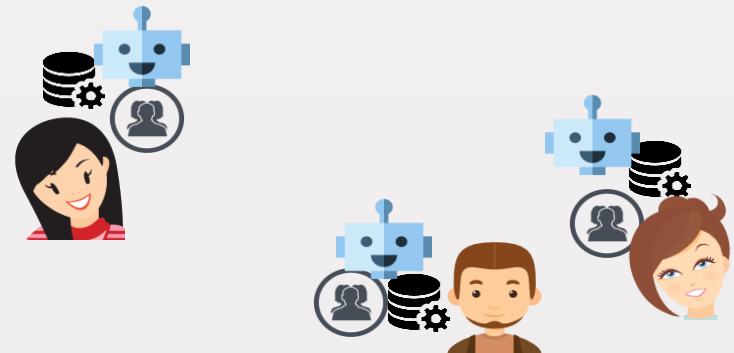
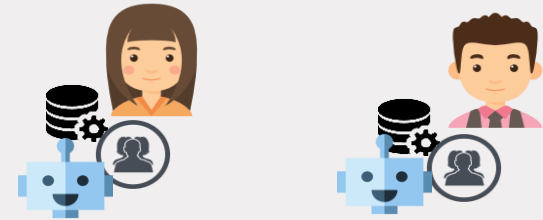
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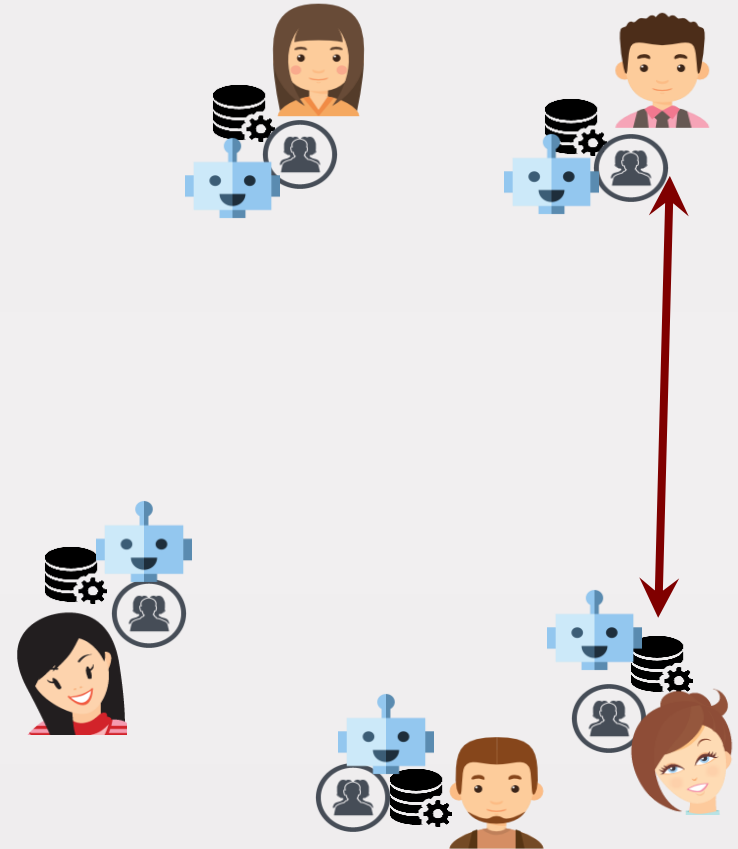
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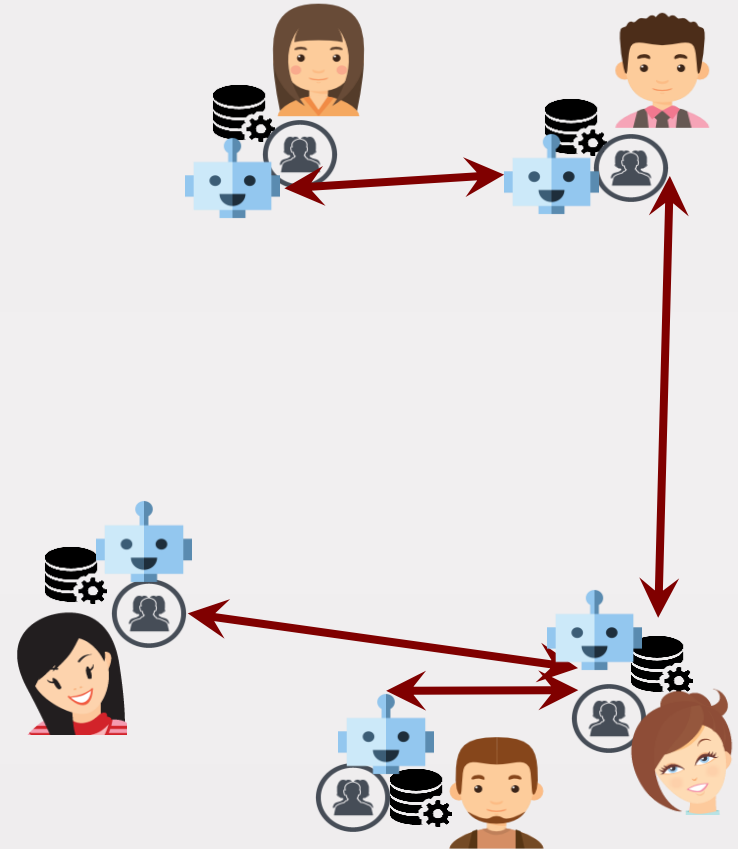
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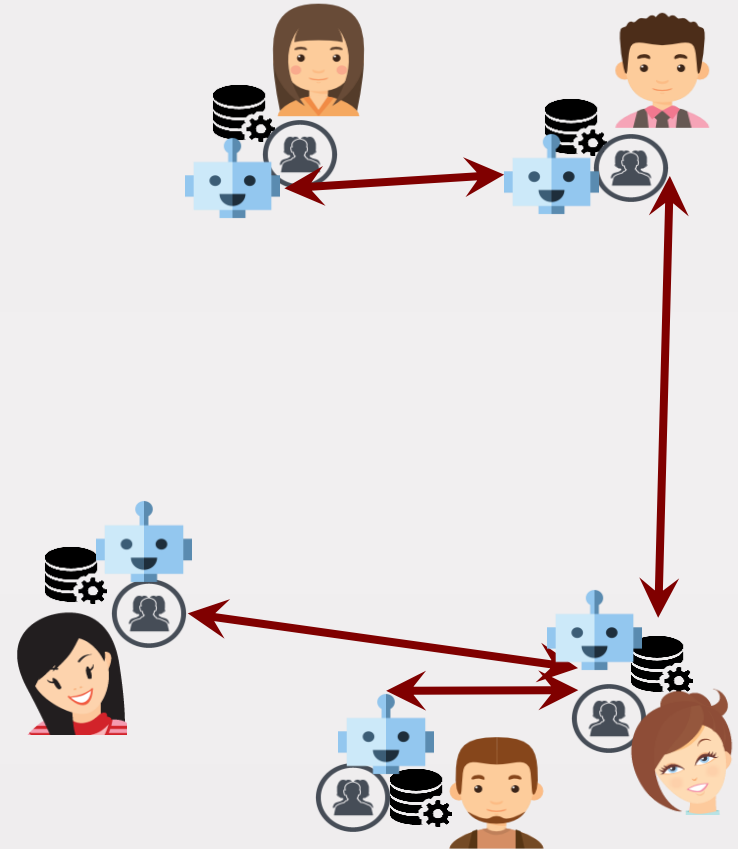
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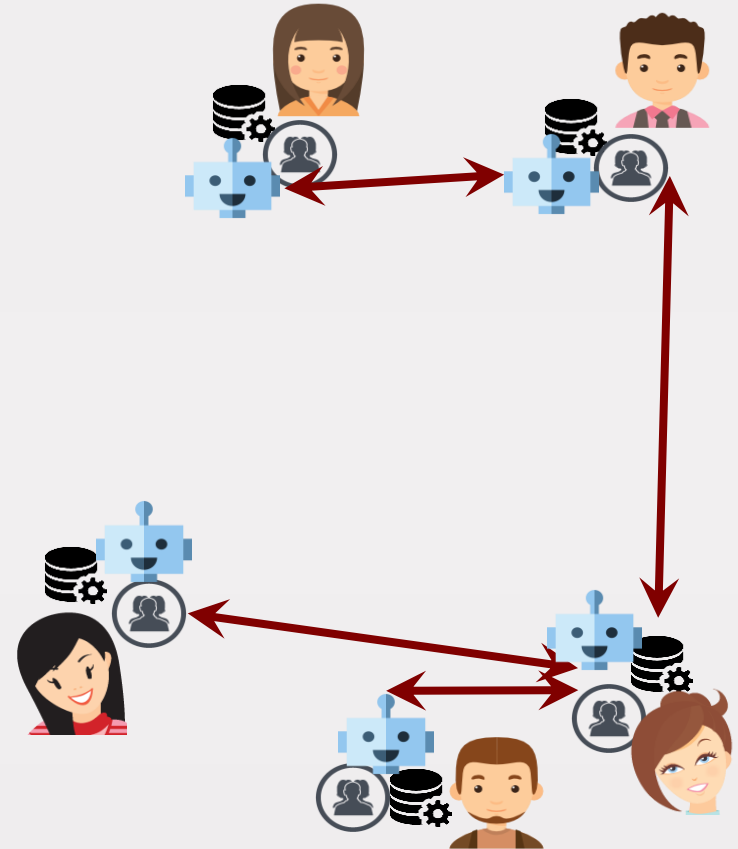
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- E.g., Diaspora active user rate:
 - During 2014: 1M.
 - By end of 2015 till now: 660K.



