

Introduction

- **Swinging Lexical Network (SLN):** Interplay between *semantic priming* (facilitation) and *lexical competition* (interference) (Abdel Rahman & Melinger, 2019).

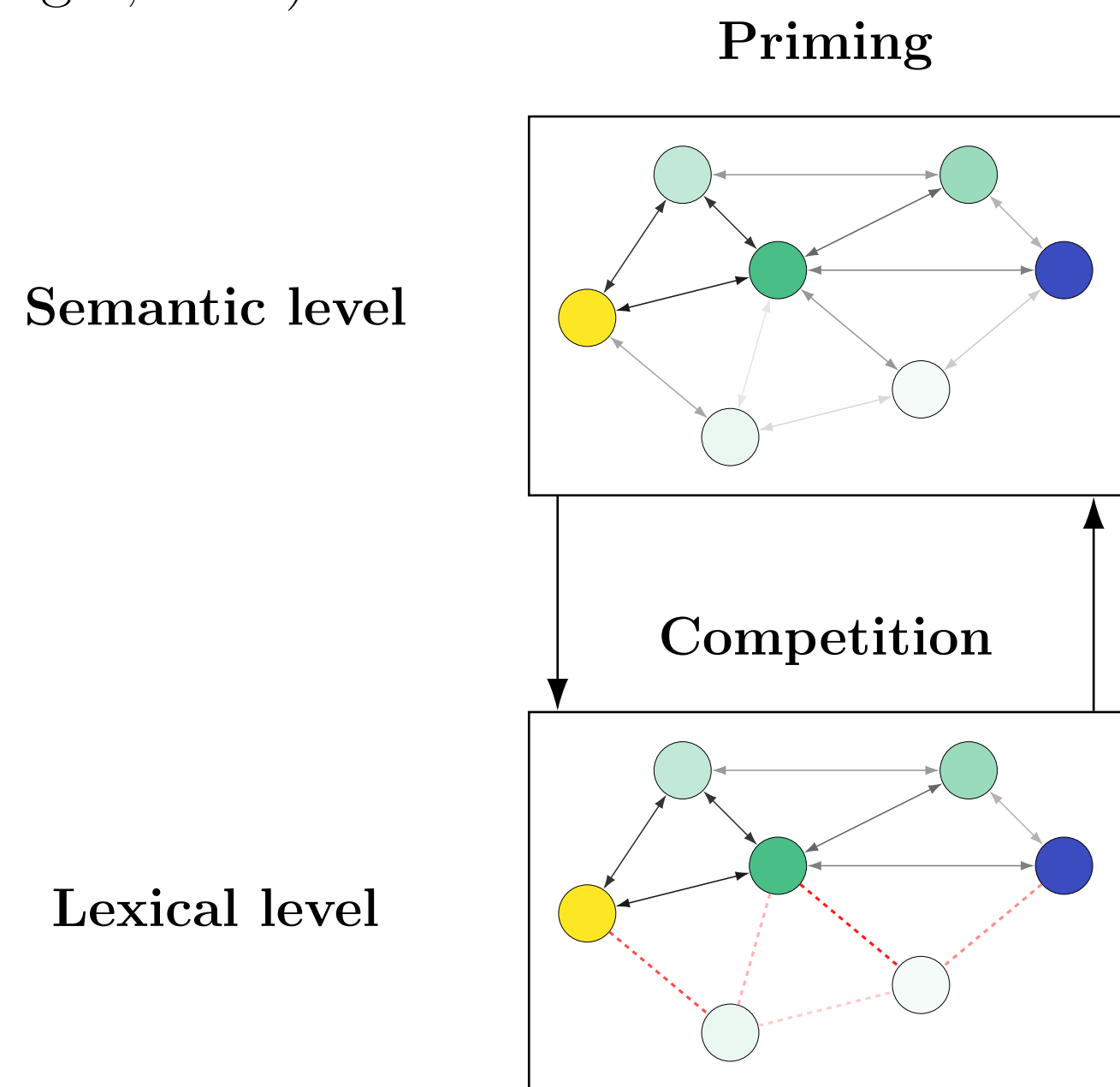


Figure 1. *Semantic-lexical cycle: Two-way flow between semantic priming and lexical competition.*

- **This study:** Implement SLN as a computational **spreading-activation** model (Rotaru et al., 2018) and evaluate on picture-word interference data.

