Categorization in the Wild: Generalizing Cognitive Models to Naturalistic Data across Languages

Lea Frermann\textsuperscript{a,}\textsuperscript{*}, Mirella Lapata\textsuperscript{b}

\textsuperscript{a}Amazon CoreAI
\textsuperscript{b}University of Edinburgh

Abstract

Categories such as ANIMAL or FURNITURE are acquired at an early age and play an important role in processing, organizing, and communicating world knowledge. Categories exist across cultures: they allow to efficiently represent the complexity of the world, and members of a community strongly agree on their nature, revealing a shared mental representation. Models of category learning and representation, however, are typically tested on data from small-scale experiments involving small sets of concepts with artificially restricted features; and experiments predominantly involve participants of selected cultural and socio-economical groups (very often involving western native speakers of English such as U.S. college students) . This work investigates whether models of categorization generalize (a) to rich and noisy data approximating the environment humans live in; and (b) across languages and cultures. We present a Bayesian cognitive model designed to jointly learn categories and their structured representation from natural language text which allows us to (a) evaluate performance on a large scale, and (b) apply our model to a diverse set of languages. We show that meaningful categories comprising hundreds of concepts and richly structured featural representations emerge across languages. Our work illustrates the potential of recent advances in computational modeling and large scale naturalistic datasets for cognitive science research.

Keywords: Categorization, Bayesian Modeling, Cognitive Modeling, Natural Language Processing

\textsuperscript{*}Corresponding author. Email: uedi@frermann.de

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1. Introduction

Categories such as ANIMAL or FURNITURE are fundamental cognitive building blocks allowing humans to efficiently represent and communicate the complex world around them. Concepts (e.g., dog, table) are grouped into categories based on shared properties pertaining, for example, to their behavior, appearance, or function. Categorization underlies other cognitive functions such as perception or language, and there is evidence that categories are not only shaped by the world they represent, but also by the language through which they are communicated. Although mental categories exist across communities and cultures, their exact manifestations differ. For example, American English speakers prefer taxonomic categorizations (e.g., mouse, squirrel) while Chinese speakers tend to prefer to categorize objects relationally (e.g., tree, squirrel).

Given their prevalent function in human cognition, the acquisition and representation of categories has attracted considerable attention in cognitive science, and numerous theories have emerged. Empirical studies of category acquisition and representation, have been predominantly based on small-scale laboratory experiments. In a typical experiment, human subjects are presented with small sets of often artificial concepts, such as binary strings or colored shapes, with strictly controlled features. Hypotheses and principles of human categorization are established based on the processes and characteristics of the categorizations produced by the participants. The distribution of subjects participating in such studies is often skewed towards members of cultural and socio-economic groups which are prevalent in the environment where the research is conducted, and typically consists to a large proportion of western, educated, wealthy and English-speaking participants often sampled from the even more specific population of college students. The demographic and socioeconomic bias has been long recognized, and the question of how this bias might impact conclusions about human cognition in general and category learning specifically is under active debate. Although laboratory studies are invaluable for understanding categorization phenomena in a controlled

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1 We denote (superordinate level) categories (such as ANIMAL or VEHICLE) in small caps; (basic level) concepts (such as cat or car) in italics, and feature types (such as function or behavior) in true type. Individual features (such as {eats, sits, barks}) are represented as {lists}.
environment, they are also expensive and time-consuming to conduct, and consequently problematic to scale.

In this work, we scale the investigation of category learning and representation along two axes: (1) the complexity of the learning environment, and consequently the richness of learnable concept and category representations, and (2) the diversity of languages and cultures considered in evaluation. We present a novel knowledge-lean, cognitively motivated Bayesian model which learns categories and their structured features jointly from large natural language text corpora in five diverse languages: Arabic, Chinese, English, French, and German. We approximate the learning environment using large corpora of natural language text. Language has been shown to redundantly encode much of the non-linguistic information in the natural environment [21], and to influence the emergence of categories [5, 6]. Besides text corpora can cover arbitrarily semantically complex domains, and are available across languages, providing an ideal test environment for studying categorization at scale.