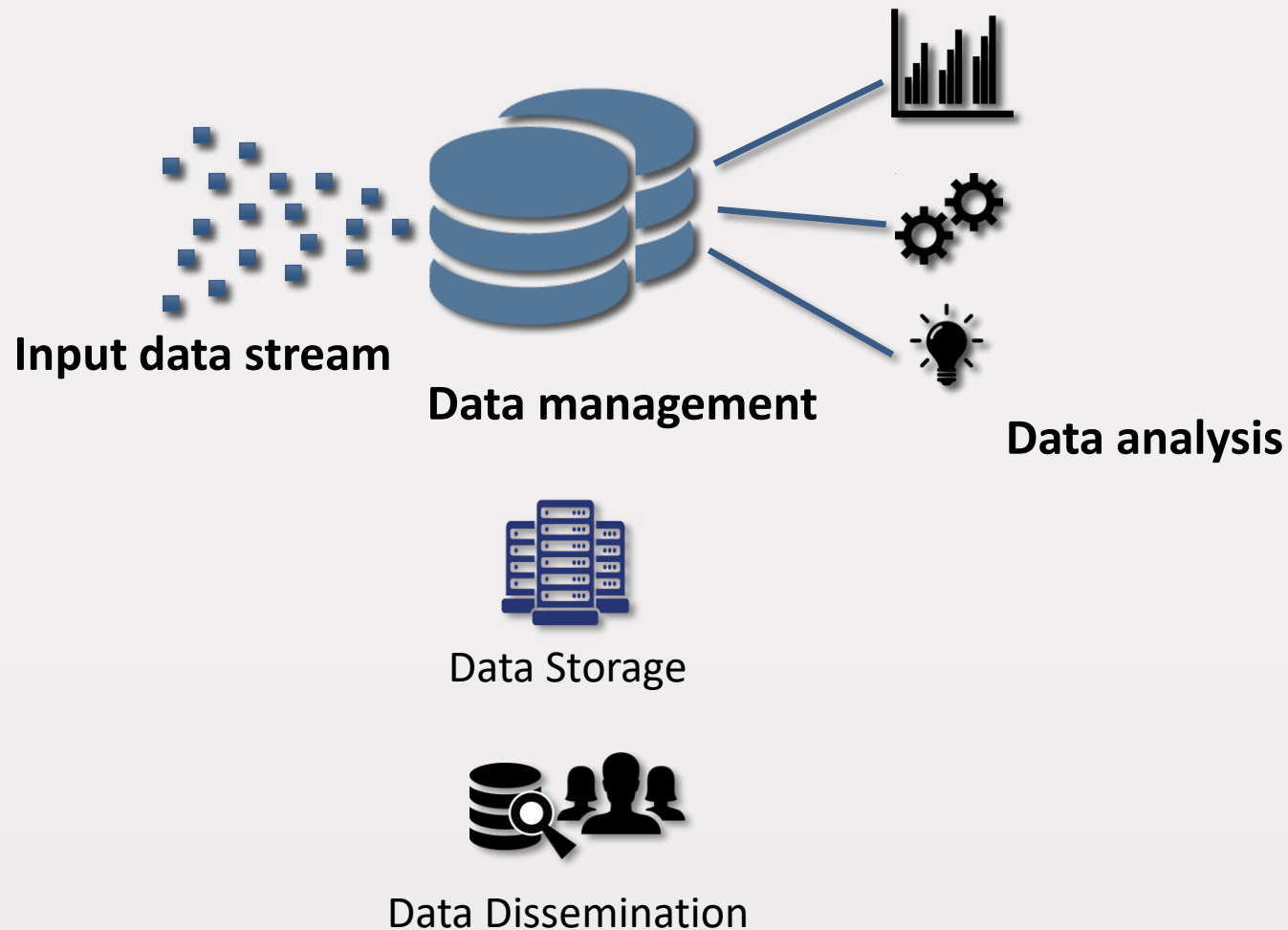


Service Categories for Social Networks



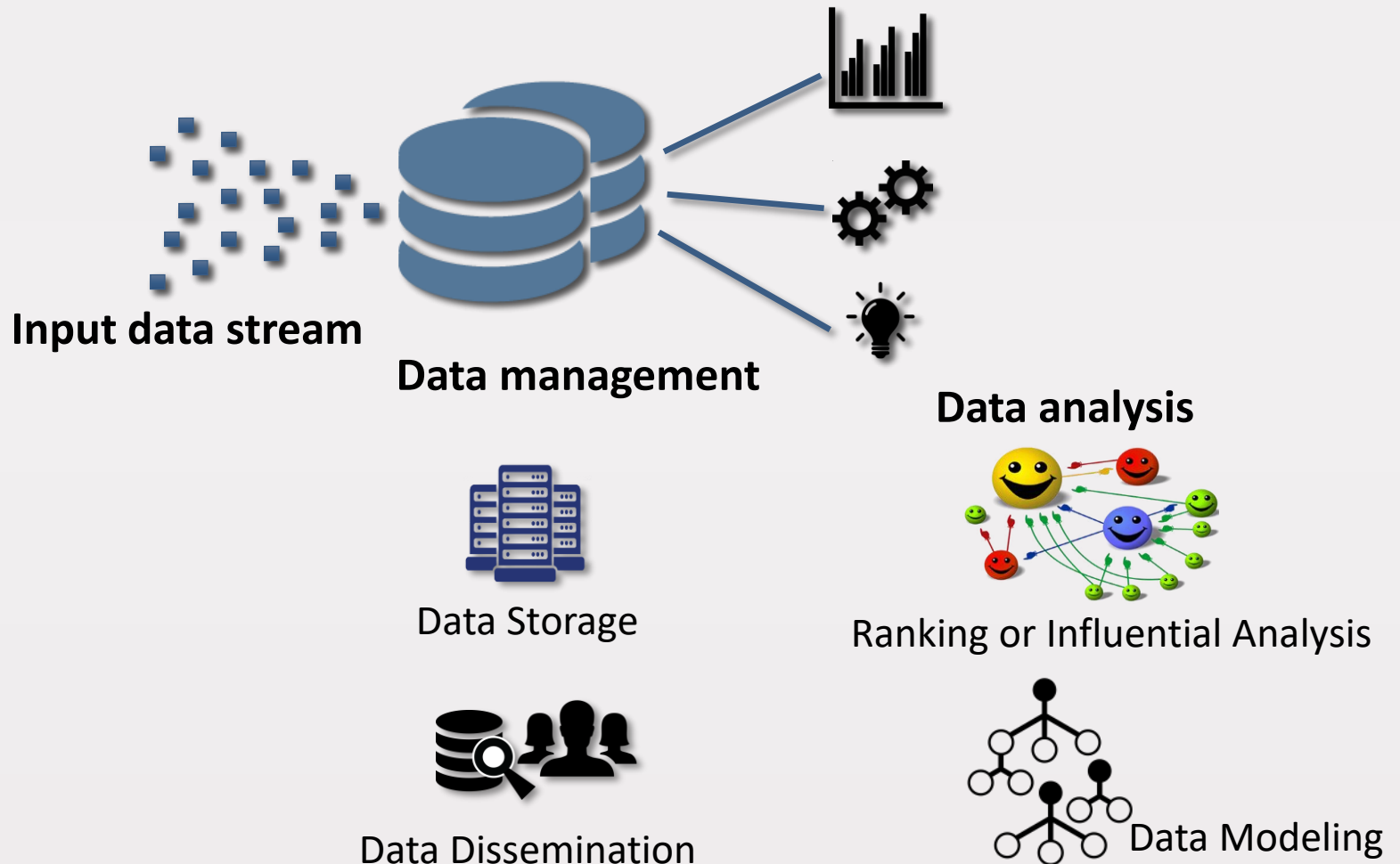


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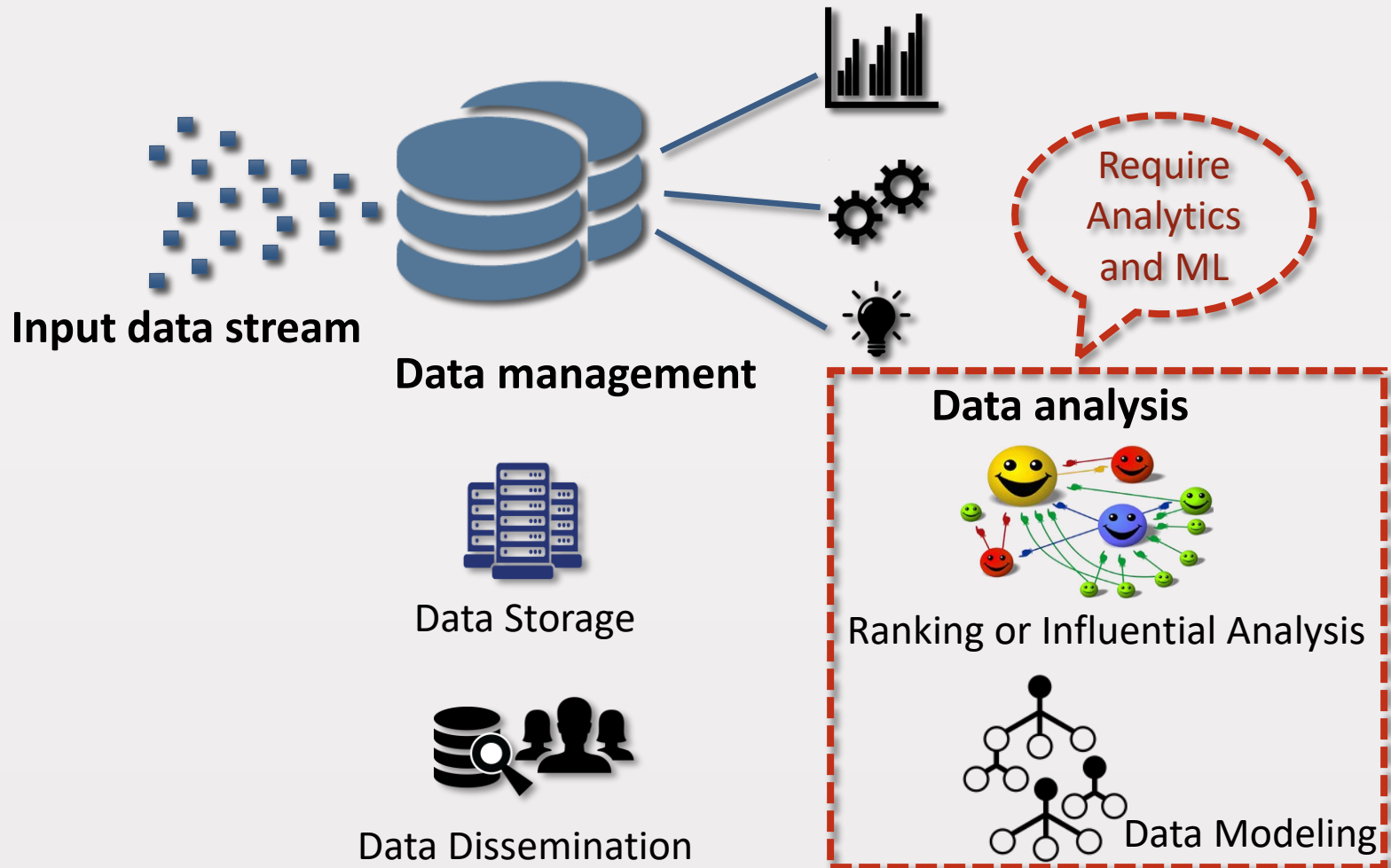


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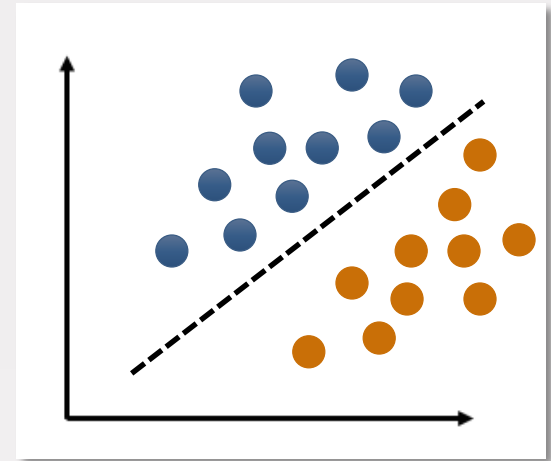


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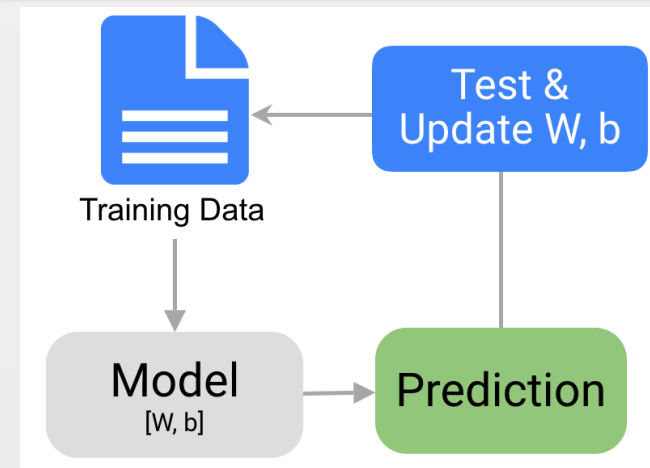
Machine Learning (ML) and DOSNs

- ML applications are iterative.



