WIMS'14

# Towards a Framework for Social Semiotic Mining

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# Overview

Semiotics: From antiquity to Pierce and beyond!

Social Media & Data Mining

Our Goal: A Framework for:

a) Re-examining social content and tagging
b) Analyzing data mining on social content

Here, we will:

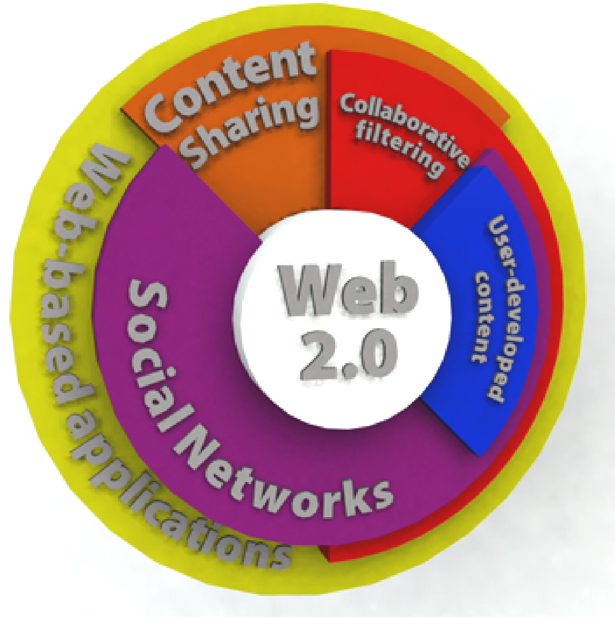
- Motivate & outline framework
- Apply to existing algorithms
- Demonstrate generalization to new

# Outline

1. Introduction
2. Signs and Semiotics
3. Social Media as Semiotic Resources
4. Social Media Clustering
5. Discussion
6. Conclusion

# 1. INTRODUCTION

# Setting




- Web 2.0
- Automated and Semi-Automated Content Analysis
- Wisdom of Crowds
- Applications: Recommender Systems, Policy Planning, Market Research etc.
- **However:** No clear theoretical framework!