Figure 1 illustrates example input to our model, and Figure 2 shows example categories and associated features as induced by our model from the English Wikipedia. Following prior work [22, 23], we create language-specific sets of stimuli, each consisting of a mention of target concept (e.g., apple),

\[ \text{kiwi} \]

2 Throughout this article we use the term concept to refer to Rosch’s [12] basic-level cat-

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**Concept Natural Language Stimuli**

| Concept | Natural Language Stimuli |
|---------|--------------------------|
| cat     | Les *chats* sont poilus.  |
|         | *Cats* are carnivores.     |
|         | Die *Katze* miaut!        |
| dog     | *Hunde* essen Fleisch.    |
|         | Les *chiens* ont des queues. |
|         | Look, the *dog* is playing! |
| apple   | I want to eat an *apple*. |
|         | *Apfel* sind rot oder grün. |
|         | An *apple* contains seeds |
| kiwi    | Can you cut me a *kiwi*? |
|         | *Kiwis* sind innen grün.  |
|         | Ce *kiwi* est savoureux.  |

Figure 1: Illustration of model stimuli for five languages. Each stimulus contains a mention of a concept (e.g., *cat* or *apple*) in its local linguistic context. Concepts are grouped into categories (e.g., *ANIMAL* or *FRUIT*) based on the similarity of the contexts they occur in.
within its local linguistic context (e.g., \{contains, seeds\}; cf., Figure 1). We consider each stimulus an observation of the concept, i.e., the word referring to the concept is an instance of the concept itself, and its context words are a representation of its features. Our model infers categories as groups of concepts occurring with similar features; and it infers feature types as groups of features which co-occur with each other. The output of our model (cf., Figure 2) are categories as clusters of concepts, each associated with a set of feature types, i.e., thematically coherent groups of features. We train a separate model on each of our target languages, each time presenting the model with input stimuli from the relevant language.

Computational models in general, and Bayesian models in particular, allow to investigate hypotheses about cognitive phenomena by systematically modifying the learning mechanism or available input while observing the learning outcome. Bayesian models have been applied to a variety of cognitive phenomena [24, 25, 26], and category acquisition is no exception. Following from Anderson’s [15, 27, 28] seminal work, a number of models have been developed, and tested in their ability to reproduce human behavior in laboratory settings by exposing the models to small sets of controlled inputs with restricted features. In this work we draw on the full potential of categories, and the term category to refer to superordinate-level categories. (Superordinate-level) categories are inferred based on the features observed with observations of (basic-level) concepts.
computational modeling by exposing our models to (a) more complex data reflecting the diversity of contexts in which concepts can be observed; and (b) input data in different languages, shedding light on the applicability of computational cognitive models beyond the prevalent English test language.

Categorization tasks in a laboratory environment typically involve stimuli with a small set of features which are relevant to the categorization target, eliminating the need to detect features, and discriminate them in their relevance. In the real world, however, concepts are observed in contexts and a substantial part of acquiring categorical knowledge involves learning which features are useful to discriminate among concepts. In fact, research has shown that humans learn features jointly with categories [29, 30] and that these features are themselves structured so as to represent the diversity and complexity of the properties exhibited in the world [31, 32, 33]. Our novel model of category learning presented in this article, jointly learns categories and their structured features from large sets of informationally rich data.

Our work exemplifies the opportunities that arise from computational models and large data sets for investigating the mechanisms with which conceptual representations emerge, as well as the representations themselves in a broader context. We simulate the acquisition of categories comprising hundreds of concepts by approximating the learning environment with natural language text. Language has been shown to redundantly encode much of the non-linguistic information in the natural environment [21], as well as human-like biases [34], and to influence the emergence of categories [5, 6]. Text corpora are a prime example of naturally occurring large-scale data sets [35, 36, 37]. In analogy to real-world situations, they encapsulate rich, diverse, and potentially noisy, information. The wide availability of corpora allows us to train and evaluate cognitive models on data from diverse languages and cultures. We test our model on corpora from five languages, derived from the online encyclopedia Wikipedia in Arabic, Chinese, French, English, and German. Wikipedia is a valuable resource for our study because it (a) discusses concepts and their properties explicitly and can thus serve as a proxy for the environment speakers of a language are exposed to; and (b) allows us to construct corpora which are highly comparable in their content across languages, controlling for effects of genre or style.

We present a series of evaluations investigating the quality of the induced categories and features. Leveraging a reference comprising hundreds of concepts and more than 30 categories, we demonstrate that our model learns meaningful categories in all five target languages. We furthermore show,
through crowd-sourced evaluations involving native speakers of each target language, that the induced feature types are (a) each thematically coherent and interpretable; and (b) are associated with categories in comprehensible ways. We discuss language-specific idiosyncrasies emerging from the induced representations.