Data

- **Data structure:** 9 German picture-word interference studies, across 17 experiments, with 690 participants and 145,058 responses
- **Word embeddings:** German fastText (300D, reduced to 30K words)

Implementation

- **Transition Matrix:** Build cosine matrix, normalize rows to sum to 1, and add self-loops to form the transition matrix **TM**.
- **k-step dynamics:** Model the spreading activation by iteratively raising **TM** to the power of k (\mathbf{TM}^k)
- **Joint Activation & Cohort Sizes:** For each trial and each of 5 steps, compute joint activation values $\bar{p}_k(t, d \rightarrow w) = \frac{1}{2}[p_k(t \rightarrow w) + p_k(d \rightarrow w)]$ for 30K neighbours of the target and distractor. Bin these values using τ_n thresholds from the global reference distribution \mathcal{D} , and count the values in each bin to obtain the shared-neighbour cohorts $C_{k,q}(t, d)$.

Key Findings

1. **Fit vs. generalization:** Overall fit, held-out trials and participants favor **Model 3**, but held-out experiments favor the simpler **Model 1**.
2. **Cohorts are broader than expected:** Results suggest that activation spreads across large parts of the vocabulary, not just close neighbours.

References

- Abdel Rahman, R., & Melinger, A. (2019). Semantic processing during language production: An update of the swinging lexical network. *Language, Cognition and Neuroscience*, 34(9), 1176–1192.
- Rotaru, A. S., Vigliocco, G., & Frank, S. L. (2018). Modeling the structure and dynamics of semantic processing. *Cognitive science*, 42(8), 2890–2917.

Model Specifications

Model 0: Covariate Model

$$\log(RT) = \beta_0 + \sum_{j=1}^{13} \gamma_j X_j + u_{0i} + v_{0j} + \varepsilon$$

Model 1: Static Similarity Model

$$\log(RT) = \beta_0 + \sum_{j=1}^{13} \gamma_j X_j + \beta_1 \cos(t, d) + u_{0i} + v_{0j} + \varepsilon$$

Model 2: Directional Activation Model

$$\log(RT) = \beta_0 + \sum_{j=1}^{13} \gamma_j X_j + \beta_1 \cos(t, d) + \sum_{k=1}^5 \beta_{2k} p_k(t \rightarrow d) + \sum_{k=1}^5 \beta_{3k} p_k(d \rightarrow t) + u_{0i} + v_{0j} + \varepsilon$$