$$y = w * x + b$$

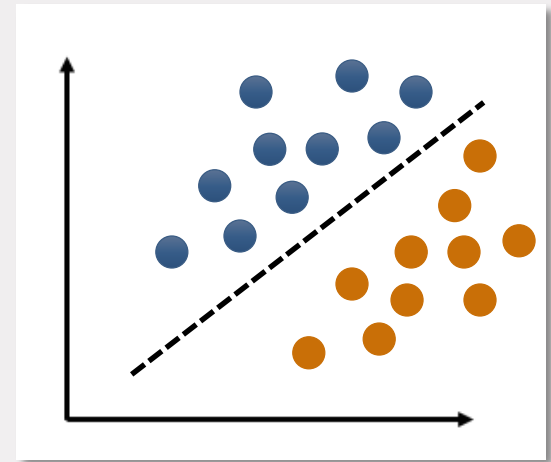
OUTPUT SLOPE INPUT Y-INTERCEPT





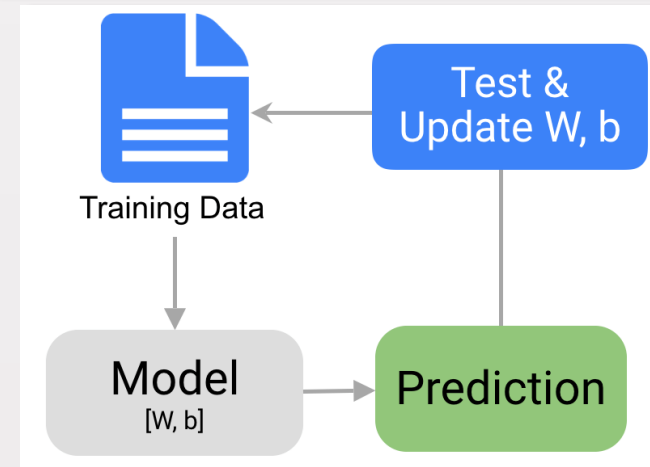
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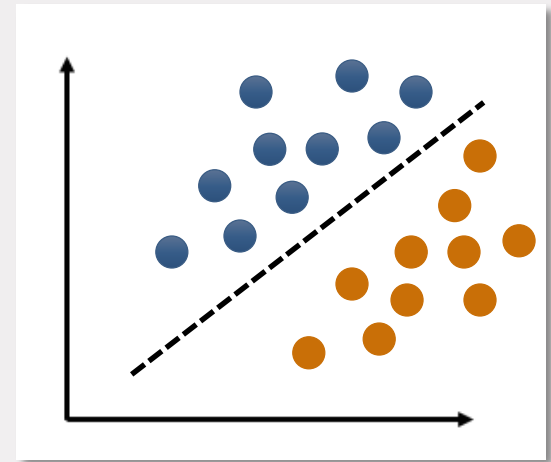
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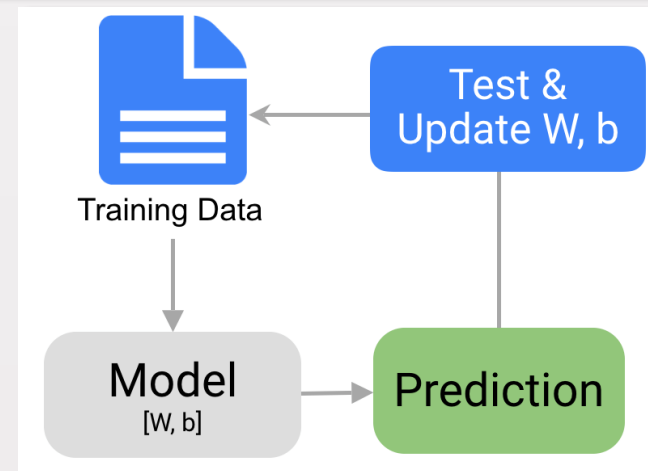
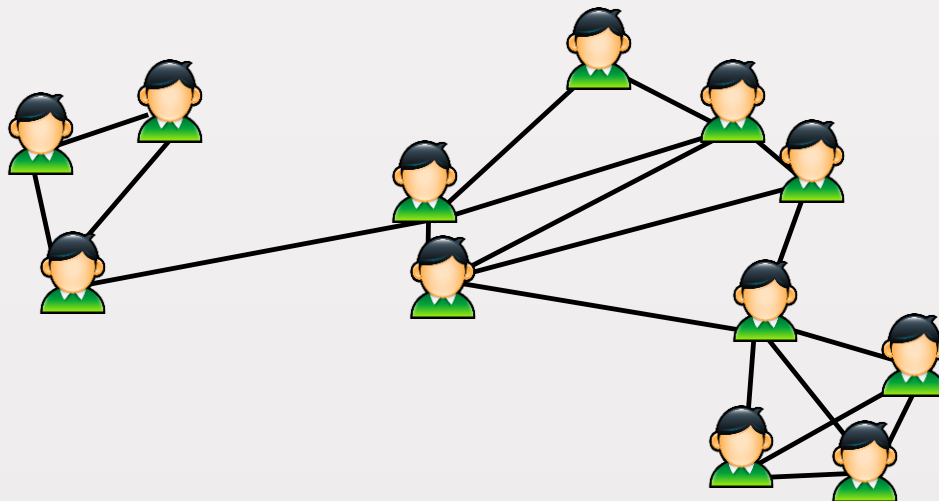


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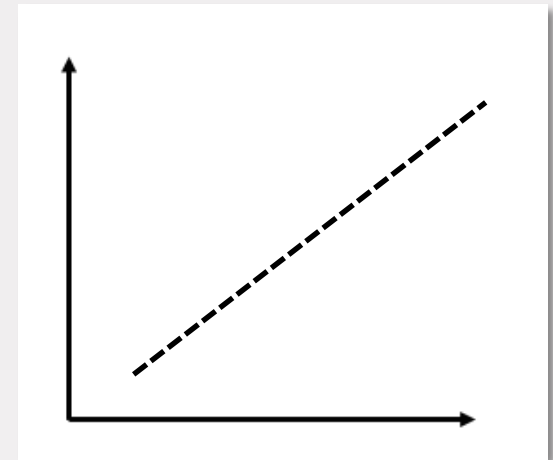
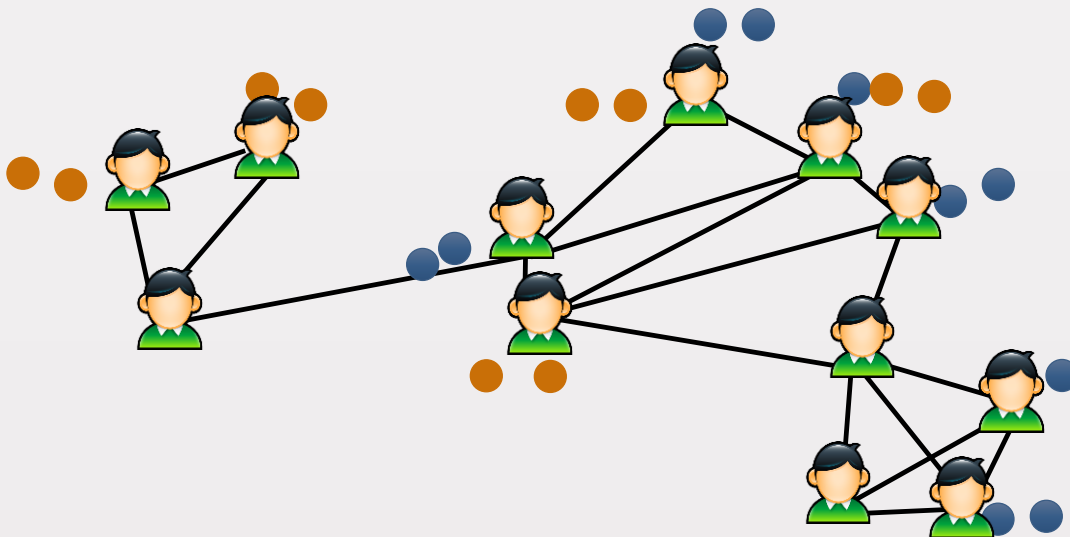


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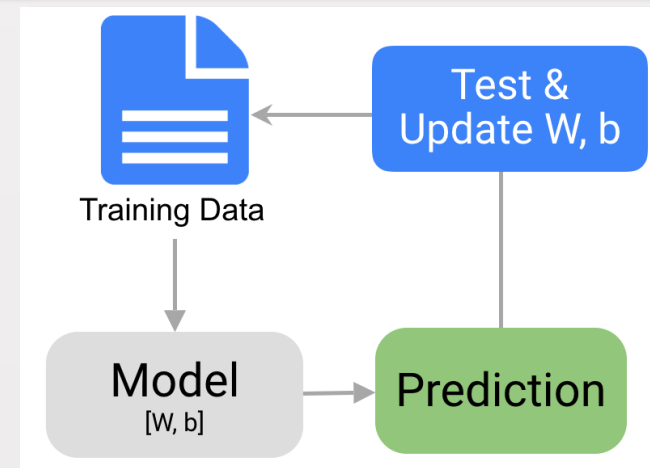


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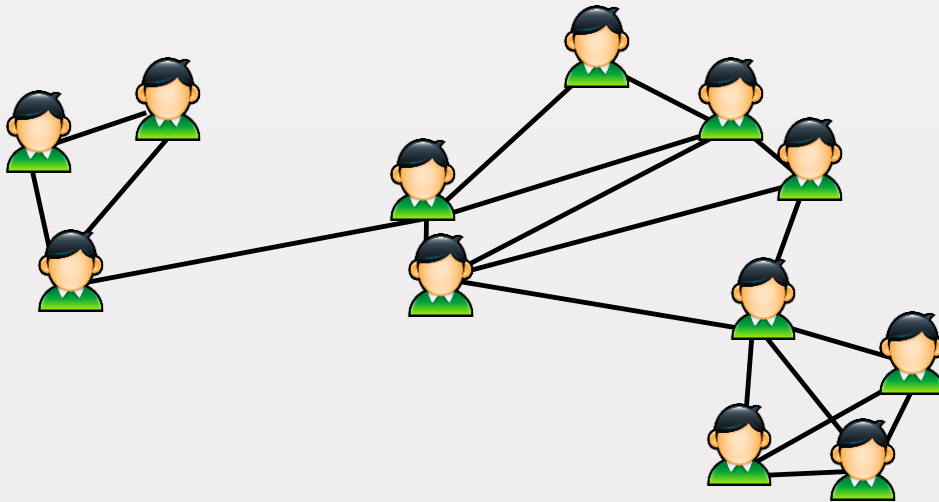