In the remainder of this article, we first review related literature, before we present a cognitively motivated model for learning categories and their structured representations from large natural language corpora. We then evaluate the quality of the emerging representations, as well as the generalizability of our model across languages. Note that the primary goal of this work is not to characterize differences in categories and features arising from different languages (even though this would be an interesting avenue for future work). Rather, we aim to demonstrate the utility of large-scale naturalistic datasets for cognitive modeling, and to verify mechanisms of categorization known from laboratory studies at scale and across communities.

2. Related Work

In this work we leverage large-scale computational simulations to advance our understanding of categories and features across languages and cultures. Our research touches on the representation of categories, concepts, and their features; the mechanisms with which these are learnt; and the use of computational models and large-scale naturalistic data sets to investigate these questions.

2.1. Feature Representations of Concepts and Categories

Even though much empirical research glosses over this observation, there is strong evidence that human conceptual representations are structured (see [38] for a recent critique and overview of cognitive studies of categorization). Categories mentally represent the complex structure of the environment. They allow to make inferences about concepts or categories that go beyond their perceived similarities capturing abstract and potentially complex properties (for example, the nutritional value of FOOD items, or the emotional benefits of PETS). Much research on human categorization is based on laboratory experiments where subjects are presented with artificial stimuli represented by a restricted set of task-relevant features. Observations of natural concepts, however, are often noisy or incomplete so that a notion
of systematic relations among features might be more important here than under artificial conditions in the lab [39].

The existence of structured features has received support through behavioral results from a variety of categorization related tasks, such as typicality rating [39] or category-based inductive inference [40, 33]. Experimental evidence suggests that categories which on the surface do not seem to contain a coherent set of members (e.g., the category pets) are represented by an underlying set of abstract features which explain the coherence of the category (e.g., \{keeps\_company, lives\_in\_the\_house\}). Varying the types of available features (e.g., providing functional information in addition to objects’ appearance) leads to different categorization behavior both in adults [40] and children [41, 42], and different feature types vary in their predictive value across categories. For example, 2-4-year old children categorize FOOD items based on their color, however, TOYS are classified based on their shape [43].

The structured nature of category features manifests itself in feature norms. Feature norms are verbalized lists of properties that humans associate with a particular concept [32]. Features collected in norming studies naturally fall into different types such as behavior, appearance or function. This suggests that structure also emerges from verbalized representations of concepts and features such as mentions in natural language corpora, used as stimuli in this work. McRae et al. [32] collected a large set of feature norms for more than 500 concepts in a multi-year study, and classified these using a variety of theoretically motivated schemata, including the feature type classification scheme developed in [44] and [45]. Their work puts forward the hypothesis that humans perform a “mental simulation” when describing a concept, scanning the mental image they create as well as situations associated with that image, and then verbalize it when producing features.

The model we present in this article aims to capture the evidence summarized above, and represent categories as structured sets of features with varying degrees of association. Category-specific features are structured into types which relate to a particular kind of property of a category (e.g., the behavior of ANIMALS). We also capture the observation that features are defining for different categories to a varying degree [46, 47] in terms of category-feature type associations (e.g., the feature function is highly defining for (or associated with) the category ARTIFACT, but not for the category ANIMAL).
2.2. Joint Learning of Categories and their Features

Although the majority of models of categorization assume a fixed set of features underlying the category acquisition and categorization process, there is increasing evidence that “[...] a significant part of learning a category involves learning the features entering its representations.” [30, p. 681]. Experimental evidence suggests that not only do features underly the categorization process but features themselves are susceptible to change over time and can be modified by the categories which emerge. Evidence ranges from changing featural perception as a result of expert education (e.g., wine tasters or doctors learning to interpret X-ray images) to neurological evidence revealing enhanced neural activity in experts when presented with pictures of their area of expertise (see [48] for an overview).

The influence of category learning on the perception and use of features has been studied extensively using visual stimuli of varying degrees of naturalness and familiarity. Experiments with drawings of 2-dimensional line segments [49] show that participants who were exposed to categorization training prior to a feature identification task identified the presence of category-defining features faster than participants without prior training. When asked to categorize pictures of (systematically manipulated) human faces, participants showed higher sensitivity to features relevant for the categorization task [29, 50].

To the best of our knowledge, we present the first computational investigation in the joint emergence of categories and features from large sets naturalistic input data.