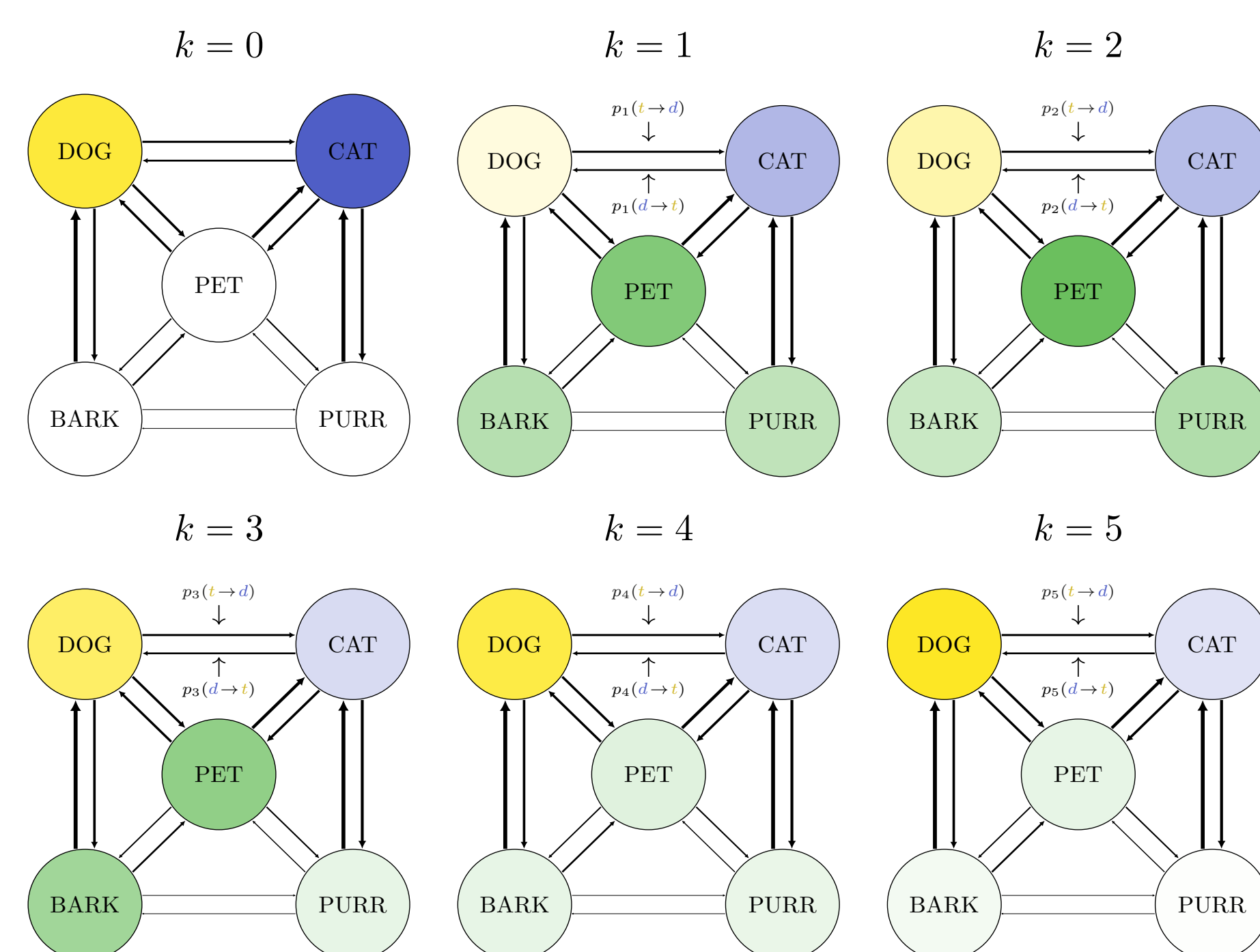


Figure 3. *Directional spreading activation between target and distractor across five time steps.*

Model 3: Shared Lexical Cohort Model

$$\log(RT) = \beta_0 + \sum_{j=1}^{13} \gamma_j X_j + \beta_1 \cos(t, d) + \sum_{k=1}^5 \beta_{2k} p_k(t \rightarrow d) + \sum_{k=1}^5 \beta_{3k} p_k(d \rightarrow t) + \sum_{k=1}^5 \sum_{q=1}^{10} \beta_{4,k,q} C_{k,q}(t, d) + u_{0i} + v_{0j} + \varepsilon$$