*Image by : hermosaschool.wikispaces.com*

# 2. SIGNS AND SEMIOTICS

# Signs

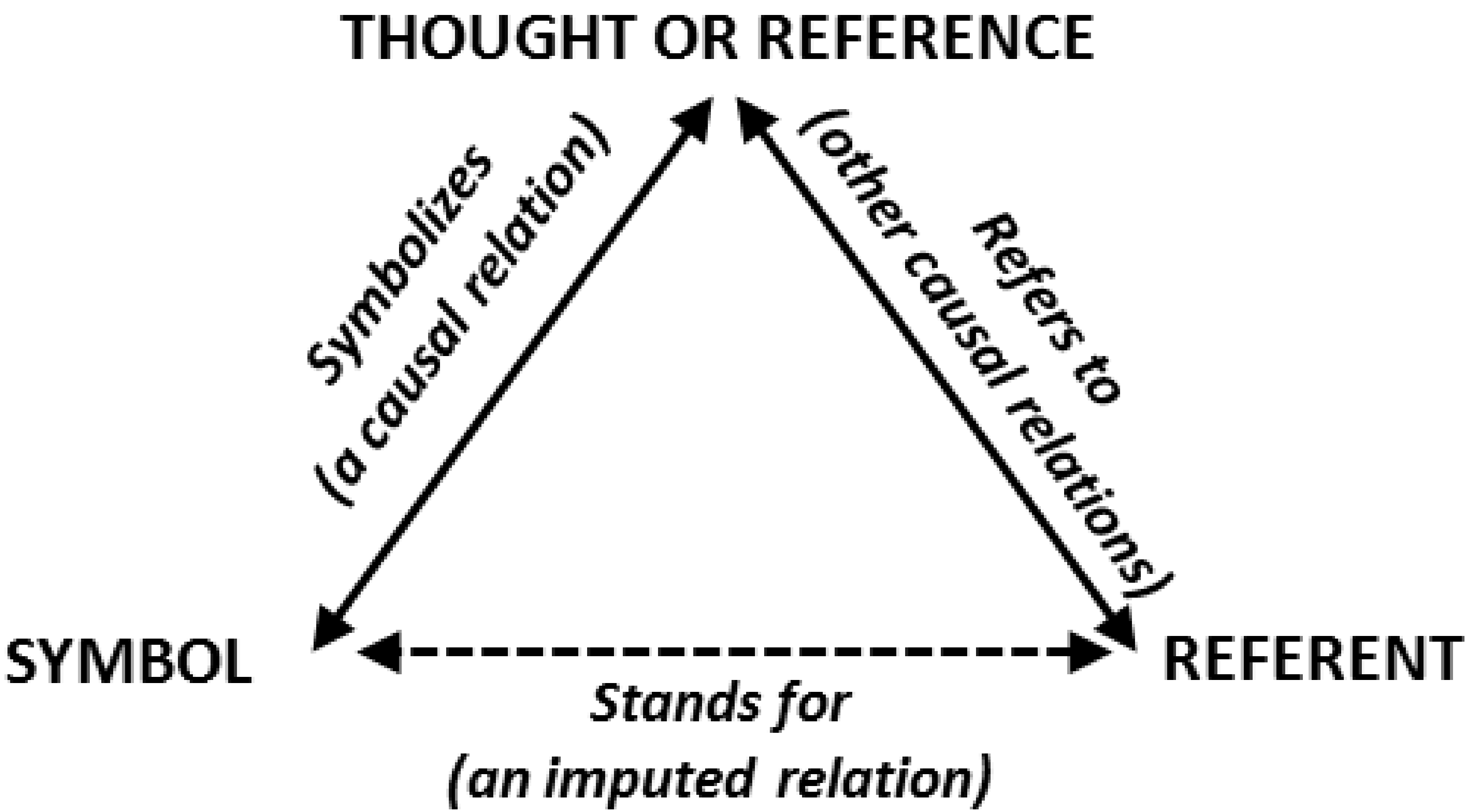
- “Nothing is a sign, unless it is interpreted as a sign” **says Pierce**
- Convention often non-conscious
- Natural Signs vs. Conventional Signs
- Symbol = “Συν” + “Βάλλω”
- Smoke + Fire
