Categorization in the Wild: Category and Feature Learning across Languages

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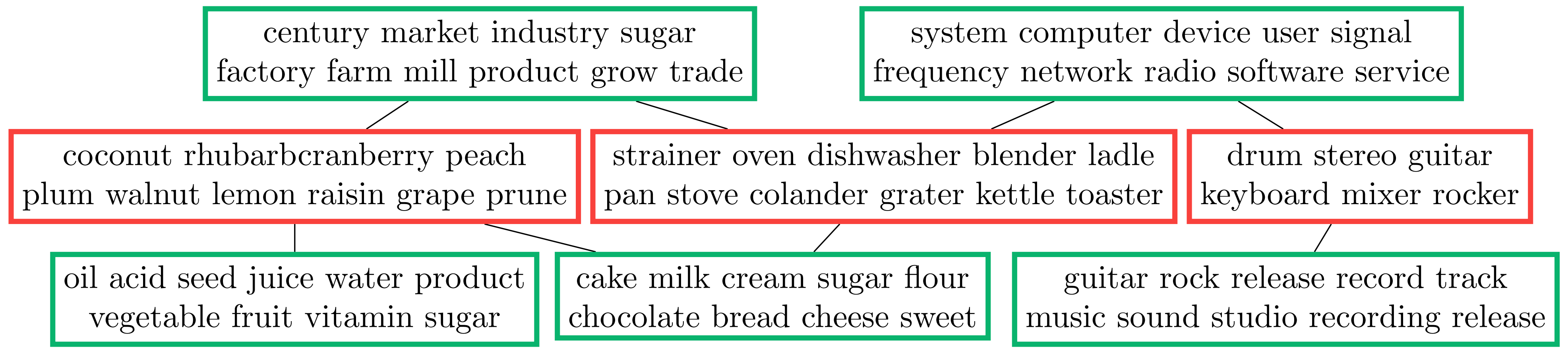
Scaling Models of Categorization I: Categories and Features

- Humans learn categories and features **jointly**
- Humans learn **structured** features
- Previous work assumed fixed, relevant features and/or unstructured representations.


century market industry sugar factory farm mill product grow trade

system computer device user signal frequency network radio software service

coconut rhubarbcranberry peach plum walnut lemon raisin grape prune

strainer oven dishwasher blender ladle pan stove colander grater kettle toaster

drum stereo guitar keyboard mixer rocker

oil acid seed juice water product vegetable fruit vitamin sugar

cake milk cream sugar flour chocolate bread cheese sweet

guitar rock release record track music sound studio recording release

Scaling Models of Categorization II: Languages

- Language as an approximation of the environment
- We apply our models to **five languages**
- **Stimuli**: mentions of *concepts* in linguistic context (*features*)