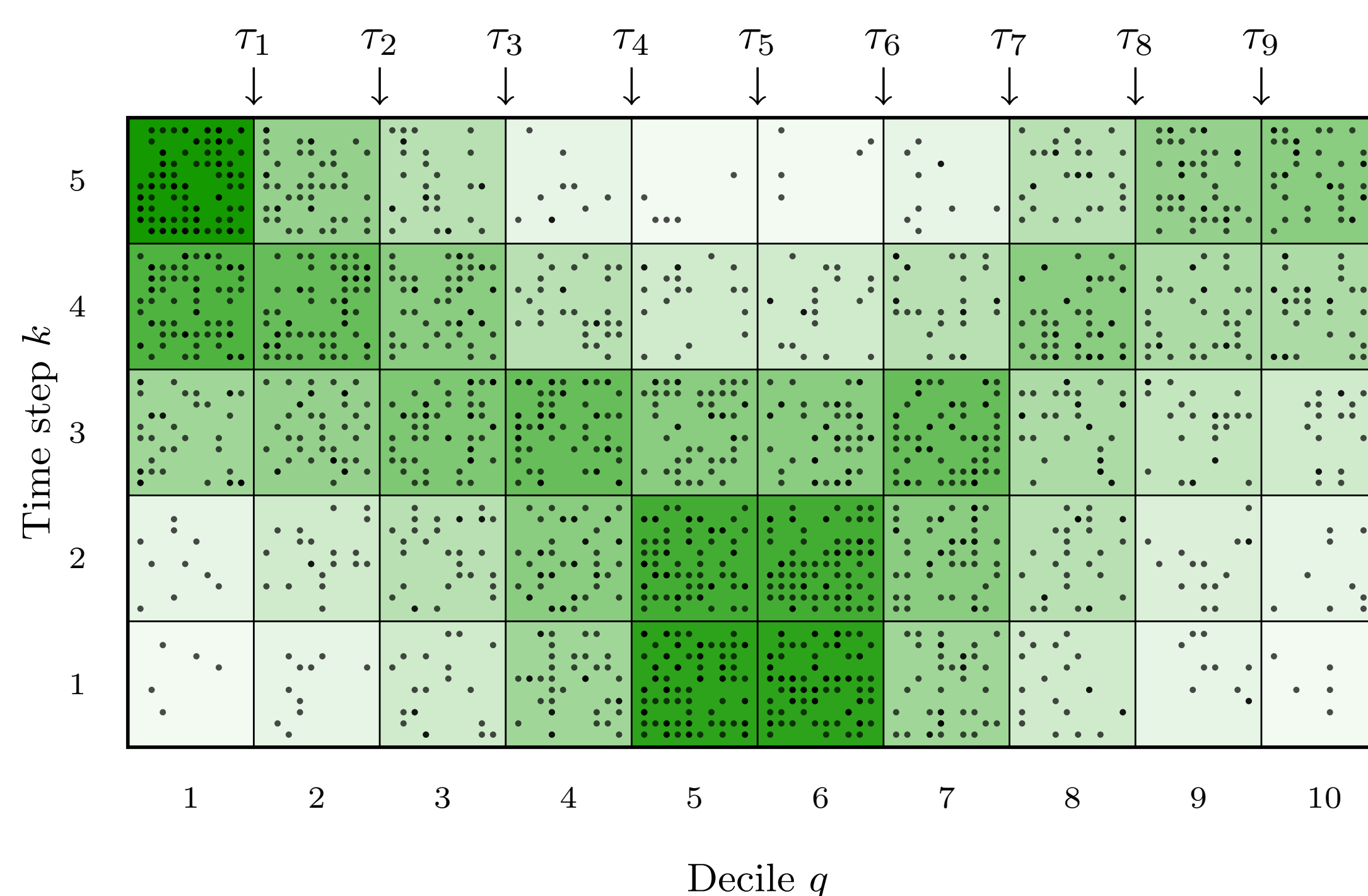


Figure 5. *Cohort sizes $C_{k,q}(t, d)$ by deciles q and steps k , showing nr. of shared neighbours jointly activated by target and distractor.*

Results

Model	n_{par}	AIC	BIC	χ^2	df	p	R_C^2	R_M^2	M (RMSE)		
									Participant	Experiment	Trial
Model 0	17	-32825	-32662				0.438	0.234	0.237	0.278	0.206
Model 1	18	-33220	-33047	397.00	1	< .001	0.440	0.238	0.237	0.277	0.205
Model 2	28	-33911	-33643	711.42	10	< .001	0.445	0.241	0.236	0.278	0.205
Model 3	73	-35257	-34558	1436.24	45	< .001	0.452	0.249	0.235	0.278	0.203

Table 1. *Model comparison between nested models with 5-fold cross-validated RMSE by CV-type.*