- But how could this apply to Social Media?

# 3. SOCIAL MEDIA AS SEMIOTIC RESOURCES

# Ancient Beginnings

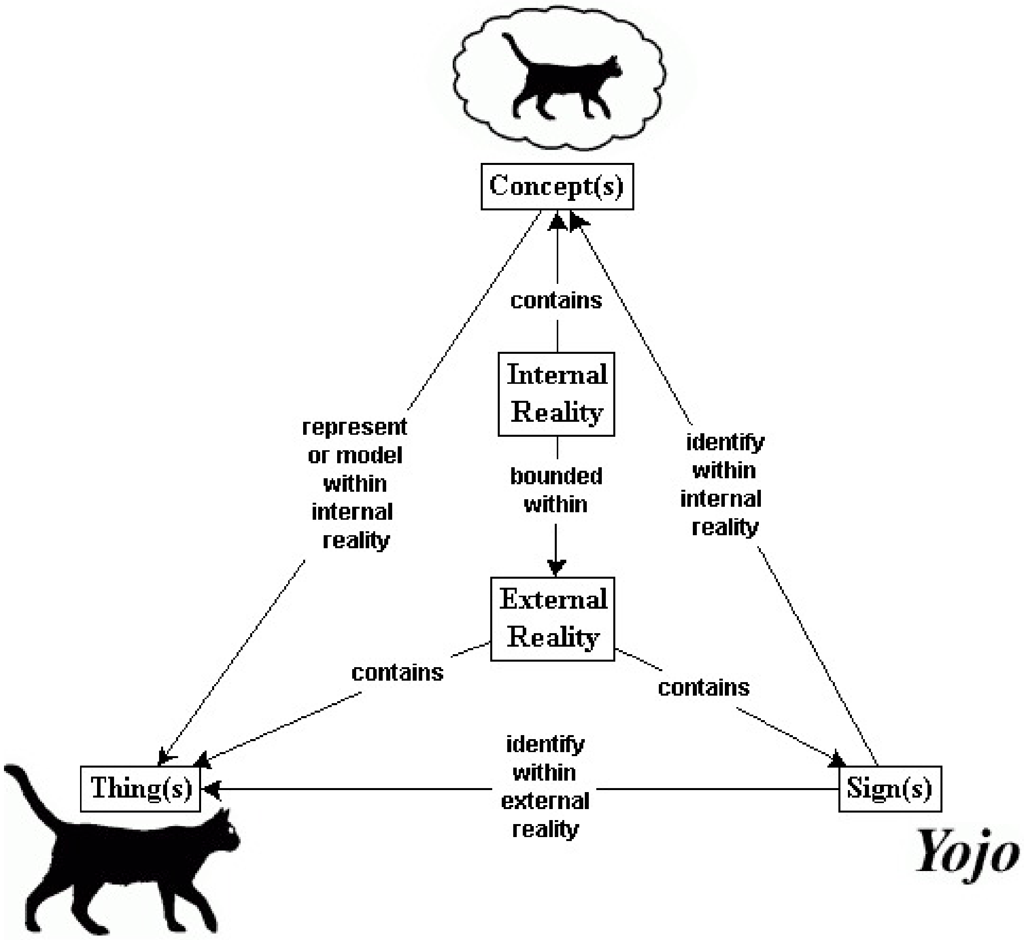
- Peri Hermineias (De Interpretazione) of Aristotle: Differentiated between objects, the words that refer to them and their corresponding experiences of the soul (psyche).
- also … Stoic Philosophers

