Poster walkthrough

Understanding the role of linguistic distributional knowledge in cognition

Cai Wingfield & Louise Connell
Lancaster University

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Poster layout

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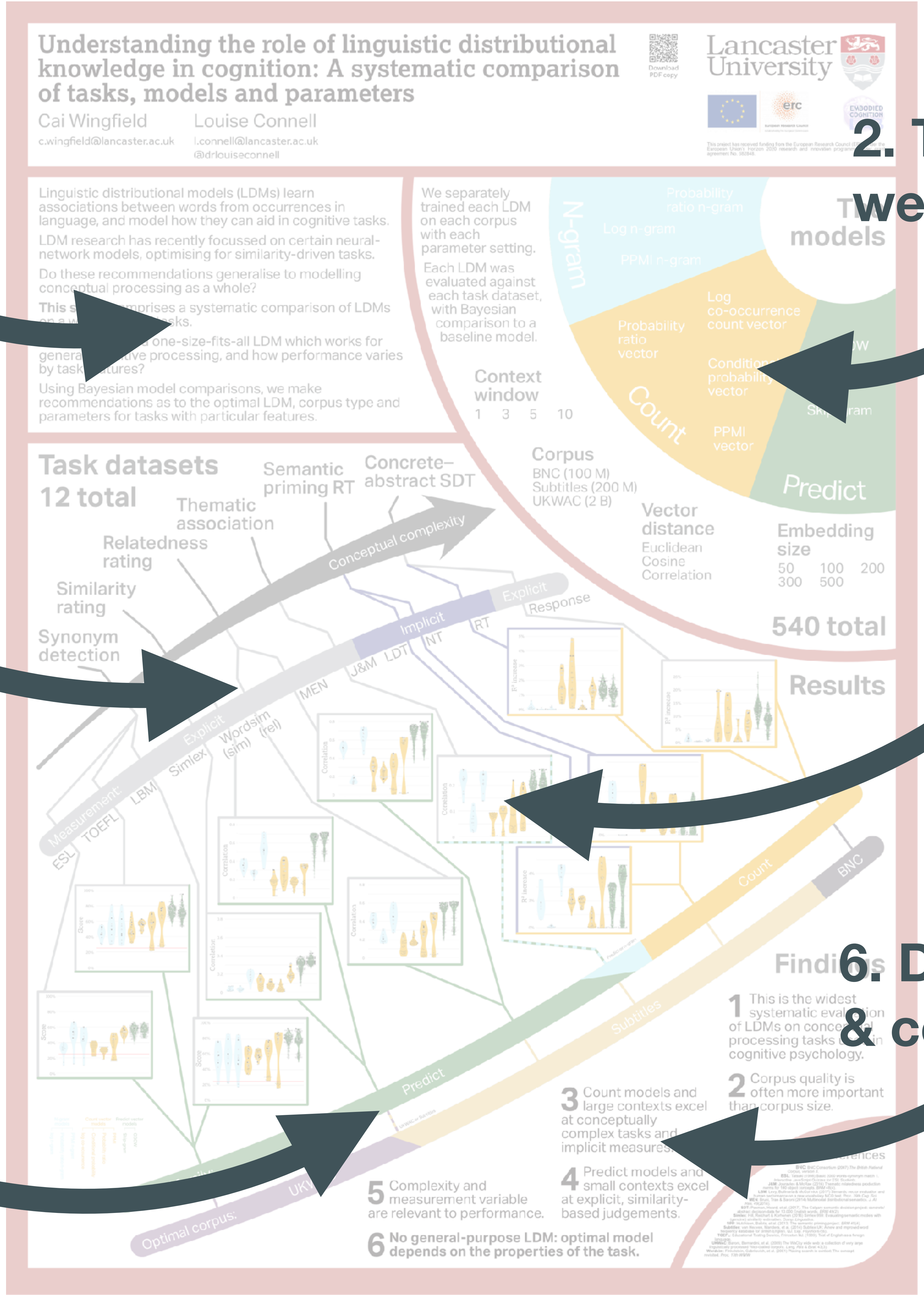
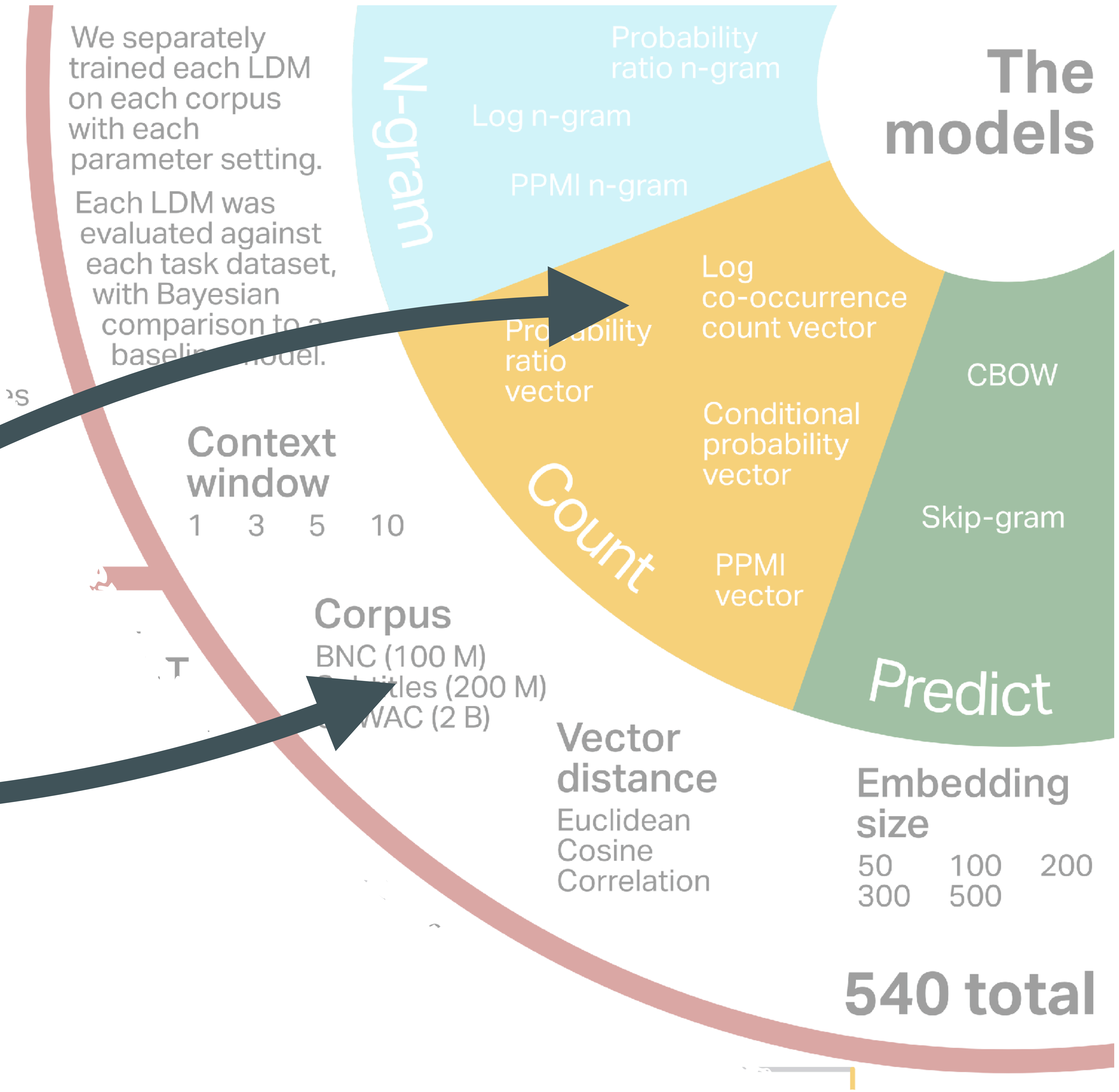