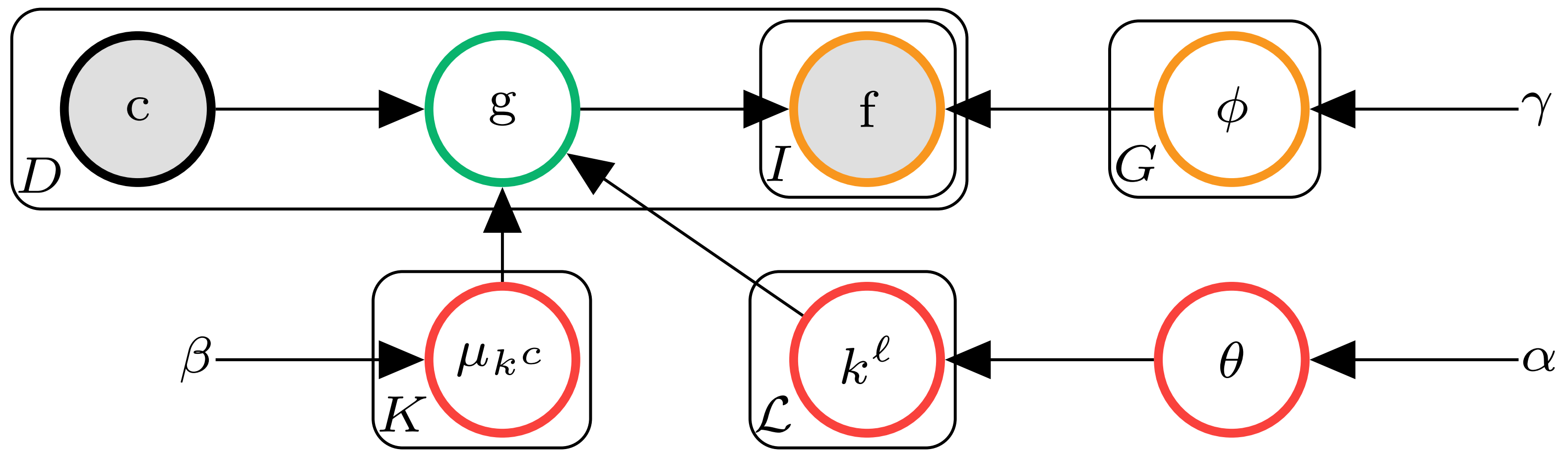
Concept		Natural Language Stimuli	
cat		Les *chats* sont poilus. *Cats* are carnivores.	猫有尾巴和爪子。 Die *Katze* miaut!
dog		.الكلب لديه الفراء *Hunde* essen Fleisch.	Les *chiens* ont des queues. Look, the *dog* is playing!
kiwi		Can you cut me a *kiwi*? .كيويس لديها بذور	*Kiwis* sind innen grün. Ce *kiwi* est savoureux.

Scaling Models of Categorization III: Diversity

	En	Fr	Ge	Zh	Ar
# Concepts	491	484	482	450	394
# Features	5,898	6,416	6,981	6,516	5,870
# Stimuli	418,755	258,499	233,175	147,386	86,908

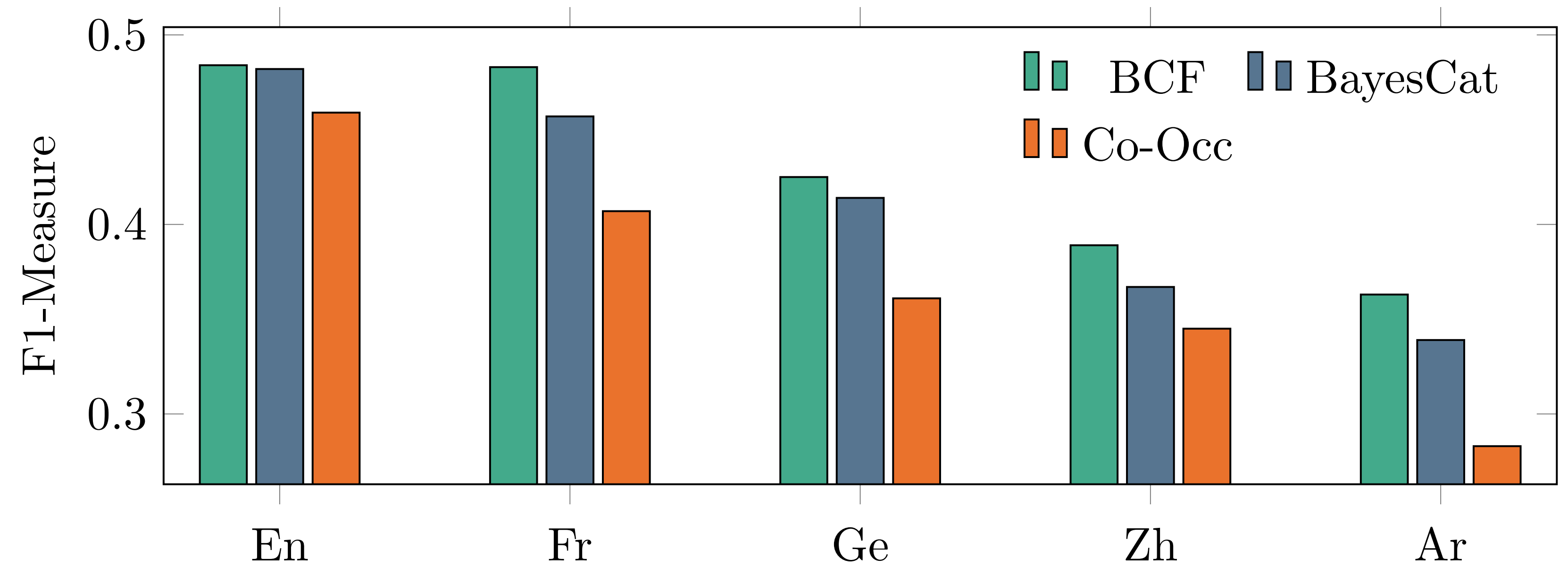
- Hundreds of concepts (from EN feature elicitation studies) Manually translated by native speakers
- In principle unrestricted features (contexts)
- Large sets of stimuli, derived from language-specific Wikipedias
- Concepts, gold categories, stimuli are available `here`