# The Semiotic Triangle



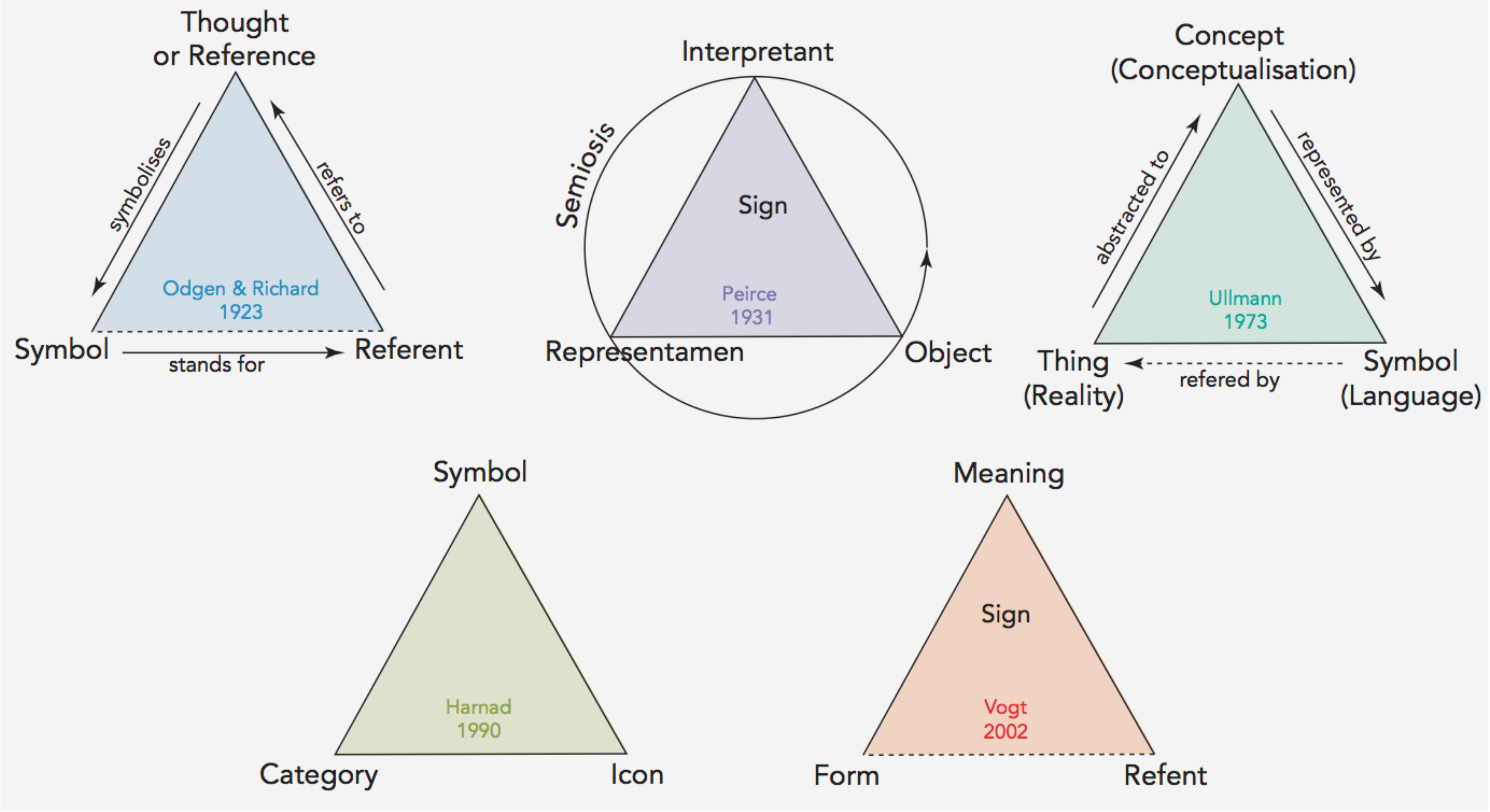

Ogden & Richards

# Extended Semiotic Triangle



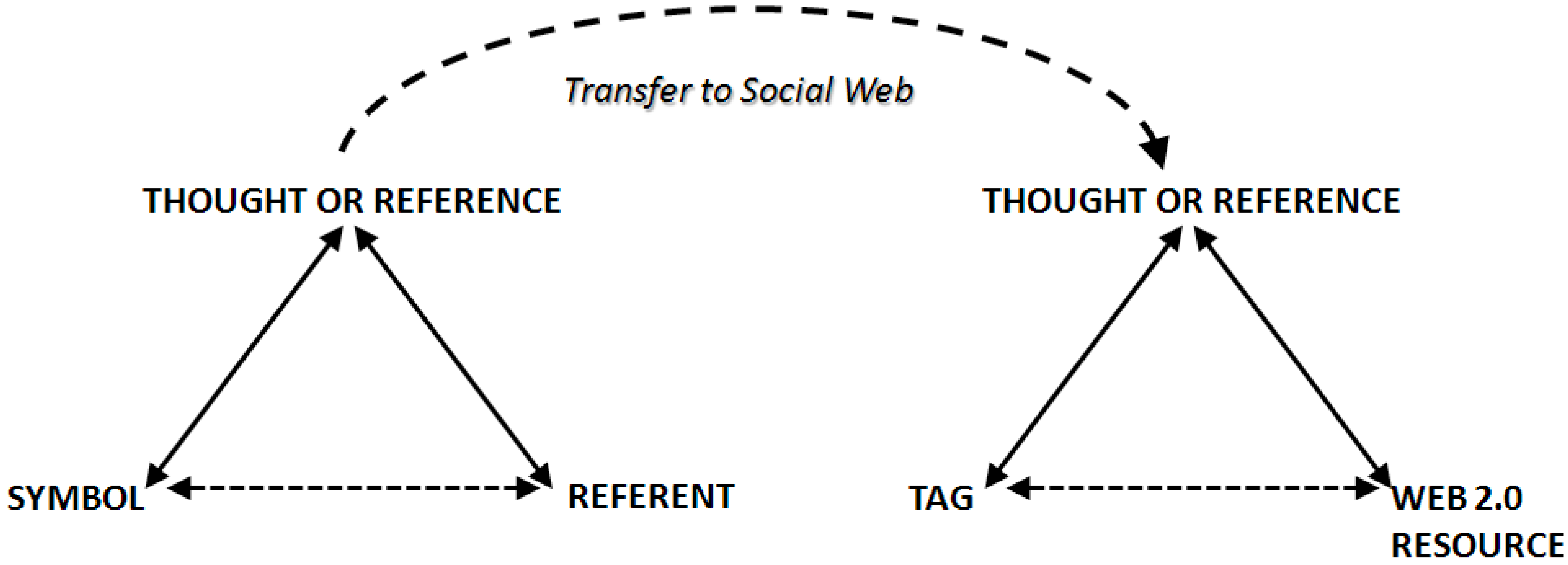

Carter, B., & Knight, D.

