# Thematic fit evaluation: an aspect of selectional preferences


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## Motivations and goals

**Thematic fit:** another way to see selectional preferences – how a processor reacts to a candidate filler given a verb and role.
("cut", `instrument`, "finger") → 1 out of 7
("cut", `instrument`, "knife") → 6 out of 7

A window into human semantic processing.

**Applications:** psycholinguistic modeling, dialogue systems, testing of coreference with previous discourse items

## Future evaluation aims

### More balanced datasets

- Greenberg et al. (2015) – datasets balanced for frequency and polysemy.
- Need more judgement data designed to contrast particular semantic features.

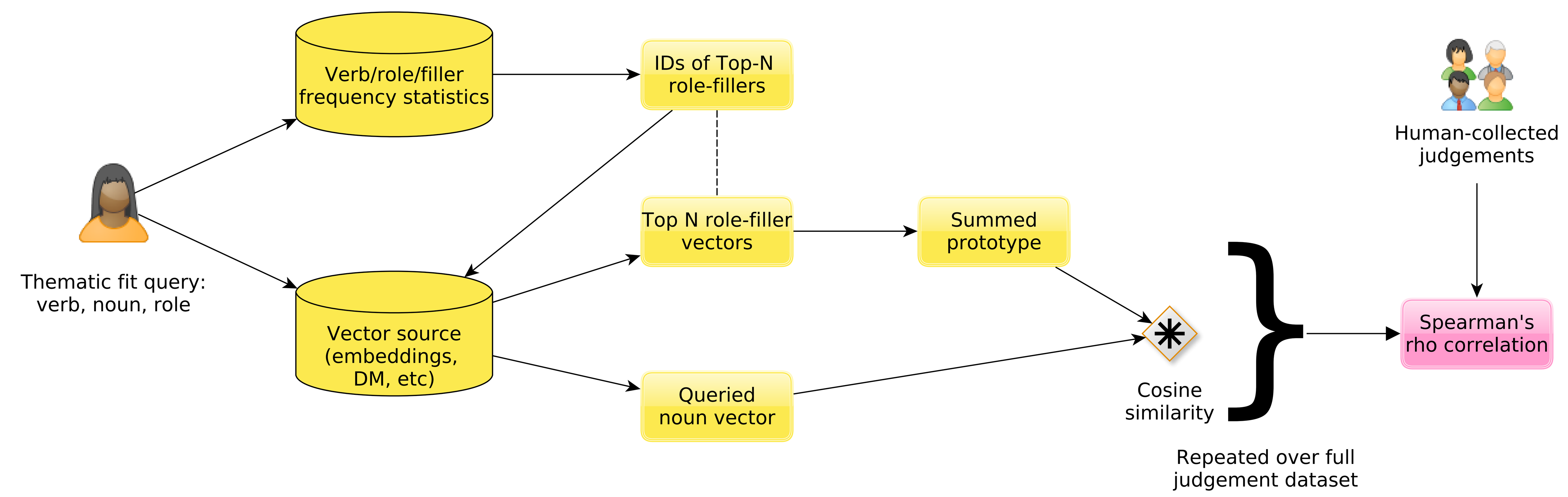
### Compositionality

- Existing evaluation datasets: verb-role-noun triplets – need new datasets with other slots filled.
- e.g. if agent is "chef", then $\theta$-*Fit*("whip", `patient`, "cream") > $\theta$-*Fit*("whip", `patient`, "horse")

### Perceptuomotor knowledge

- Existing thematic fit models – distributional.
- Can semantic knowledge fully be captured by distributional stats?
- Rating scheme to distinguish different semantic "knowledges"?