2.3. Computational Models of Category and Feature Induction

The tasks of category formation and feature learning have been considered largely independently in the context of computational cognitive modeling. Bayesian categorization models pioneered by Anderson [15] and recently reformalized by Sanborn et al. [51] aim to replicate human behavior in small scale category acquisition studies, where a fixed set of simple (e.g., binary) features is assumed. Informative features are pre-defined and available to the model. The BayesCat model [52] is similar in spirit, but was applied to large-scale corpora, while investigating incremental learning in the context of child category acquisition (see also [22] for a non-Bayesian approach). BayesCat associates sets of features (context words) with categories as a by-product of the learning process, however these feature sets are independent across categories and are not optimized during learning.
A variety of cognitively motivated Bayesian models have been proposed for the acquisition of complex domain knowledge. Shafto et al. [53] present a joint model of category and feature acquisition in the context of cross-categorization, i.e., the phenomenon that concepts are simultaneously organized into several categorizations and the particular category (and features) that are relevant depend on the context (e.g., concepts of the category FOOD can be organized based on their nutritional or perceptual properties). However, while [53] present their model with category-specific data sets tailored towards their learning objective, we are interested in acquiring categories and structured associated features jointly from thematically unconstrained corpora of natural text.

Another line of work [54, 55] models the joint learning of relevant features and domain-specific feature type biases in children. They focus on the acquisition of domain-specific representational structures (such as hierarchies or clusters) and discuss results in the context of word learning. In contrast to our work, their model assumes a priori established categories (such as FOOD and ANIMALS), and learns from task-specific data representations in the form of objects described by a limited set of relevant features (even though a weighting of those features is learnt). Perfors et al. [56] present a Bayesian model which simultaneously learns categories (i.e., groupings of concepts based on shared features) and learns to learn categories (i.e., abstract knowledge about kinds of featural regularities that characterize a category). They compare their model predictions against behavioral data from adult participants, which limits the scope of their experiments to small data sets.

The ability to automatically extract feature-like information for concepts from text would facilitate the laborious process of feature norming, i.e., eliciting features associated with concepts verbally from human annotators [32], and improve the coverage of concepts and their features. A few approaches to feature learning from textual corpora exist, and they have primarily focused on emulating or complementing norming studies by automatically extracting norm-like properties from corpora (e.g., elephant has-trunk, scissors used-for-cutting). Steyvers [57] uses a flavor of topic models to augment data sets of human-produced feature norms. While vanilla topic models [58] represent documents as sets of corpus-induced topics, [57] additionally use topics derived from feature norms. The learnt topics yield useful extensions of the original feature norms, with properties that were previously not covered, suggesting that corpora are an appropriate resource for augmenting feature norms of concepts.
Another line of research concerns text-based feature extraction. A common theme in this line of work is the use of pre-defined syntactic patterns [59], or manually created rules specifying possible connection paths of concepts to features in dependency trees [60, 61]. While the set of syntactic patterns pre-defines the relation types the system can capture, the latter approach can extract features which are a priori unlimited in their relation to the target concept. Once extracted, the features are typically weighted using statistical measures of association in order to filter out noisy instances. Similar to our own work, the motivation underlying these models is large-scale unsupervised feature extraction from text. These systems are not cognitively motivated acquisition models, however, due to (a) the assumption of involved prior knowledge (such as syntactic parses or manually defined patterns), and (b) the two-stage extraction-and-filtering process which they adopt. Humans arguably do not first learn a large set of potential features for concepts, before they infer their relevance. The systems discussed above learn features for individual concepts rather than categories.

To our knowledge, we propose the first Bayesian model that jointly learns categories and their features from large sets of naturalistic input data. Our model is knowledge-lean, it learns from raw text in a single process, without relying on parsing resources, manually crafted rule patterns, or post-processing steps; it is more plausible from a cognitive point of view, and language agnostic. We present simulations with the same model on several languages varying in word order, morphology, and phonology.

3. Category and Feature Learning at Scale

Computational models as simulators of cognitive processes have been used successfully to shed light on a wide variety of phenomena [25], including language acquisition [28], generalization, and reasoning [62]. Bayesian models in particular are amenable towards this goal, because they allow the modeler to formalize hypotheses rigorously through sets of random variables and their relations. They use the principled rules of Bayesian probability to select “good” models which explain the observed data well. We present a Bayesian model to investigate cognitive processes of categorization, in correspondence to Marr’s [63] computational level of analysis, i.e., abstracting away from the algorithms and biological substrates in which these processes are situated. Starting from Anderson’s [15] pioneering work on rational models of categorization, a variety of models, both Bayesian [51, 53, 28] and non-
Bayesian \cite{19, 22} have been proposed. Our work advances prior research by investigating for the first time joint category and feature learning from noisy stimuli, across diverse languages.