BCF: A Bayesian Model of Category and Features



- Observe **concept** c; Retrieve **category**; Generate **feature type** given category; Generate **features** given feature type
- Approximate inference via Gibbs Sampling

Experiment 1: Category Quality



- **BCF**: our model, **BayesCat**: categorization model with unstructured features, **Co-occ**: co-occurrence model
- Model categorization vs. human-created reference
- Metric: F-1 measure of purity/collocation

Experiment 2: Feature Quality

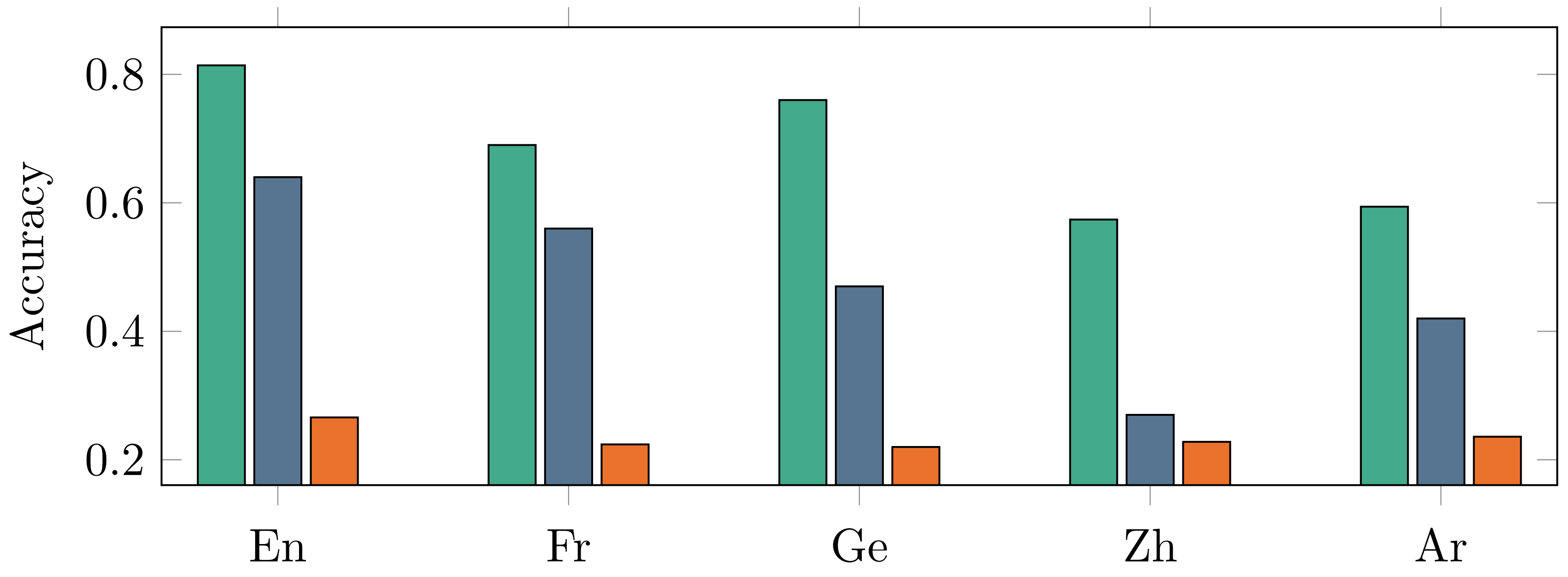
Setup

- Human evaluation through crowd-sourcing; native speakers of the respective languages
- Intrusion paradigm: spot the "intruder" word (feature), which was randomly inserted in the list

Feature Coherence

'Select the intruder word.'