## Standard evaluation procedure



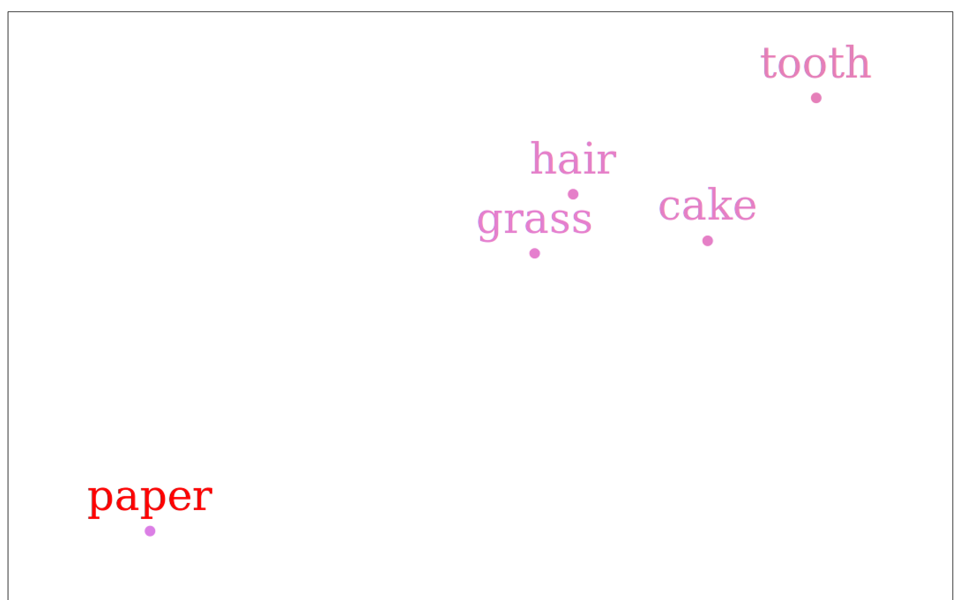

**Areas for improvement:**

thematic fit scoring process

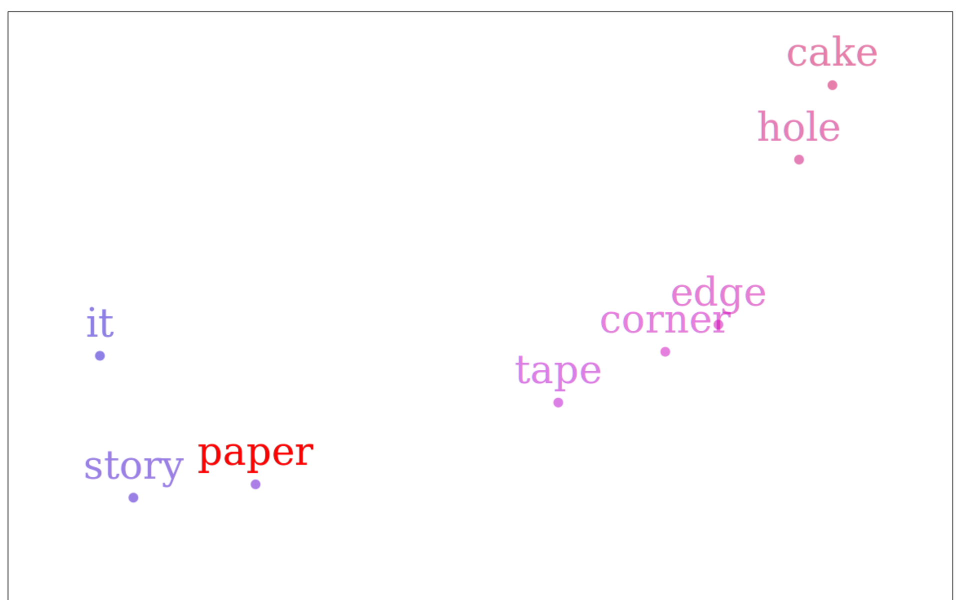
evaluation objective

## Visualizations from Roleo (Sayeed et al., 2016 ACL demos)

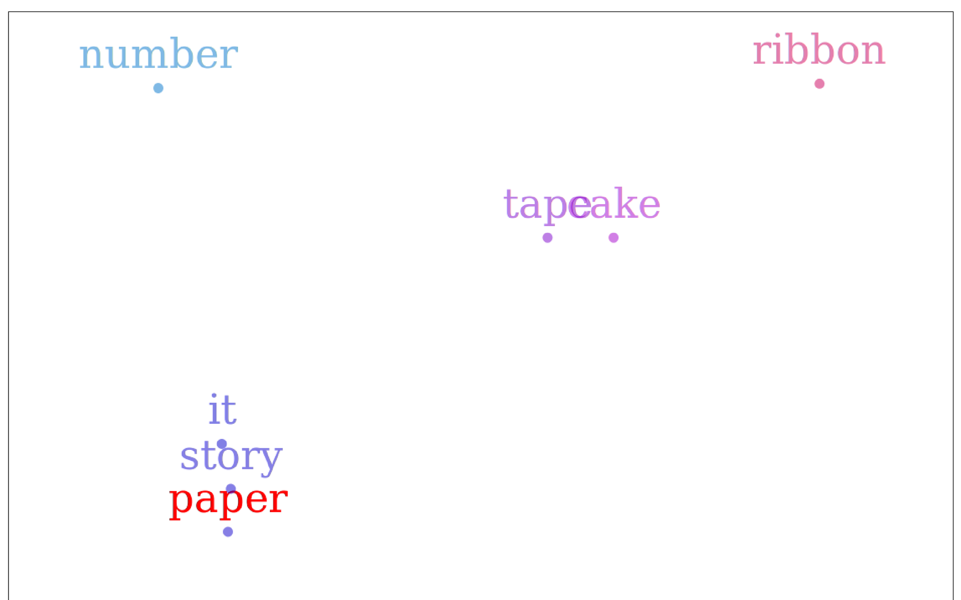
$\theta$-*Fit*("cut", `patient`, "paper"): excerpts of plots of top candidate vectors with "paper" vector.




SENNA-based count vectors (Sayeed et al., 2015)




word2vec pretrained




Role-based NN embeddings (Tilk et al., 2016)

## Existing datasets and correlations

### Descriptions of datasets

**MSTNN**: 1444 agents & patients, items drawn from many experiments (see table on right)
**P07**: 414 agents & patients, systematic selection frequent predicates and arguments
**F-Loc**: 274 locations, **F-Inst**: 248 instruments, these roles tend to be less stable
**GDS-mono**: 240 patients with monosemous verbs, verbs matched for freq. with GDS-poly
**GDS-poly**: 240 patients with polysemous verbs. Each noun had a freq. and infreq. variant

| verb | role-filler | agent | patient |
|---|---|---|---|
| accept | friend | 6.1 | 5.8 |
| accept | student | 5.9 | 5.3 |
| accept | teenager | 5.5 | 4.1 |
| accept | neighbor | 5.4 | 4.4 |
| accept | award | 1.1 | 6.6 |

| Dataset | Centroid | Greenberg-Clusters | SDS2015-average | SDS2015-swap |
|---|---|---|---|---|
| P07 | 59 | 55 | 59 | 48 |
| MSTNN | 34 | 38 | 34 | 25 |
| F-Loc | 23 | 29 | 21 | 19 |
| F-Inst | 36 | 42 | 39 | 45 |
| GDS-mono | 66 | 68 | - | - |
| GDS-poly | 43 | 47 | - | - |

Spearman's $\rho \times 100$ correlation with human judgements

- Embeddings seem to perform more poorly when used on their own (Baroni et al., 2014).
- Greenberg clusters systematically improve correlations on datasets with wide freq. range.
- Spaces built on semantic vs. syntactic links capture complementary information.