We present BCF, a cognitively motivated Bayesian model for learning Categories and structured Features from large sets of concept mentions and their linguistic contexts (see Figure 1). Our model induces categories (as groups of concepts), feature types which are shared across categories (as groups of features or context words), and category-feature type associations. Figure 2 shows example output of BCF as learnt from the English Wikipedia, and Figure 4 shows example categories and features learnt for five additional languages.

BCF is a statistical Bayesian model. Given a large set of stimuli, it learns meaningful categories and features from a countably infinite set of all possible categorizations and representations. The probability (or ‘meaningfulness’) of any hypothetical categorization and representation \( h \) under the stimuli data \( d \) can be evaluated using Bayes’ rule:

\[
p(h|d) \propto p(d|h)p(h),
\]

where \( p(h) \) is the prior probability of \( h \) under the specified model and its assumptions; and \( p(d|h) \) is the likelihood to observe data \( d \) given that hypothesis \( h \) holds.

3.1. The BCF Model

BCF learns from an input corpus which consists of stimuli covering \( \mathcal{L} \) target concepts, where the set of target concepts is specified by the modeler a priori. The model induces a categorization of these target concepts into \( K \) categories; as well as a characterization of each category in terms of \( G \) different feature types pertaining to different relevant properties. The number of categories, \( K \), and the number of feature types, \( G \), are model parameters.

A notational overview is provided in Table 1. The generative story of our model is displayed in Figure 3a, and Figure 3b shows the plate diagram representation of BCF. The generative story proceeds as follows. We assume a global multinomial distribution over categories \( \text{Mult}(\theta) \). Its parameter vector \( \theta \) is drawn from a symmetric Dirichlet distribution with hyperparameter \( \alpha \). For each target concept \( \ell = [1...\mathcal{L}] \), we draw a category \( k^\ell \) from \( \text{Mult}(\theta) \). For each category \( k \), we draw an independent set of multinomial parameters over feature types, \( \mu_k \), from a symmetric Dirichlet distribution with hyperparameter \( \beta \), reflecting the relative relevance of each
(a) Generative story of BCF.

Generate category distribution, \( \theta \sim Dir(\alpha) \)

for concept type \( \ell = 1..L \) do
  Generate category, \( k^\ell \sim Mult(\theta) \)

for category \( k = 1..K \) do
  Generate feature type distribution, \( \mu_k \sim Dir(\beta) \)

for feature type \( g = 1..G \) do
  Generate feature distribution, \( \phi_g \sim Dir(\gamma) \)

for stimulus \( d = 1..D \) do
  Observe concept \( c^d \) and retrieve category \( k^{cd} \)
  Generate a feature type, \( g^d \sim Mult(\mu_{k^d}) \)
  for feature position \( i = 1..I \) do
    Generate a feature \( f_{d,i} \sim Multi(\phi_{g^d}) \)

(b) Plate diagram of BCF.

Figure 3: Top (a): The generative story of the BCF model. Observations \( f \) and latent labels \( k \) and \( g \) are drawn from Multinomial distributions (\( Mult \)). Parameters for the multinomial distributions are drawn from Dirichlet distributions (\( Dir \)). Bottom (b): The plate diagram of the BCF model. Shaded nodes indicate observed variables, clear nodes denote latent variables, and dashed nodes indicate constant hyperparameters.
symbol explanation
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\(d \in \{1..D\}\) stimulus (e.g., “This dog likes to catch balls.”)
\(c \in \{1..C\}\) concept mention in stimulus (e.g., “dog”)
\(i \in \{1..I\}\) context word positions in stimulus
\(\ell \in \{1..L\}\) concept types (e.g., cat, dog, chair, table)
\(f \in \{1..V\}\) features (e.g., \{runs, barks, eats, red, made_of_wood\})
\(k \in \{1..K\}\) categories (e.g., ANIMAL, FURNITURE)
\(g \in \{1..G\}\) feature types (e.g., behavior, appearance)
\(\theta\) \(K\)-dimensional parameter vector of category distribution
\(\{\mu_k\}_{k=1}^K\) \(G\)-dimensional parameter vectors of feature type distributions
\(\{\phi_g\}_{g=1}^G\) \(V\)-dimensional parameter vectors of word distributions

Table 1: Notational overview of the BCF model (the category and feature type labels are provided for illustration; BCF is an unsupervised clustering model which induces unlabeled categories and feature types).