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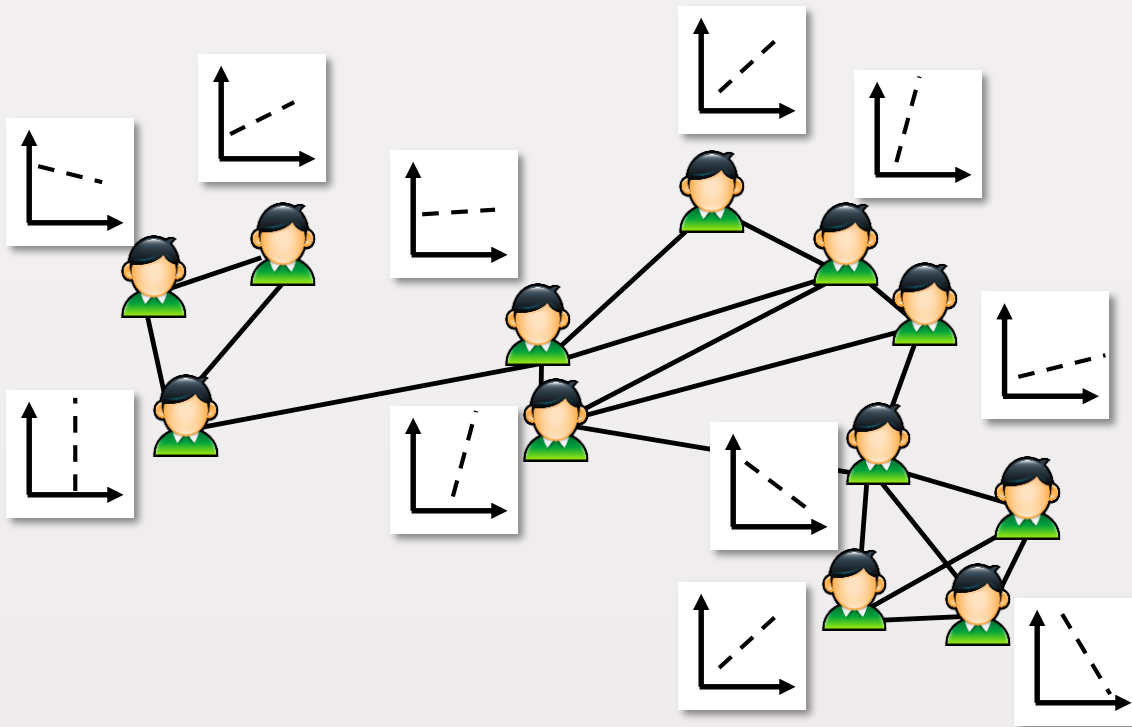
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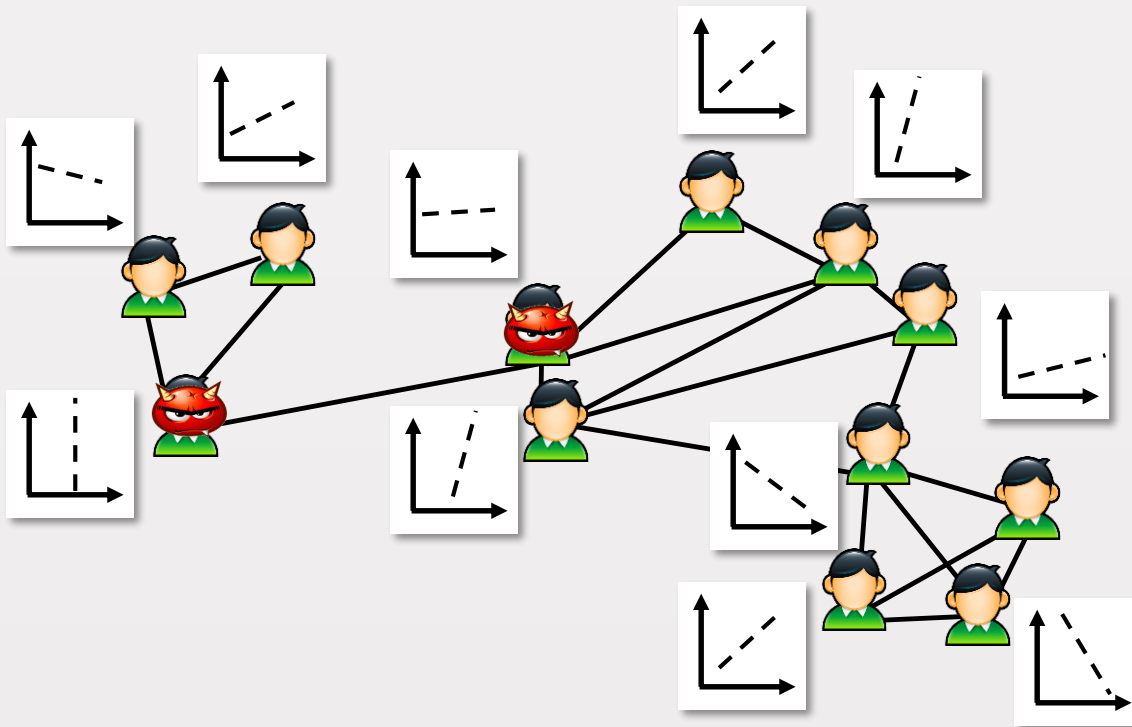
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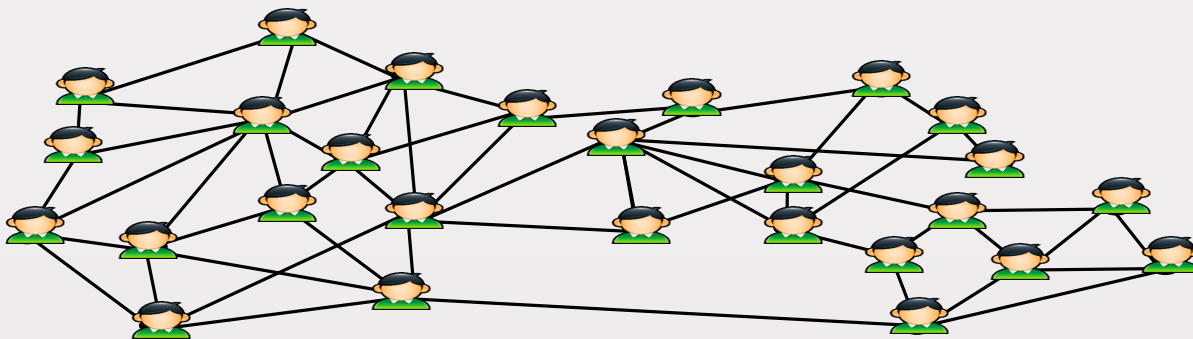
Machine Learning (ML) and DOSNs

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- DOSNs introduce new challenges.
 - ✧ Data is fully distributed.
 - ✧ Data movement is constrained.
 - ✧ Communication is limited.
 - ✧ Deviation from workflow protocol is possible.



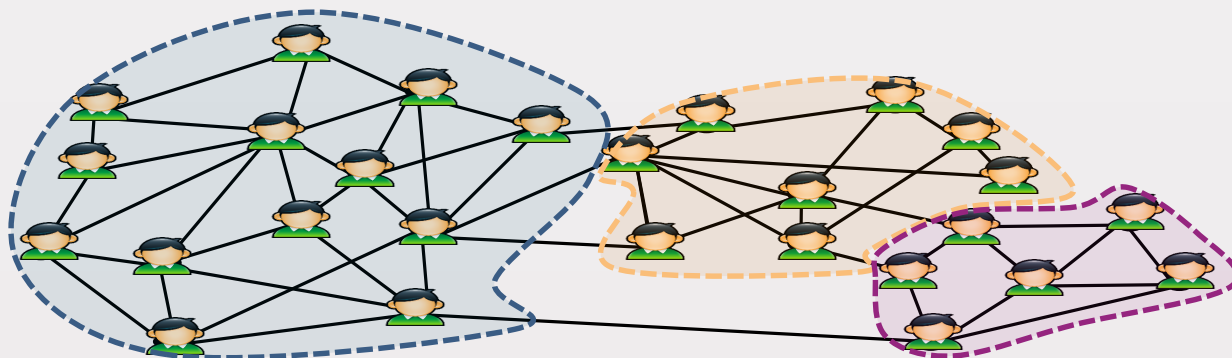
Community-aware Learning

- Homophily: from ancient Greek ὁμοῦ (homou, "together") and Greek φιλία (philia, "friendship") is the tendency of individuals to associate and bond with similar others [Wikipedia].
- Integrating community structure with analytic tasks enhances data analytic insights and improves results (e.g., validating online identities and spam detection).



Community-aware Learning

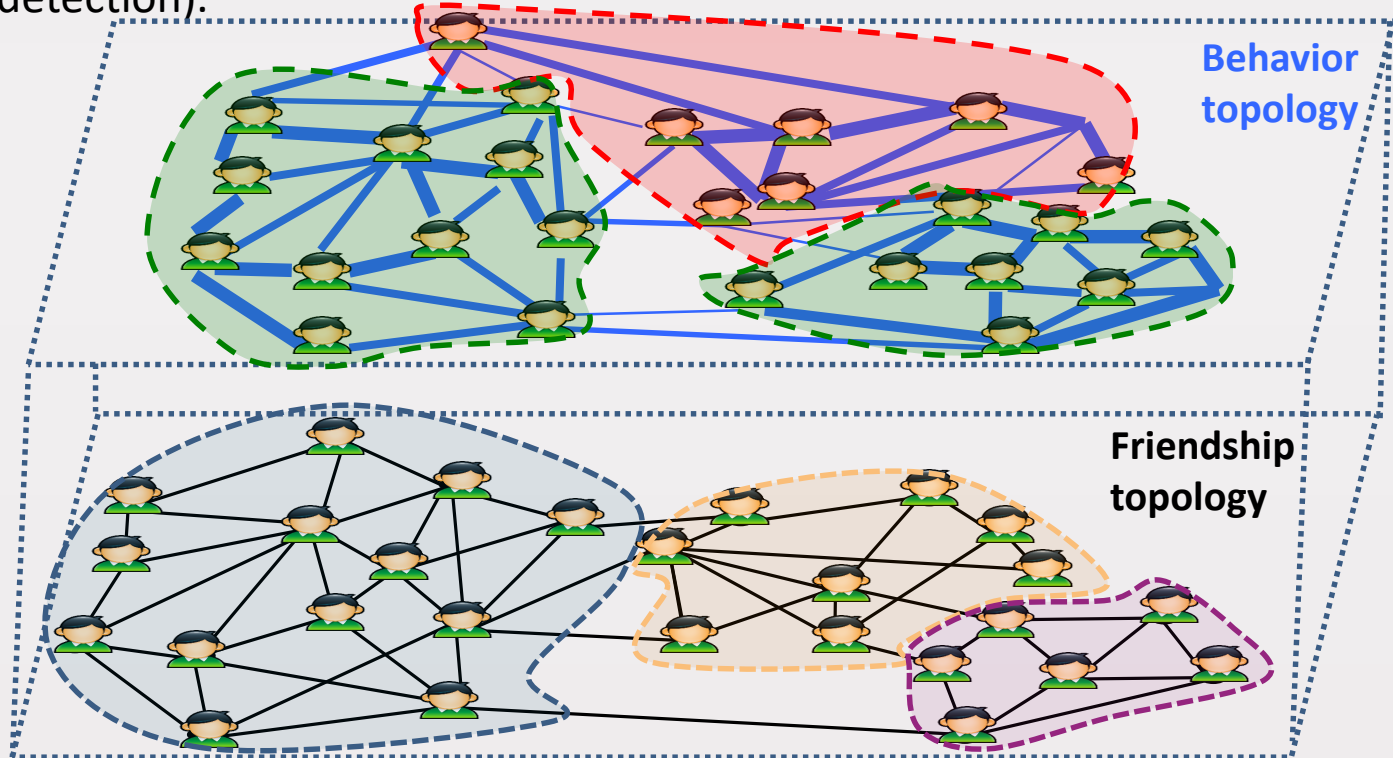
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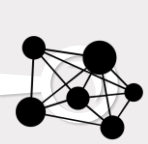
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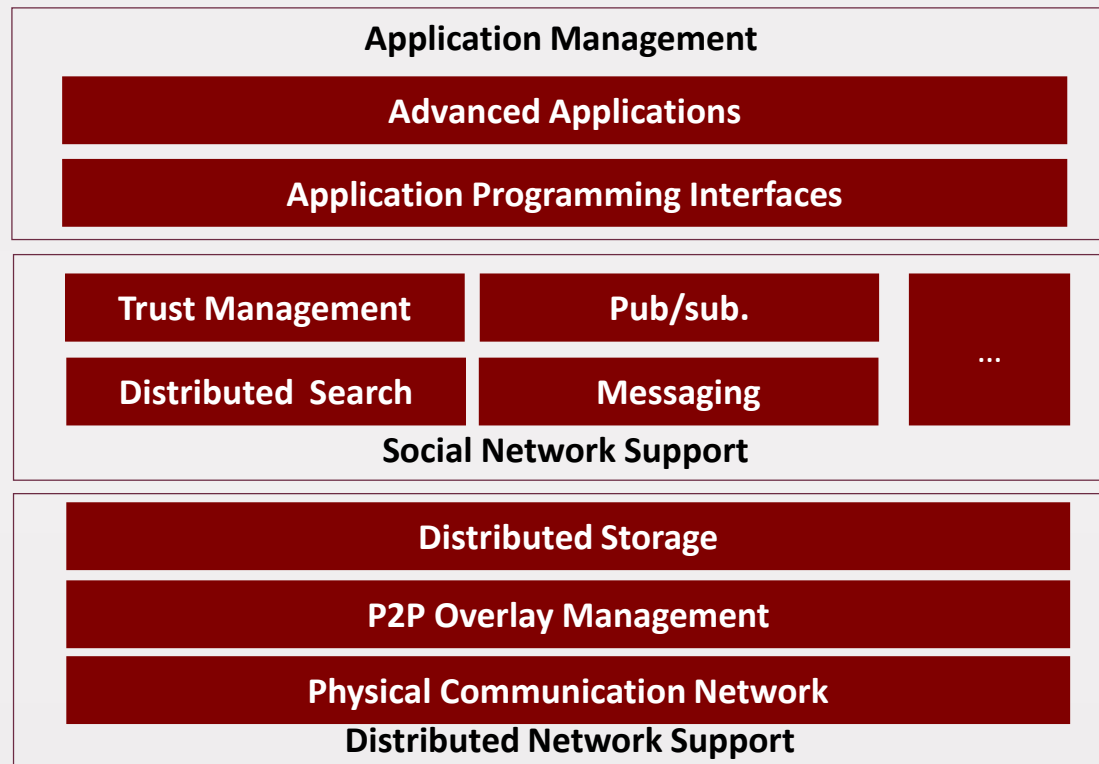