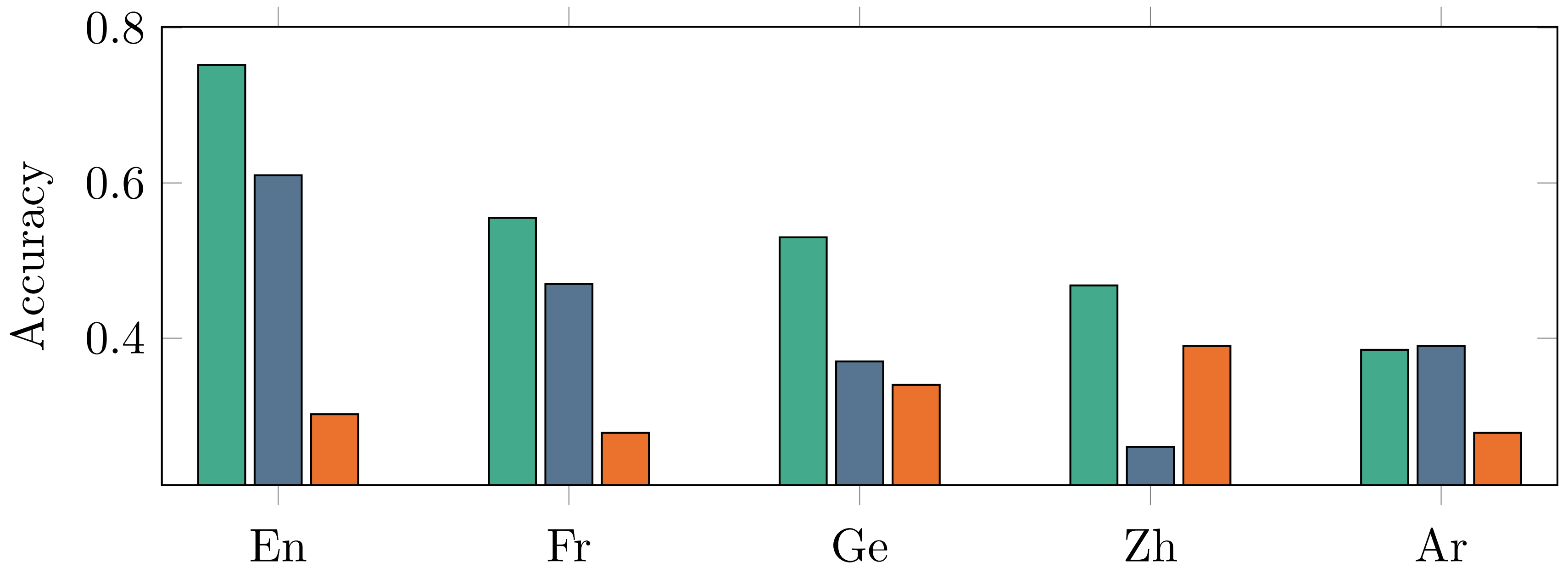
○ `color`	○ `green`	○ `blue`	○ `white`	● `milk`	○ `red`
○ `cell`	● `violin`	○ `study`	○ `protein`	○ `human`	○ `disease`



Feature Relevance

'Select intruder feature type (right) wrt category (left).'

wasp ant	○	`insect beetle family larva spider`
caterpillar	○	`tree leaf plant nest grow`
hornet moth	●	`guitar piano clarinet flute`
housefly		`trumpet`
beetle	○	`male female egg length cm`
honeydew	○	`white brown dark tail color`
grasshopper	○	`population habitat bird forest`
		`water`


Accuracy
En
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