According to the generative story outlined above, the joint probability of the model over latent categories, latent feature types, model parameters, and data factorizes as:

\[
p(g, f, \mu, \phi, \theta, k|c, \alpha, \beta, \gamma) = p(\theta|\alpha) \prod_\ell p(k^\ell|\theta) \prod_k p(\mu_k|\beta) \prod_g p(\phi_g|\gamma) \prod_d p(g^d|\mu_{k^d}) \prod_i p(f^{d,i}|\phi_{g^d}).
\]  

Since we use conjugate priors throughout, we can integrate out the model parameters analytically, and perform inference only over the latent variables, namely the category and feature type labels associated with the stimuli.

In sum, our model takes as input a text corpus of concept mentions in their local context, and infers a concept categorization, a global set of
Algorithm 1 The Gibbs sampling algorithm for the BCF model.

1: Input: model with randomly initialized parameters.
2: Output: posterior estimate of $\theta$, $\phi$, and $\mu$.
3: repeat
4: for stimulus $d$ do  
5:     - decrement stimulus $d$-related counts
6:     - Sample $g^d \sim p(g^d_{k^d} = i | g^{-d}_{k^d}, f^-, k^c_d, \beta, \gamma)$ Equation (5)  
7:     - update stimulus $d$-related counts
8: for concept $c$ do  
9:     - retrieve category $k^c$
10:     - decrement concept $c$-related counts
11:     - Sample $k^c \sim p(k^c = j | g_{k^c}, k^-, \alpha, \beta)$ Equation (7)  
12:     - update concept $c$-related counts
13: until convergence

feature types, as well as a distribution over feature types per category. After integrating out model parameters where possible, we infer two sets of latent variables:

(1) feature type-assignments to each stimulus $\{g\}^D$,

(2) category-assignments to each concept type $\{k\}^C$.

The next section introduces a learning algorithm in the form of a Gibbs sampler for approximate estimation of these parameters.

3.2. Approximate Inference for BCF

Exact inference in the BCF model is intractable, so we turn to approximate posterior inference to discover the distribution over value assignments to latent variables given the observed data. In this section we introduce a Gibbs sampling algorithm [64, 65] which is a Markov chain Monte Carlo algorithm which iteratively computes values of individual random variables in the model, based on the current value assignments of all other random variables. The sampling procedure for BCF is summarized in Algorithm 1. The Gibbs sampler repeatedly iterates over the training corpus and resamples values of the latent variables. One Gibbs iteration for our model consists of two blocks:
Resampling stimulus-feature type assignments. In the first block we iterate over input stimuli $d$, and resample each stimulus-feature type assignment $g^d$ from its full conditional posterior distribution over feature types conditioned on (a) the values assigned to all other latent variables unrelated to the current variable of interest, i.e., all features except those in stimulus $d$, $(f^-)$, and all stimulus-feature type assignments except the one to stimulus $d$, $(g^-_{k^d})$; (b) the category currently assigned to $d$’s target concept $c$, $(k^c)$; and (c) the relevant hyperparameters $(\beta, \gamma)$:

$$
p(g^d_{k^c} = i \mid g^-_{k^d}, f^-, k^c = j, \beta, \gamma)
= p(g^d_{k^c} = i \mid g^-_{k^d}, k^c = j, \beta) \times p(f^-|g^-_{k^d}, g^d_{k^c} = i, \gamma)
\propto \frac{(n^i + \beta)}{(\sum_i n^i + \beta)} \times \frac{\prod_v \prod_{a=1}^{f_v} (n^i_v + \gamma + a)}{\prod_{a=1}^{f_*} (\sum_v n^i_v + \gamma + a)}.
$$