Main Objectives

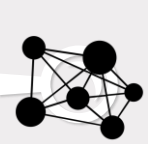
DOSN requires graph-based algorithms and methods that allow generation of efficient ML models using user local data in fully decentralized, iterative, massively parallel, and highly scalable manner, thereby *enabling decentralized ML and analytic tasks on DOSNs, without violating privacy preservation constraints.*



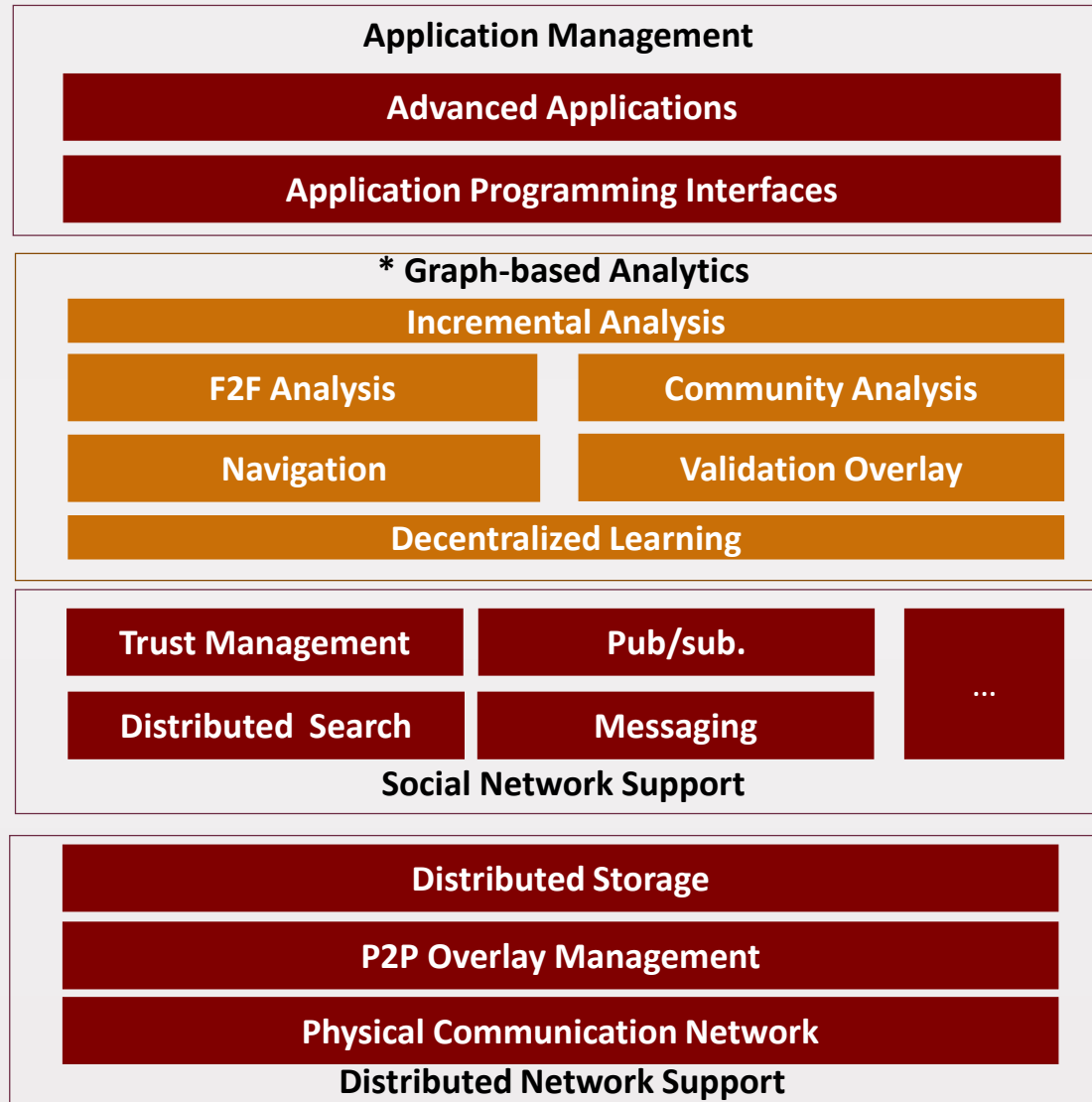
The Stack of Services

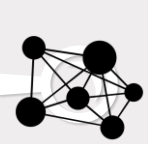


A. Datta, S. Buchegger, L.-H. Vu, T. Strufe, and K. Rzadca, “Decentralized online social networks,” in Handbook of Social Network Technologies and Applications . Springer, 2010, pp. 349–378.



The Stack of Services





Our Contributions

Community Detection

Soliman, A., Rahimian, F., and Girdzijauskas, S. Stad: Stateful Diffusion for Linear Time Community Detection. 38th International Conference on Distributed Computing Systems (ICDCS), pp. 1074-1085. IEEE, 2018.

Stad

Spam Detection

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AdaGraph

DLSAS

Validation Mechanism

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Identity Validation

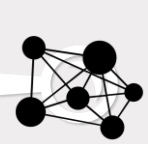
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CADIVa