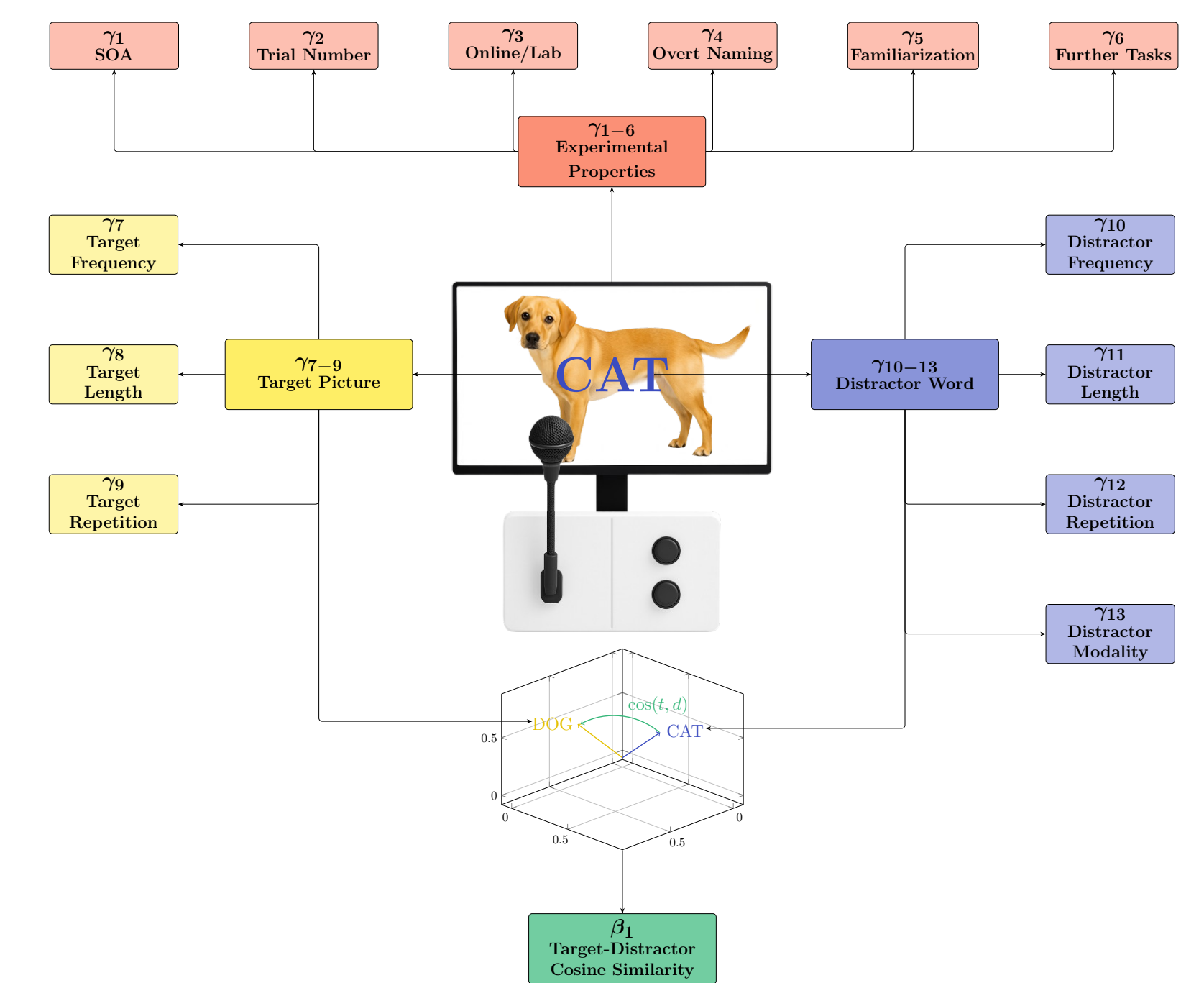


Figure 2. *Overview of Predictors for Model 0 + 1.*

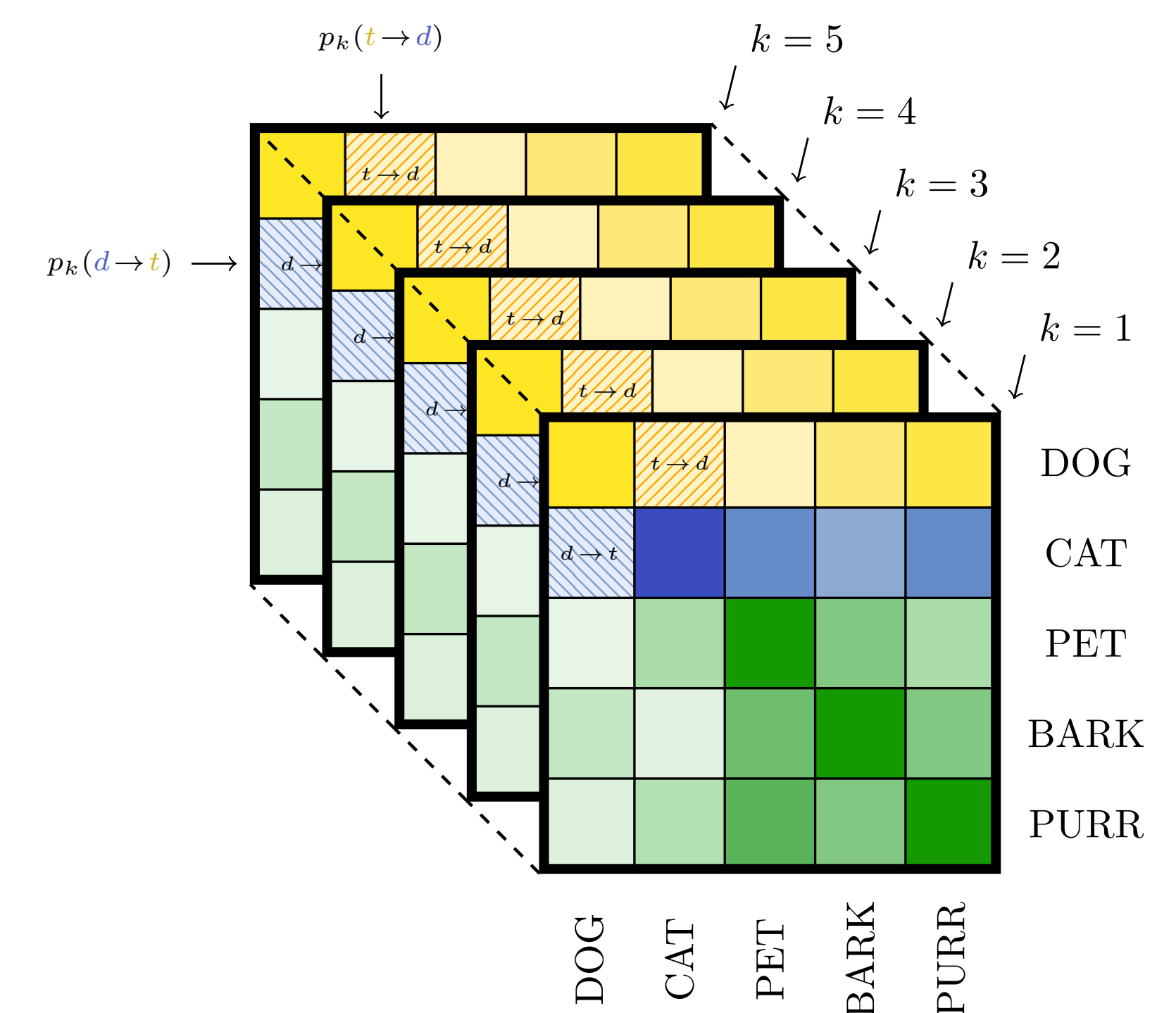


Figure 4. *Transition matrices \mathbf{TM}^k and computation of $p_k(t \rightarrow d)$ and $p_k(d \rightarrow t)$.*