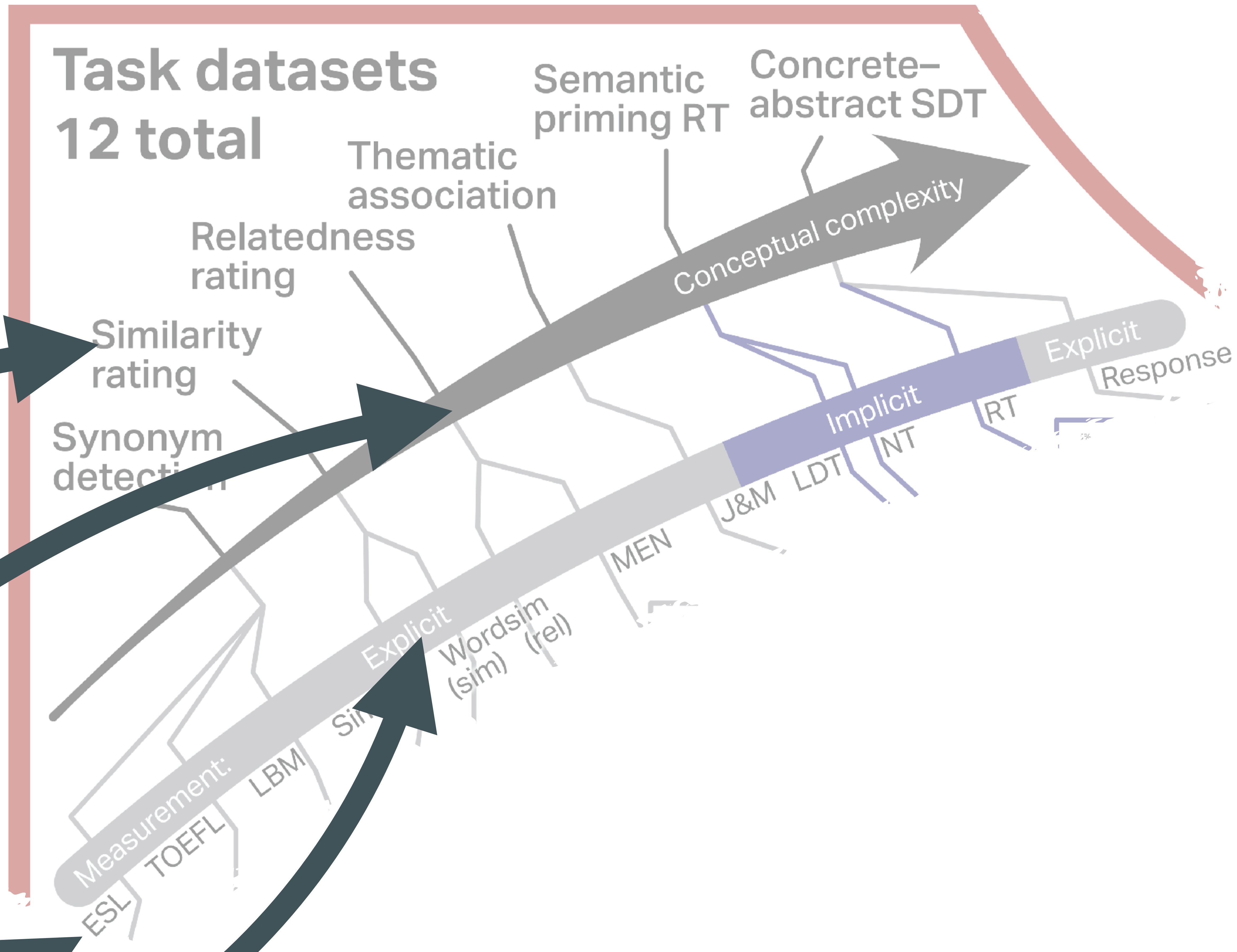
The models

- We trained **linguistic distributional models from three families**: n-gram, count-vector and predict-vector. Nine types of model in total.
- We varied **parameters for each model**: training corpus and context-window size for all models, vector distance for all vector models, and embedding size for all predict models.