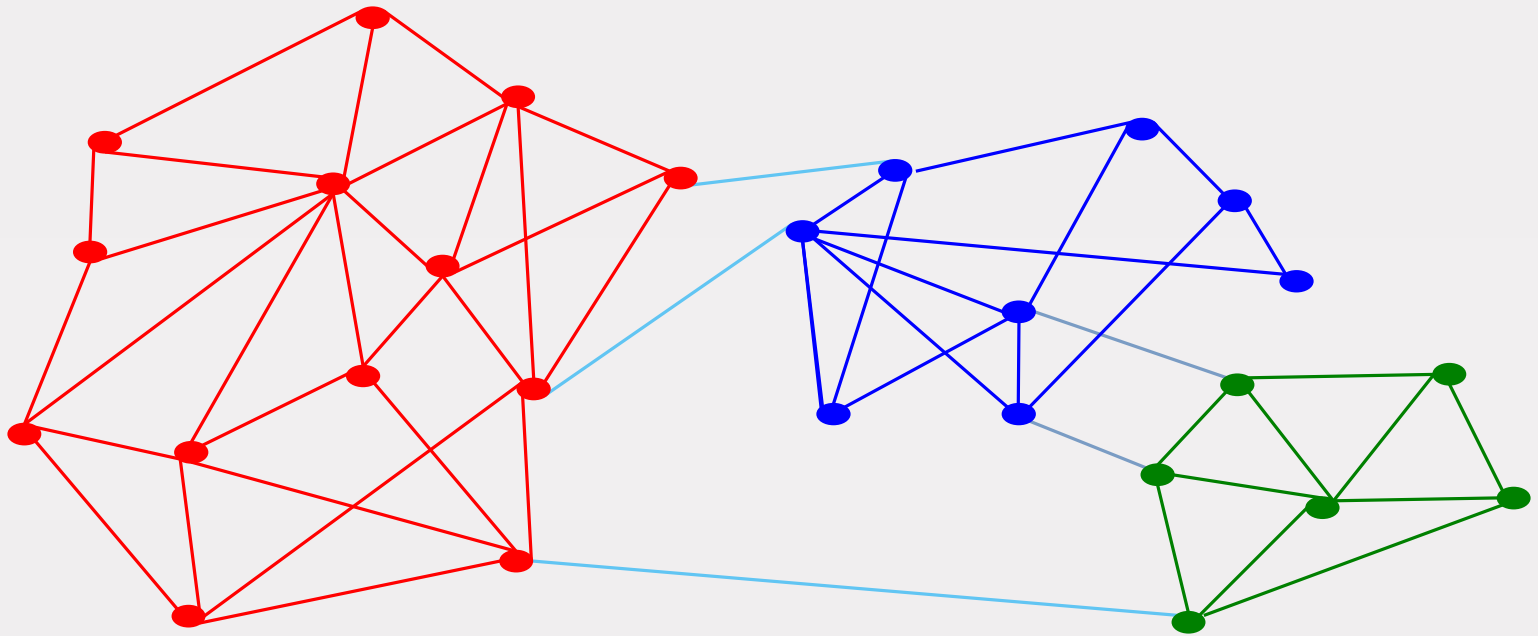
DIVa

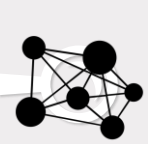
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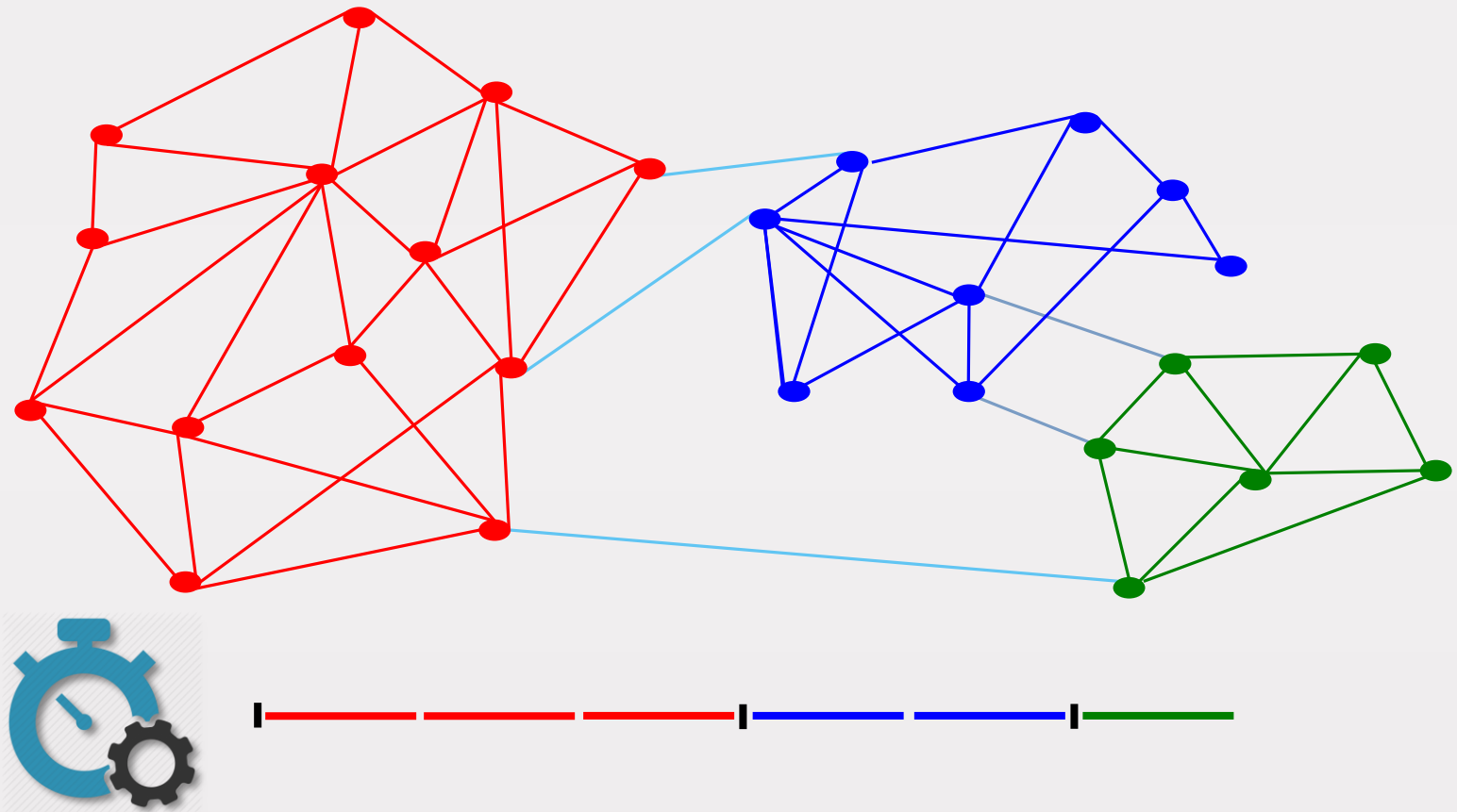


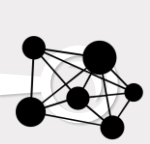
Stad: Performing Adaptive Diffusion for Community Detection





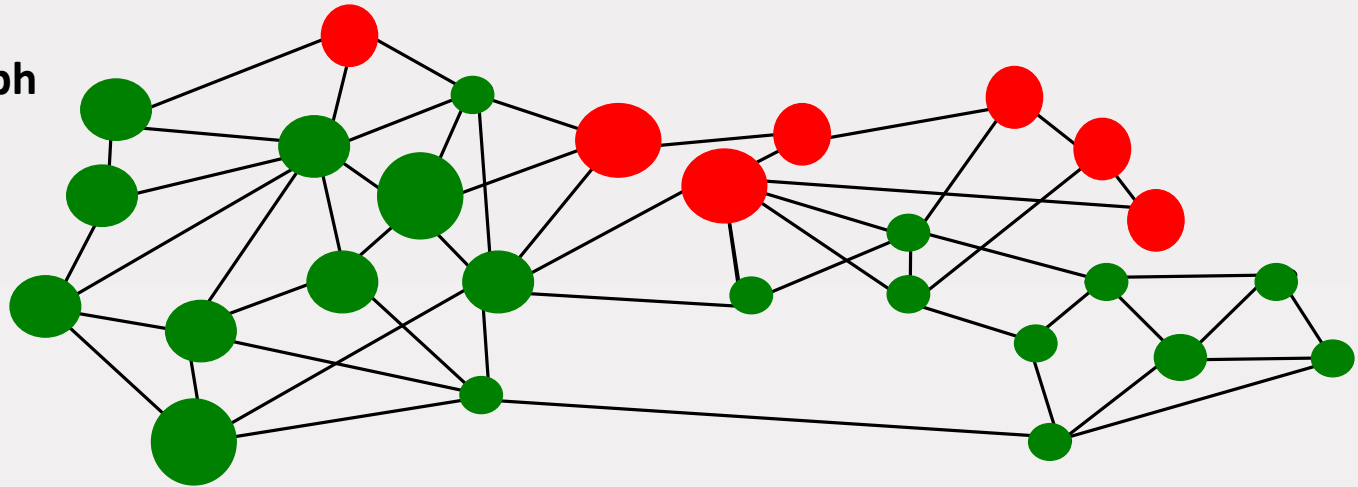
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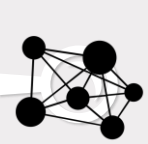




AdaGraph: Spam Detection using Graph Clustering

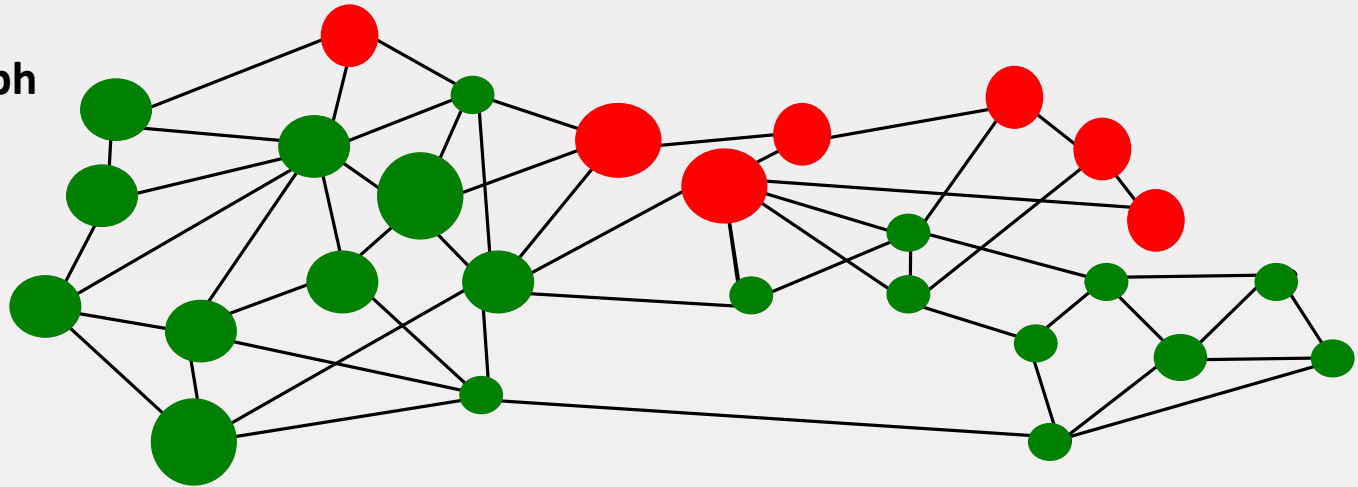
Social Graph



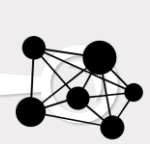


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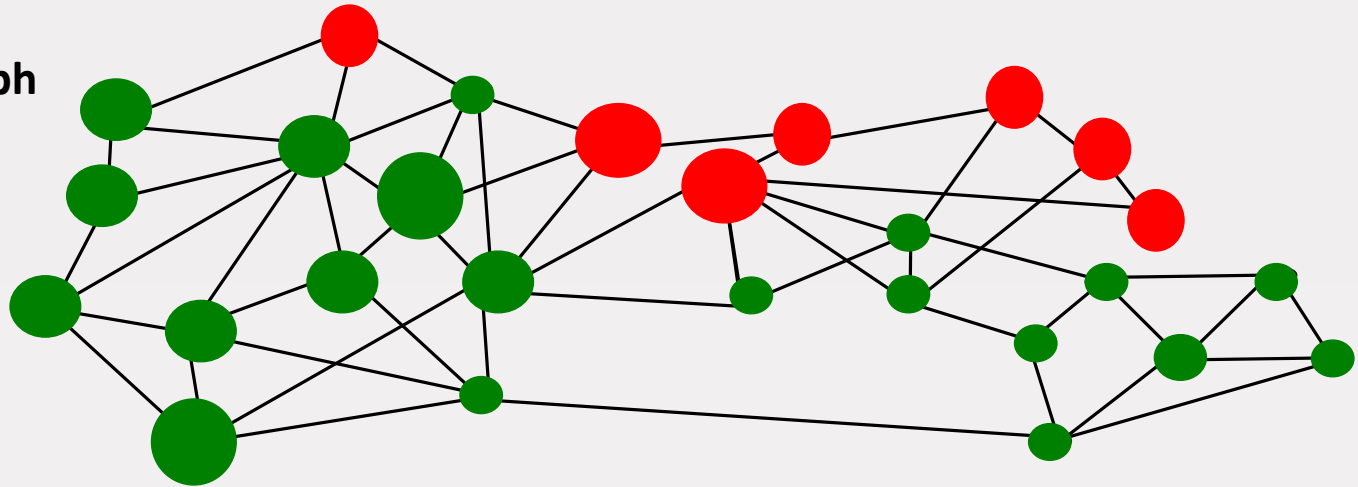