# Other Versions



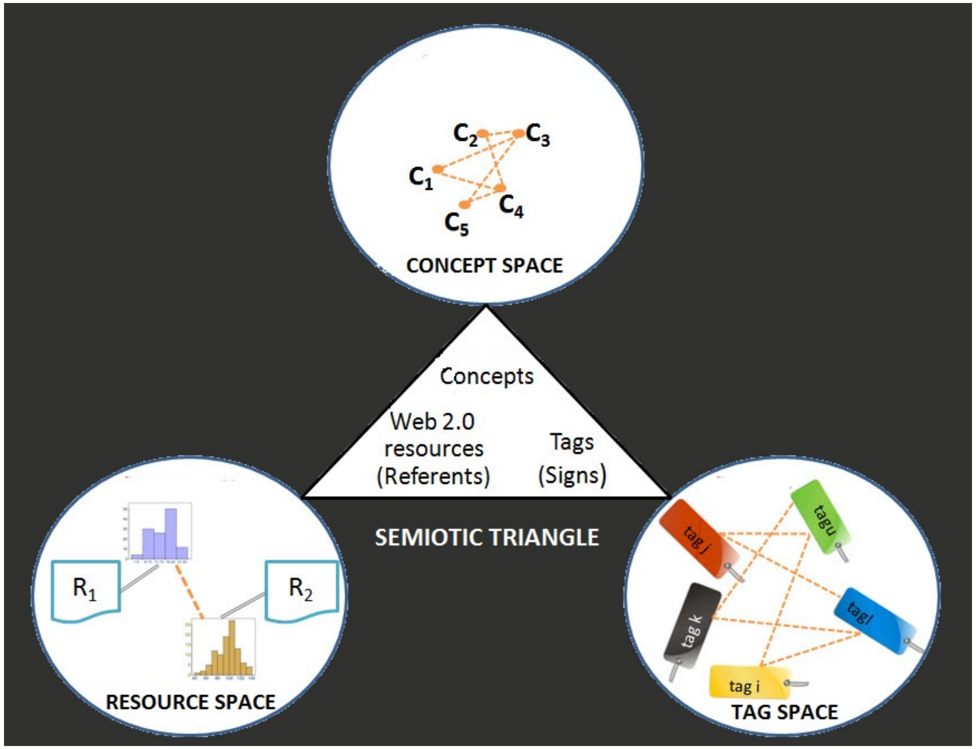

Versions exist by Pierce, Ullman, Harnad, Vogt etc.

# Transfer to Social Web



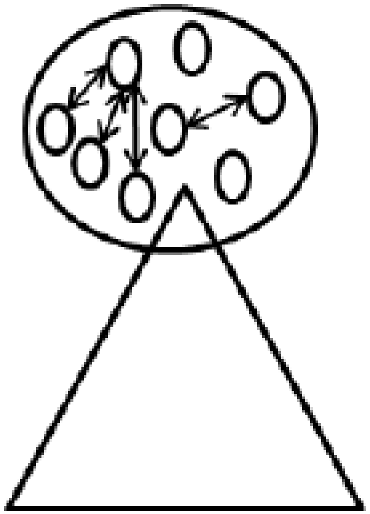
# The three spaces

- Tag space
- Concept space
- Resource space



# Ways to search for relations between entities (I)

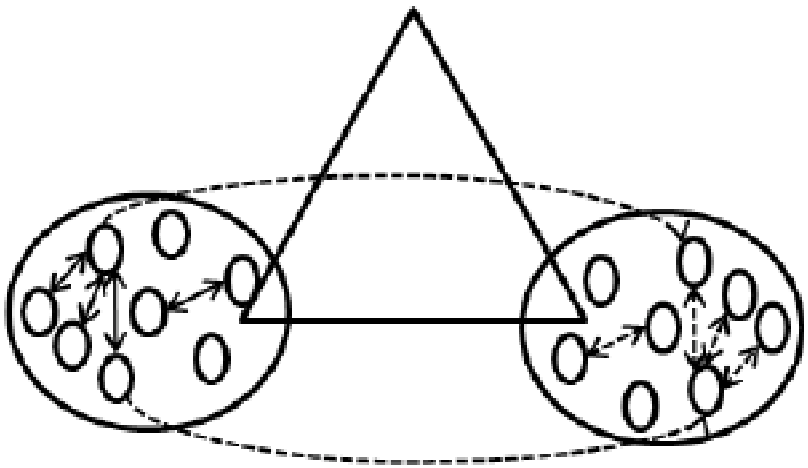
**1)** Examination of first level relationships (taking into account entities in one vertex only)