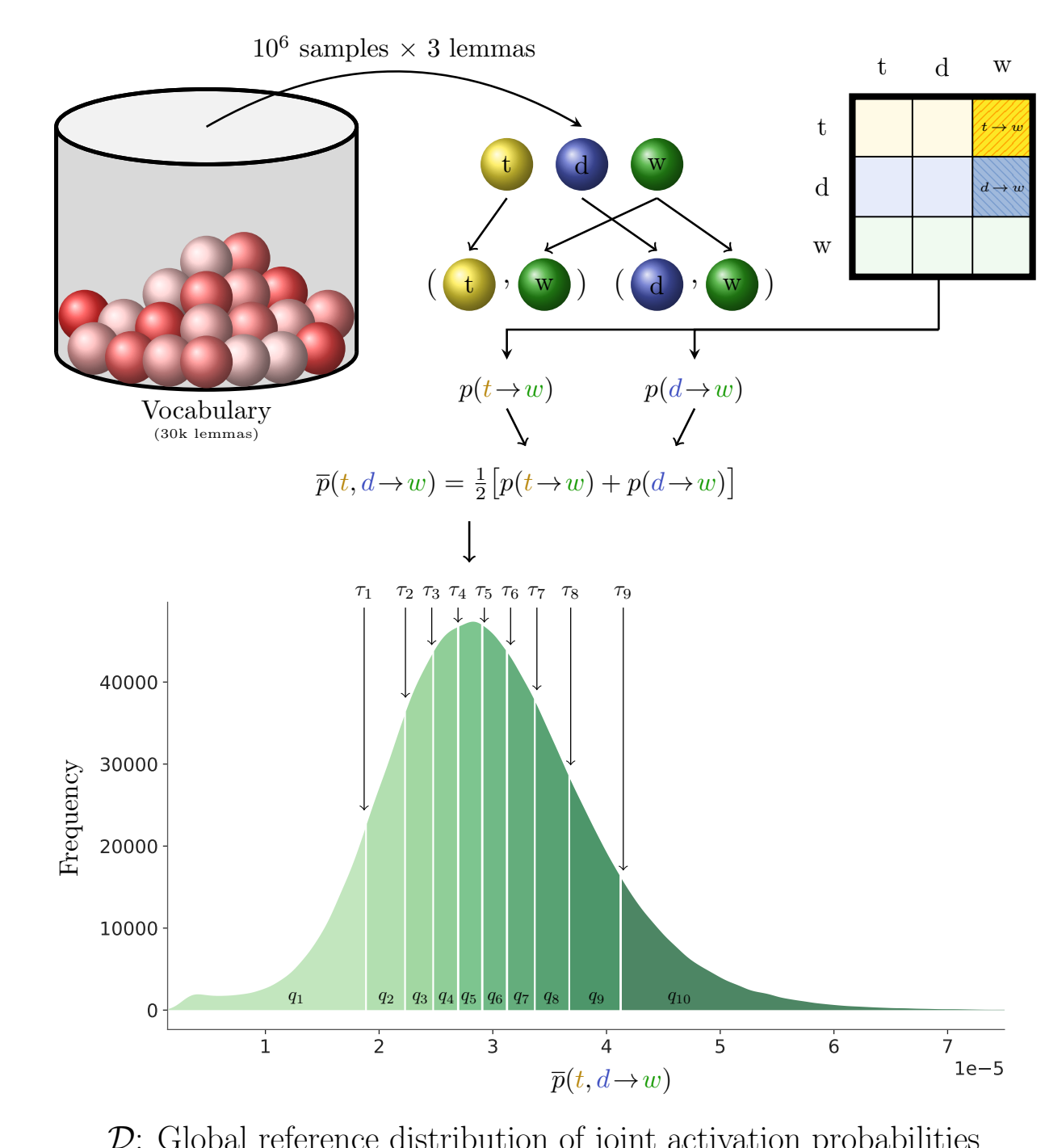


Figure 6. *Procedure for computing cohort thresholds τ_n using 10^6 samples.*