Similarity Graph

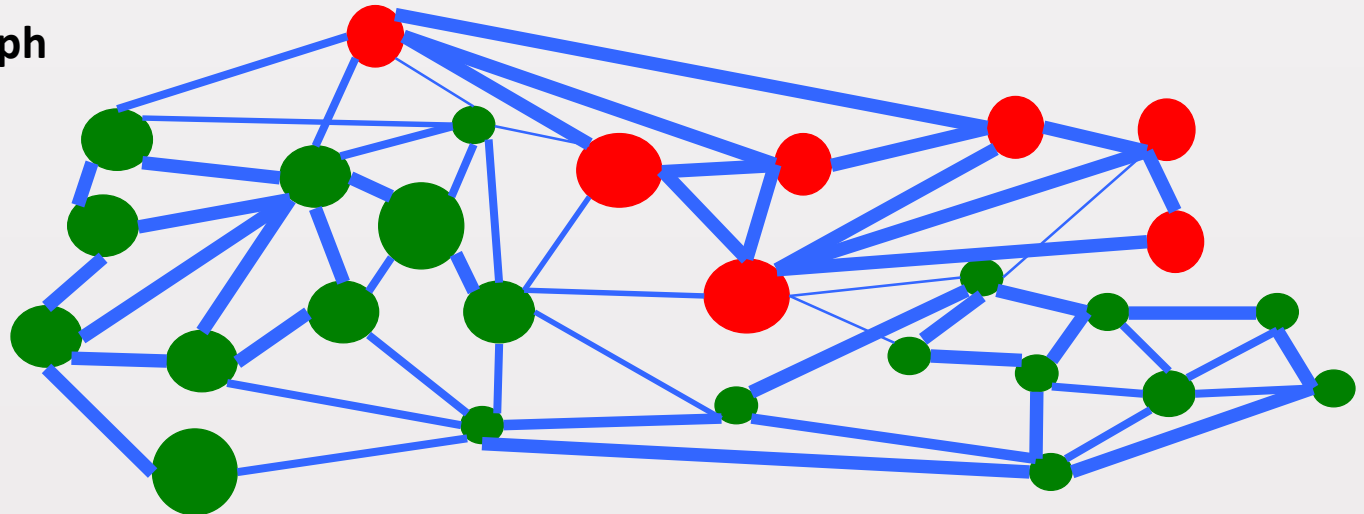


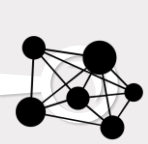
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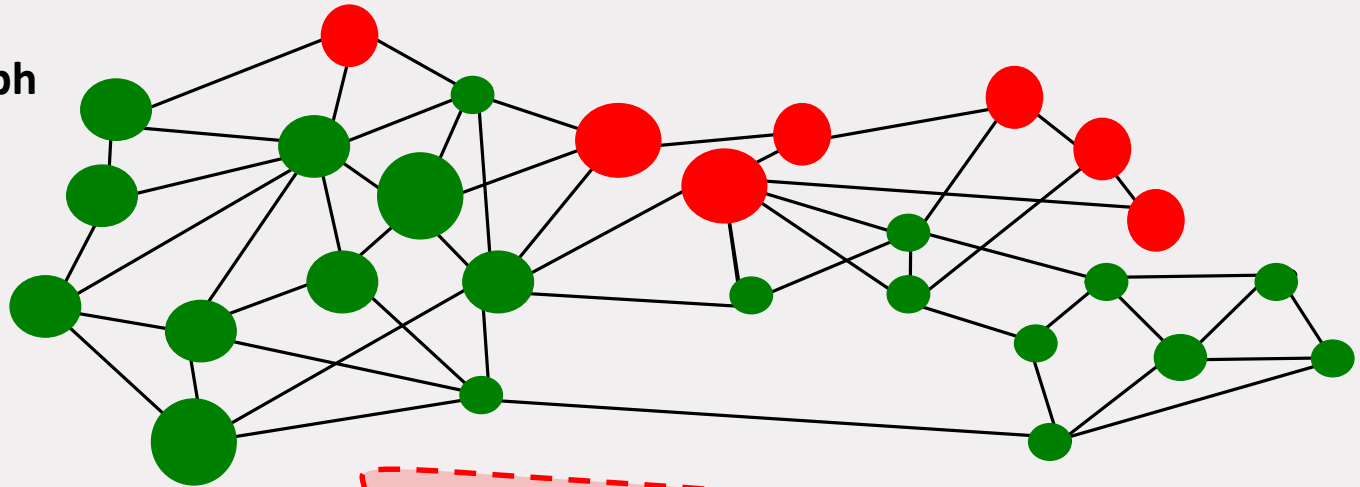
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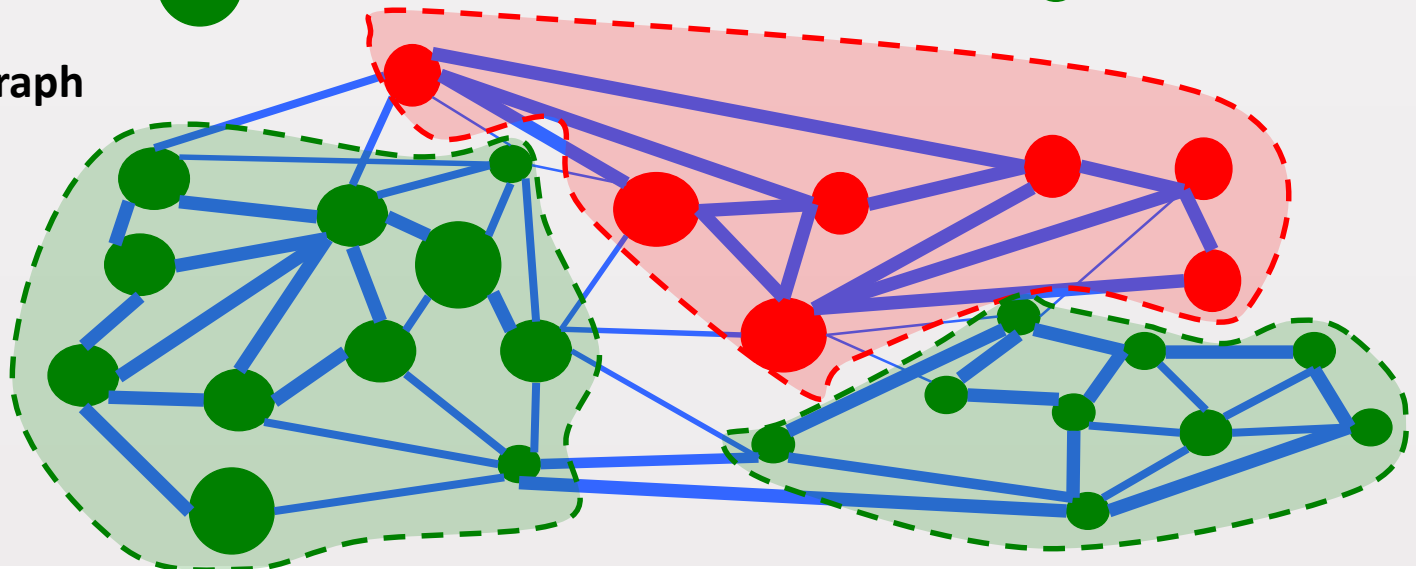


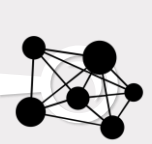
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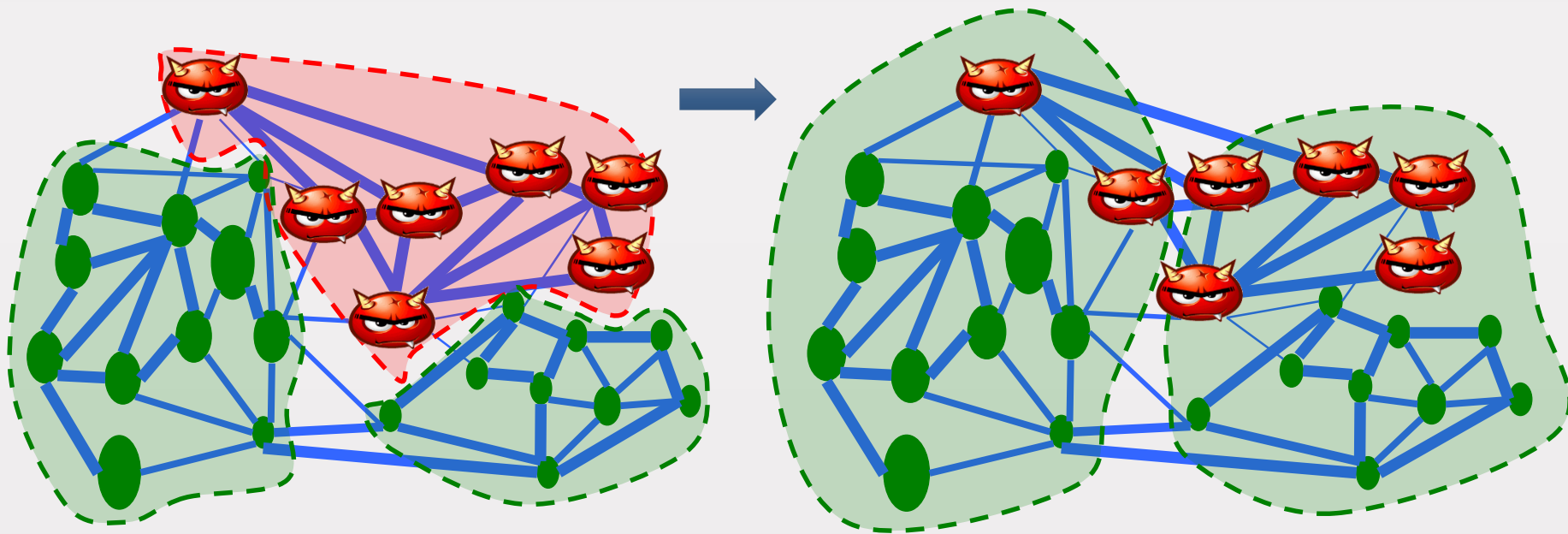
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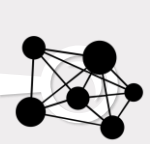
AdaGraph and Adversarial Manipulations

Malicious nodes collaborate with each other to falsify detected communities.