(a') Entities of the same vertex

# Ways to search for relations between entities (II)

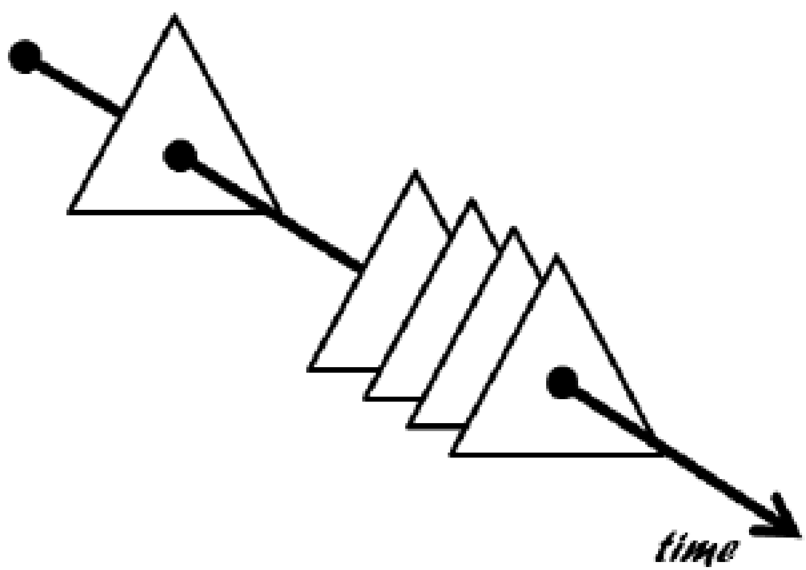
2) Examination of second level relationships (taking into account entities in two vertices)



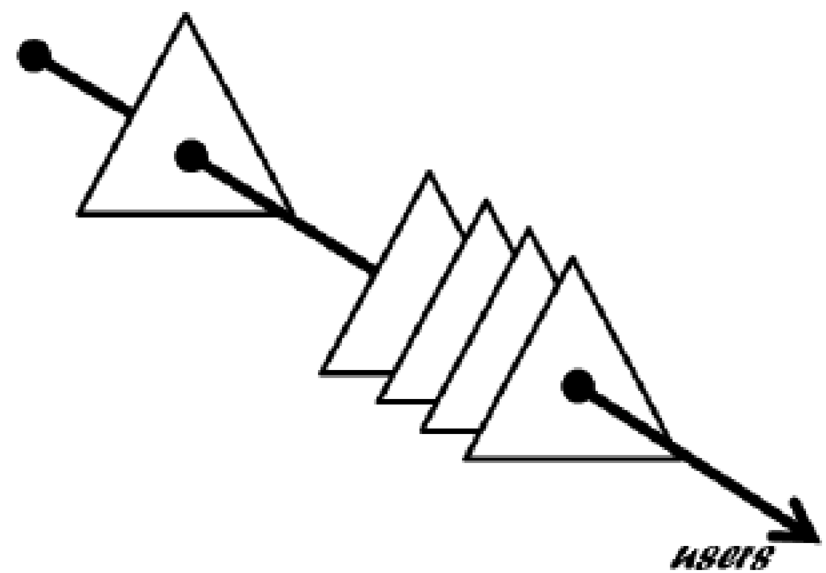
(β') Entities of multiple vertices

# Ways to search for relations between entities (III)

3) Extension of the semiotic triangle across multiple axis (for example across the temporal axis or the user axis)




(γ') Time axis




(δ') User axis

# 4. SOCIAL MEDIA CLUSTERING

# Generalized
# Social Clustering Framework (I)

Step 1) Chose type of clustering: One-way clustering (L1), co-clustering (L2)

Step 2) Determine which subset of vertices U from V=(T,C,R) will be used for the distance function for the clustering, i.e.