The task datasets we modelled

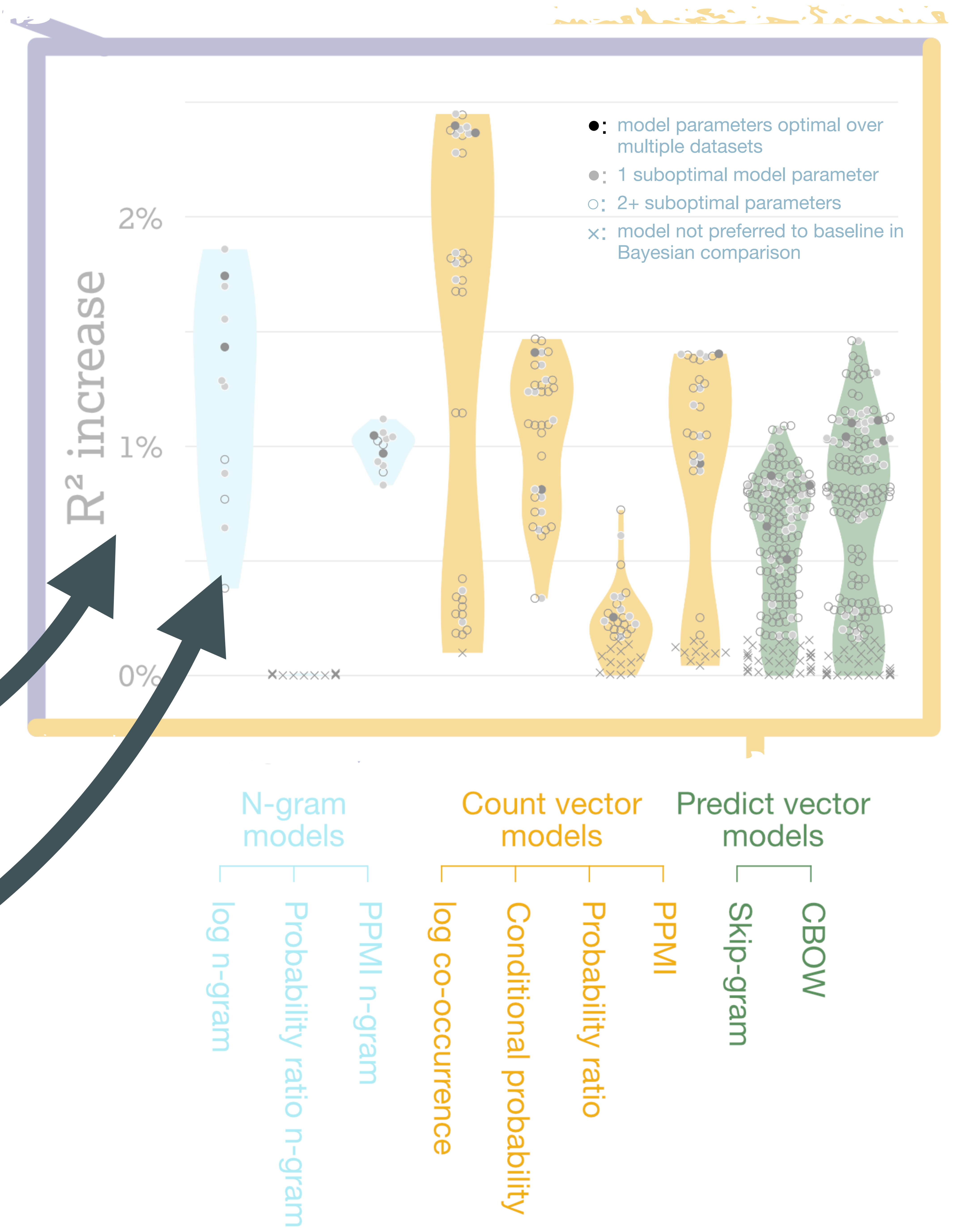
- We looked at **6 tasks** used in cognitive psychology.
- These tasks varied in **conceptual complexity**, from low (e.g. detecting synonyms) to high (e.g. making judgements about concept abstractness).
- We instantiated the tasks using **12 example datasets**.
- Some dependent variables were **explicit** measures of conceptual processing (e.g. rating similarity of word pairs), others were **implicit** (e.g. lexical decision reaction times).



ESL: *English as a Second Language quiz* (Tatsuki, 1998)
TOEFL: *Test of English as a Foreign Language* (Educational Testing Service, 1989)
LBM: *Vocabulary MCQ test* (Levy et al., 2017)
Simlex: *Similarity judgements* (Hill et al., 2016)
Wordsim: *Similarity (**sim**) & relatedness (**rel**) judgements* (Finkelstein et al., 2001)
MEN: *Relatedness judgements* (Bruni et al., 2014)
J&M: *Thematic relatedness norms* (Jouravlev & McRae, 2016)
LDT: *Lexical decision semantic priming* (Hutchison et al., 2013)
NT: *Word naming semantic priming* (Hutchison et al., 2013)
RT: *Concrete/abstract semantic decision reaction times* (Pexman et al., 2017)
Response: *Concrete/abstract semantic decision responses* (Pexman et al., 2017)

Reading the results graphs

- For each dependent variable in each task, we compared the relative performance of different model types, and different parameters. Here is **an example: word naming RT**.
- The test statistic is on **the vertical axis**. For example here, it's R^2 increase for the model predictor. For other tests, it's correlation or prediction accuracy.
- Each graph has **one distribution for each type of model**, showing performance for each parameter setting.



Summarising the results

- We found **a general trend**:
    - Explicitly measured, conceptually simple tasks were best predicted by predict models trained on large, low-quality corpora.
    - Implicitly measured and conceptually more complex tasks were best predicted by count-based models trained on smaller, higher-quality corpora.
- Upper coloured bar: **recommendations for the optimal model family**, reflecting consistently superior performance using consistently good parameters.
- Lower coloured bar: **recommendations for optimal corpus**, reflecting consistently superior performance over a range of models and parameters.
- Overall, the optimal model, and parameters was highly task-dependent, with no candidate performing consistently well in all scenarios.