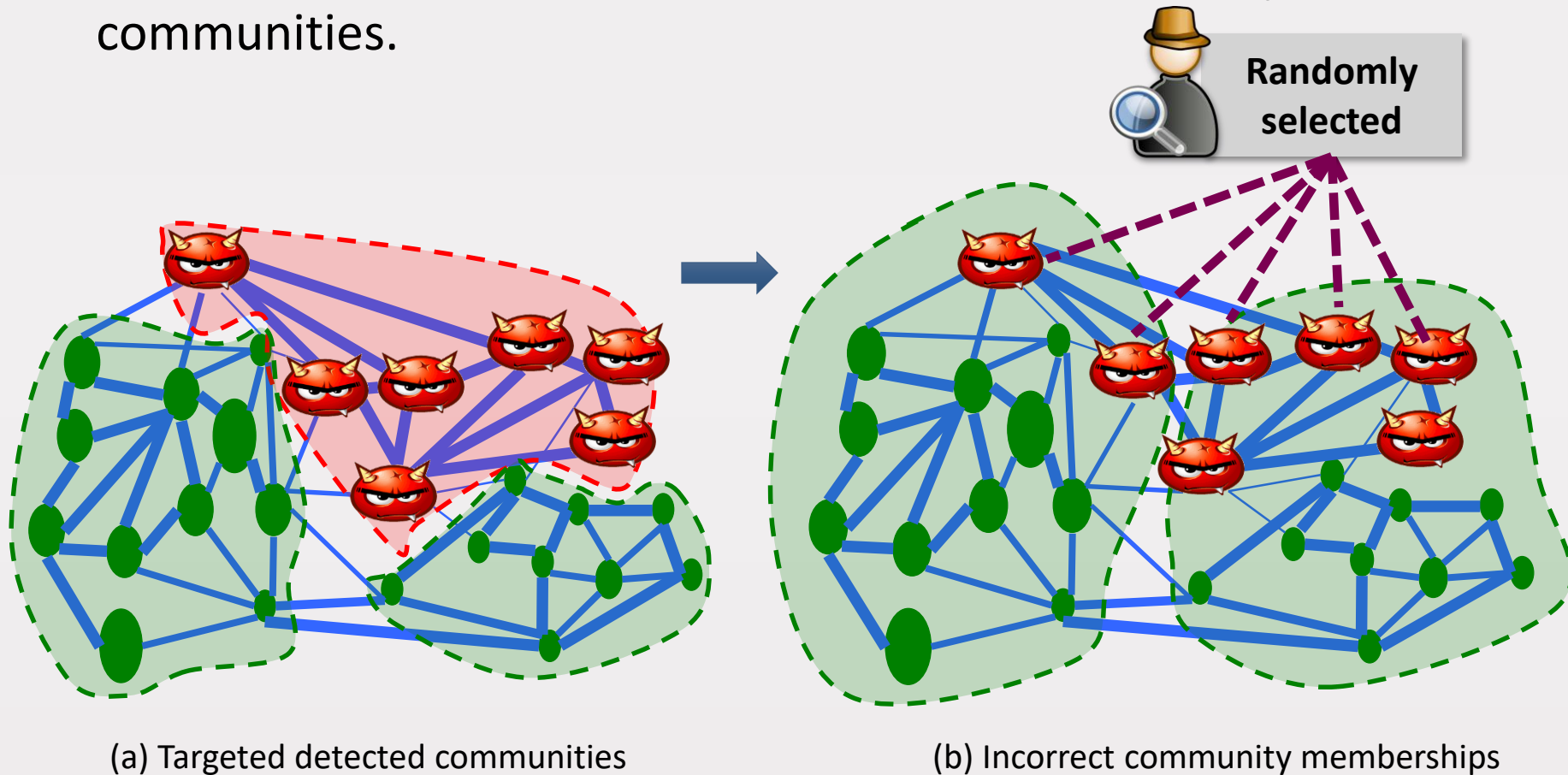
(a) Targeted detected communities


(b) Incorrect community memberships



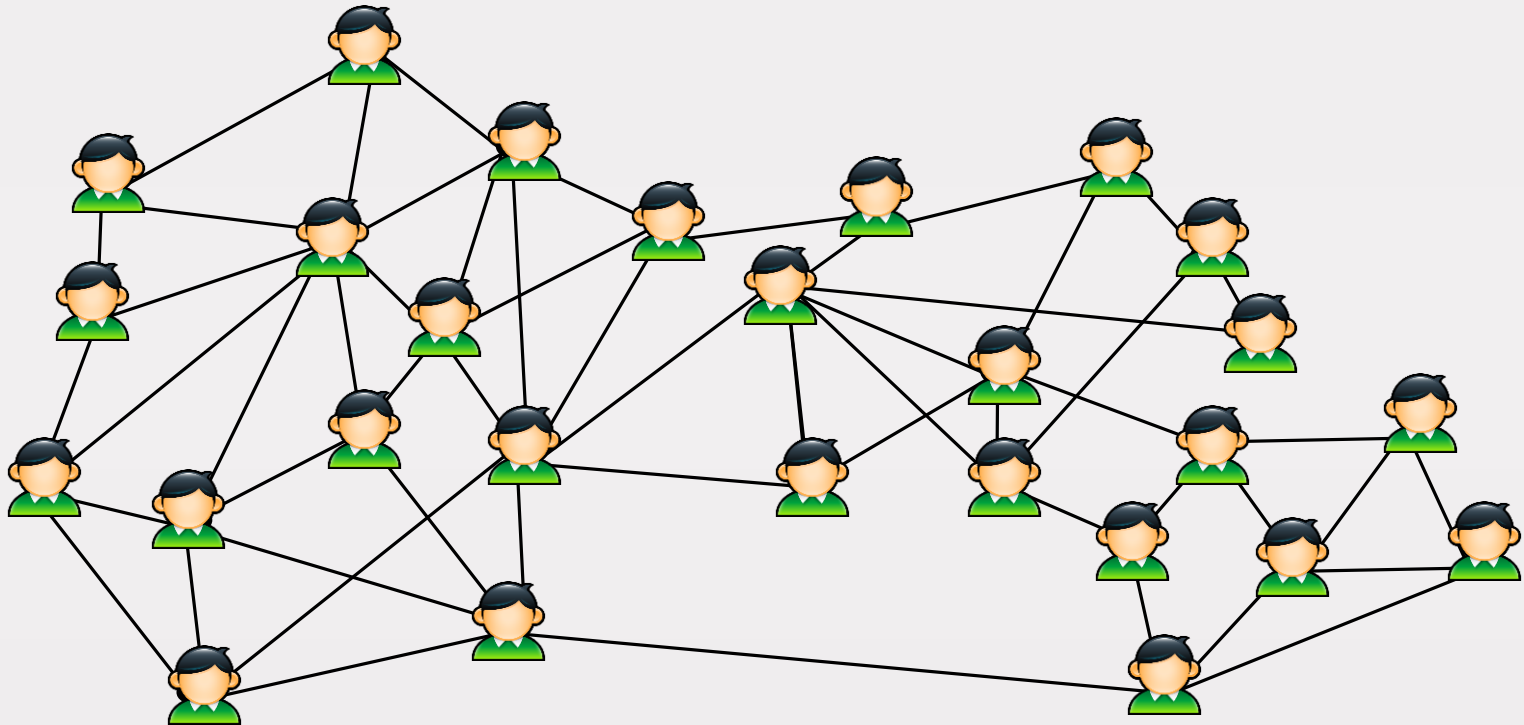
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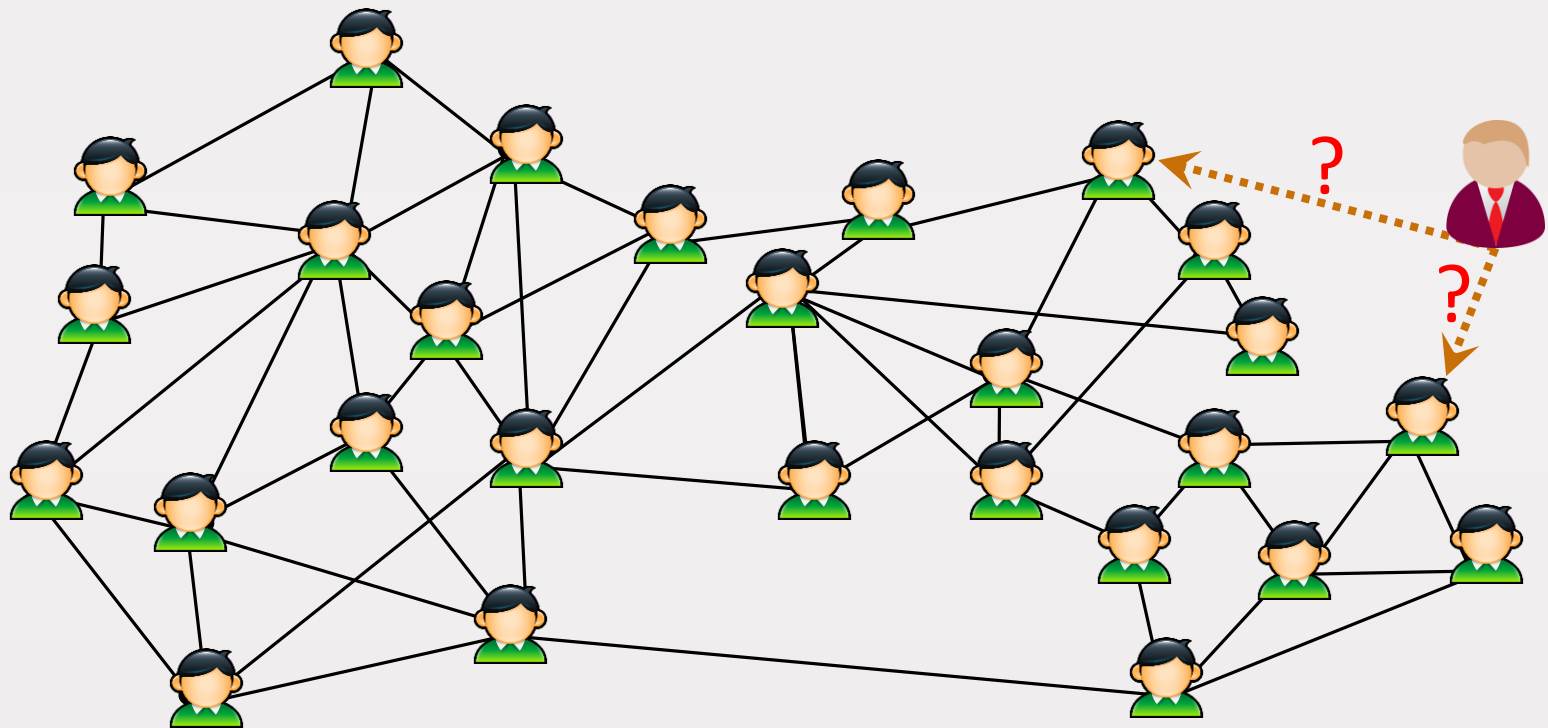



DIVa & CADIVa: How much trustworthy a profile is?



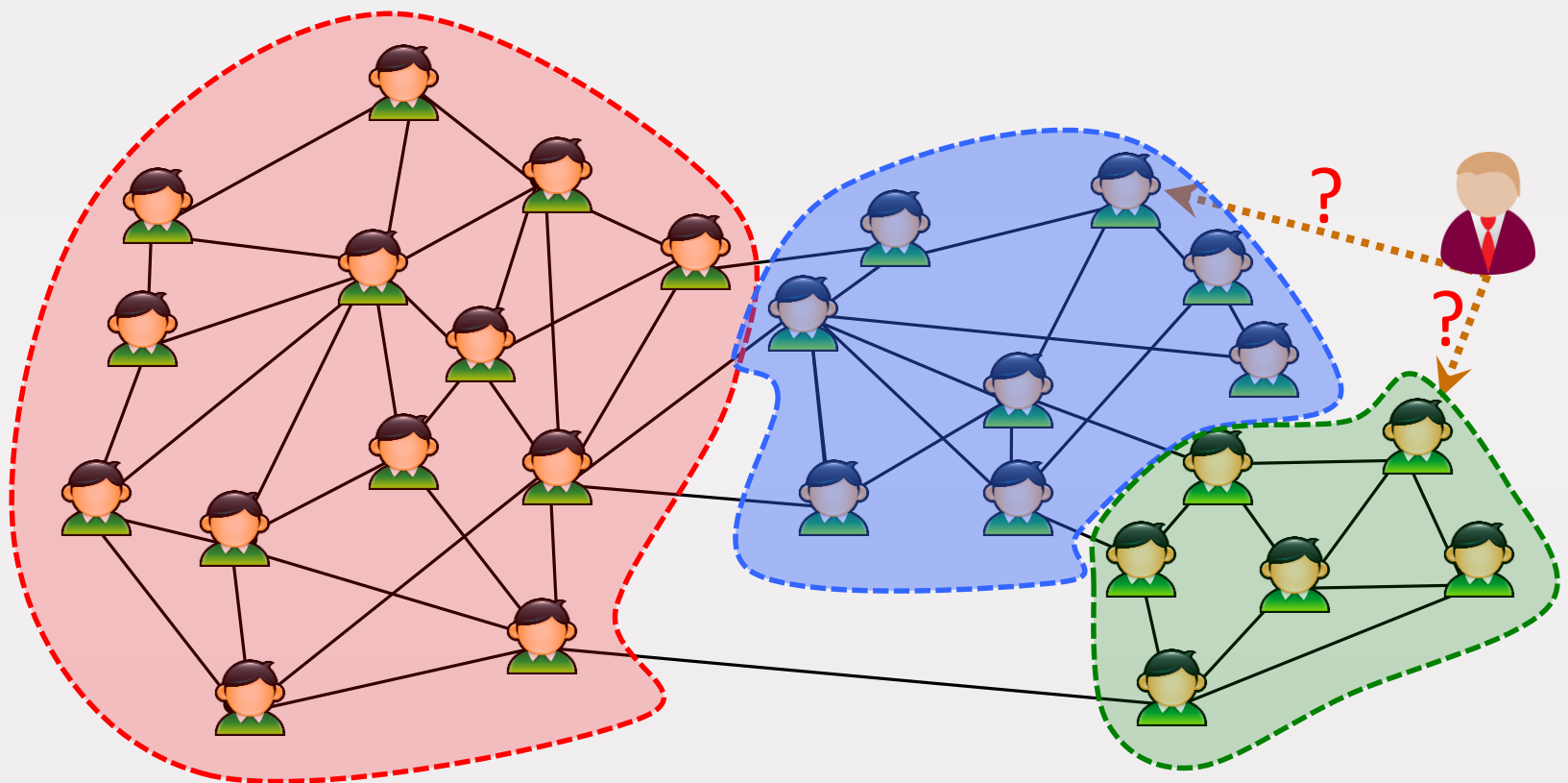


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List of Publications

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3. Soliman, A. and Girdzijauskas, S. (2016). DLSAS: Distributed Large-Scale Anti-Spam Framework for Decentralized Online Social Networks. Invited paper in the 2nd IEEE International Conference on Collaboration and Internet Computing, IEEE, pages 363-372.
4. Soliman, A., Bahri, L., Girdzijauskas, S., Carminati, B., and Ferrari, E. CADIVa: Cooperative and Adaptive Decentralized Identity Validation Model for Social Networks. Social Network Analysis and Mining 6, no. 1 (2016): 1-22.
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Thanks 😊