- 1 chosen vertex set out of V for the case of one-way clustering (L1), i.e. U=(V1) where V1 belongs to V (T, C, or R)
- 2 chosen vertex sets out of V for the case of co-clustering (L2), i.e. U=(V1,V2) where V1 and V2 belong to V but V1 not equal to V2

# Generalized
# Social Clustering Framework (II)

Step 3) Form similarity spaces within each vertex of the semiotic triangle: introduce symmetric similarity/distance metrics, one for each vertex of the semiotic triangle.

Step 4) Introduce transformation mappings across the three vertices of the semiotic triangle, i.e. T(R), T(C), R(T), R(C), C(T), C(R), where for example C(T) refers the set of concepts C that is related to a specific tag or set of tags T

# Generalized
# Social Clustering Framework (III)

<u>Step 5)</u> Introduce generalized distances, depending on whether the case is L1 or L2:

<u>Example:</u>

dG(V1,V1) = w1*dV1(V1,V1) + w2*dV2(V2,V2) + w3*dV3(V3,V3) (1)

where V2 = V2(V1), i.e. the set of entities belonging to vertex V2 that arise out of the transformation mapping V2(V1).

e.g. if V2=C (concepts) and V1=T (tags),

then V2(V1) = C(T) = the concepts that correspond to tag T

then, proceed by clustering according to the distance dG(V1,V1)

# Application to previous work

- Begelman, G., Keller, P., & Smadja, F. 2006. Automated tag clustering: Improving search and exploration in the tag space. In Collaborative Web Tagging Workshop at WWW2006, Edinburgh, Scotland 15-33.
- Peter Mika. 2007. Ontologies are us: A unified model of social networks and semantics. Web Semant. 5, 1 (March 2007), 5-15. DOI=10.1016/j.websem.2006.11.002 http://dx.doi.org/10.1016/j.websem.2006.11.002
- Schmitz, P. (2006, May). Inducing ontology from flickr tags. In Collaborative Web Tagging Workshop at WWW2006, Edinburgh, Scotland (Vol. 50).
- Bumgardner J. 2006. Experimental colr pickr. Available at: http://www.krazydad.com/

***V = T***
***w1, w2, w3 = (1,0,0)***

***V= R***
***w1,w2,w3 = (0,0,1)***

- Giannakidou, E., Kaklidou, F., Chatzilari, E., Kompatsiaris, I., & Vakali, A. (2010). Harvesting Intelligence in Multimedia Social Tagging Systems. In Emergent Web Intelligence: Advanced Information Retrieval (pp. 135-167). Springer London.
- Aurnhammer, M., Hanappe, P., Steels, L., Augmenting navigation for collaborative tagging with emergent semantics. In Proc. of the 5th ISWC (2006)
- Börkur Sigurbjörnsson and Roelof van Zwol. 2008. Flickr tag recommendation based on collective knowledge. In Proceedings of the 17th international conference on World Wide Web (WWW '08). ACM, New York
- Anastasia Stampouli, Eirini Giannakidou, and Athena Vakali. 2010. Tag disambiguation through Flickr and Wikipedia. In Proceedings of the 15th international conference on Database systems for advanced applications (DASFAA'10),

***V = T***
***w1,w2,w3 = (x,y,z)***
***where 0 ≤ x,y,z < 1***

# Application
# to previous work

- another case L2 (co-clustering) where 2 vertices are used for the co-clustering: tags and resources (artists) [26].... numerous other such examples exist.

.... ***moving beyond*** single-vertex and dual-vertex one way

clustering, and also beyond co-clustering, there exist methods that

extend the ***semiosis*** across users and across the temporal axis.

For example, although in [18] the first stage of clustering uses tags only, at the second stage the user axis is utilized. In numerous other papers the temporal axis is also taken into account for clustering [28].

# 5. DISCUSSION

# Discussion

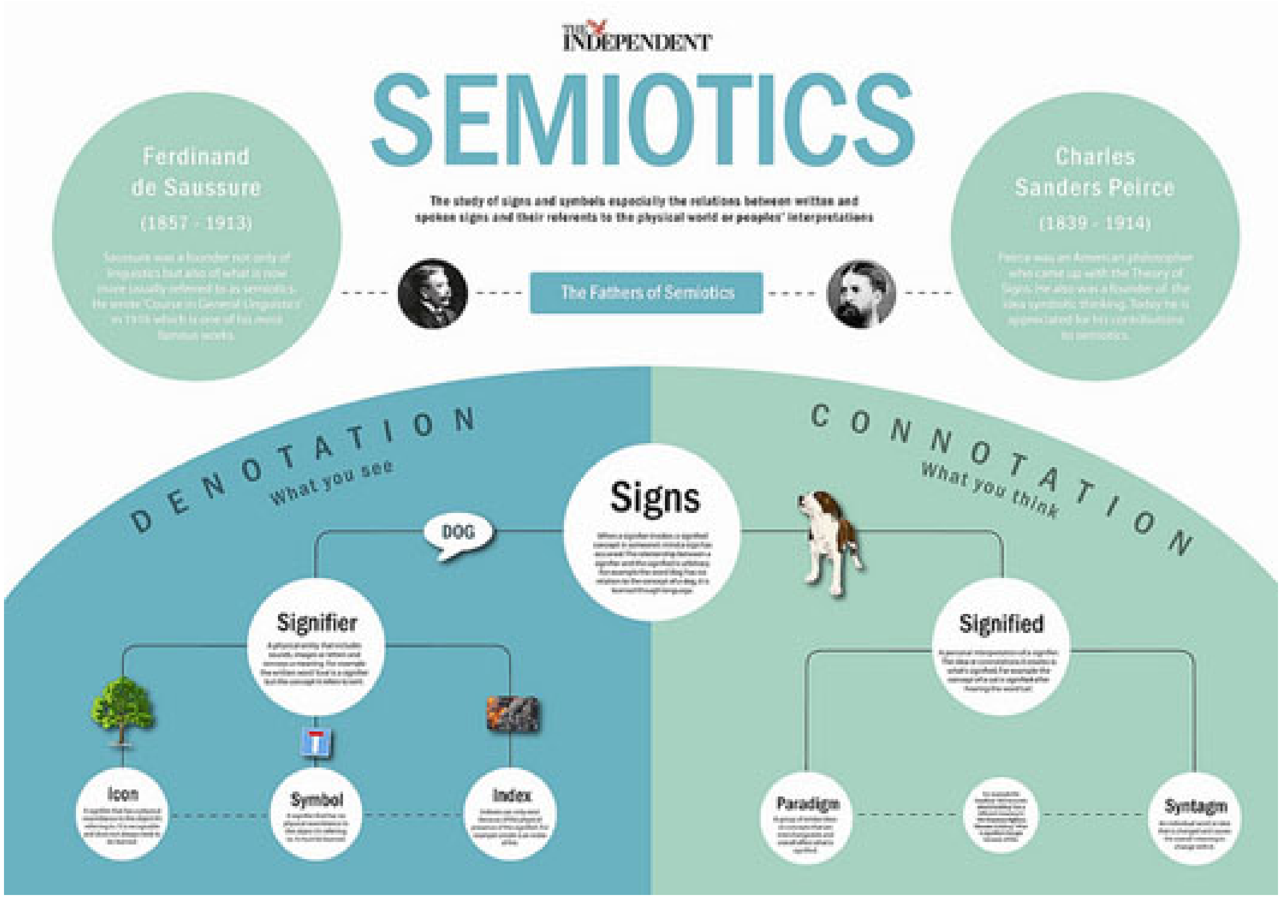
- Existing cases covered by framework;
- One extend to novel cases:

can also produce novel combinations that fall within the generative power of the framework.

For example, one could create novel methods by choosing appropriate similarity metrics within each vertex, choosing subsets of vertices in order to create generalized weighted distances that contain similarities arising across more than one vertex (for example, one could use the triple combination tags – concepts – auditory features of resources), and perform either one-way clustering, or co-clustering, or even extend to higher-dimensional tensor-based methods.

Future extensions to framework:

- better treatment of user and temporal axis
- Move beyond clustering to classification and regression

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THANK YOU!