The factorization of the posterior distribution in (4) follows from the model structure as described above and shown in the plate diagram in Figure 3b. The posterior distribution factorizes into the probability of a particular feature type $i$ and the probability of the observed features in the stimulus given that feature type. Because of the Dirichlet-Multinomial conjugacy in our model, these two distributions can be straightforwardly computed using only the counts of current value-assignments to all variables in the model except the ones currently resampled (equation (5)): the probability of a hypothetical feature type $i$ is proportional to the number of times it has assigned previously to stimuli with observed category $j$, $n^i_j$, smoothed by the Dirichlet parameter $\beta$. Similarly, the probability of the observed features of stimulus $d$ under hypothetical feature type $i$ is proportional to the number of times each individual feature $v$ in $d$ has been observed under feature type $i$, $n^i_v$ (smoothed by the Dirichlet parameter $\gamma$). In the second term in (5), $f_v$ refers to the count of any particular feature $v$ in stimulus $d$, and $f_*$ refers to the number of features in $d$ (irrespective of their value).

We compute the (unnormalized) probabilities of individual hypothetical feature types $i$ as explained above. These values are then normalized and a new feature type is sampled from the resulting distribution.

Resampling concept-category assignments. The second block of our Gibbs sampler performs a sweep over all concept types $\ell \in \{1...L\}$, and resamples
each concept type $\ell$’s category assignment $k^\ell$. Similarly to the process described above, the new category assignment of concept $\ell$ is resampled from its full conditional distribution over categories conditioned on (a) all concept-category assignments except for $k^\ell$, $(k^-)$; (b) the feature type assignments relevant to concept $\ell$, $(g^-_k)$; and (c) all relevant hyperparameters $(\alpha, \beta)$:

$$p(k^\ell = j | g^-_k, k^-, \alpha, \beta) = p(k^\ell = j | k^-, \alpha) \times p(g^-_k | g^-_k, k^\ell = j, \beta)$$

$$\propto (n^j + \alpha) \times \frac{\prod_g \prod_{a=1}^{f^\ell_g} (n^j_g + \beta + a)}{\prod_{a=1}^{f^\ell} (\sum_g n^j_g + \beta + a)}.$$  

Based on the independence assumptions in our model, this probability factorizes into the prior probability of hypothetical category $j$ and the probability of feature types observed with concept $\ell$ under the hypothetical category $j$ (equation (6)). As above, these probabilities can be computed purely based on counts of variable-assignments in the current sampler state (equation (7)). In the second term of (7), $f^\ell_g$ refers to the number of times feature type $g$ was assigned to a stimulus containing concept type $\ell$, and $f^\ell$ to the number of stimuli containing $\ell$ (irrespective of the assigned feature type).

Using the procedure described above we compute an (unnormalized) probability for each hypothetical category, normalize the probabilities and resample concept $\ell$’s category $k^\ell$ from the resulting distribution.

4. Experimental Setup

Can we simulate category acquisition from large amounts of textual data using cognitively motivated computational models, and infer meaningful representations across languages?

We approach this question by applying BCF to data sets in five languages: English, French, German, Arabic, and Chinese. We train five models in total, one per language, each time using stimuli from the respective language alone. We evaluate induced categories by comparison against a human-created reference categorization; and collect judgments on the coherence of learnt feature types, and their relevance to their associated categories from large crowds of native speakers.

Is the structure and architecture of BCF appropriate and necessary for category and structured feature learning? We answer this question by comparing BCF against a variety of related models. First, we report a random
baseline which assigns concepts to categories at random. Secondly, we compare against a model entirely based on word co-occurrence. Unlike BCF, the co-occurrence model cannot learn categories and features jointly, and has no notion of feature structure. It uses $k$-means clustering \cite{66} to group concepts into categories, and, subsequently, group features into feature types for each category (see Section 4.2). Finally, we compare BCF against BayesCat, a cognitively motivated Bayesian model of category acquisition \cite{23}. Like BCF, it draws inspiration from topic modeling, however, BayesCat does not learn categories and features jointly, and does not acquire structured feature representations.

In the following we describe our data set, as well as the set of models we compare BCF against. Next, we present a series of simulations evaluating the quality of the induced categories, their features, and their relevance to the associated categories.

4.1. Experimental Stimuli

Our simulations focused on 491 basic-level concepts of living and non-living things, taken from two previous studies of concept representation \cite{32, 67}, for which we learn (a) a categorization and (b) structured feature representations. Human-created gold standard categorizations of the concepts into 33 categories are available \cite{67, 68}. Since the original studies were conducted in English, we collected translations of the target concepts and their categories into Arabic, Chinese, French, and German, created by native speakers of the target language. The final number of concepts differs across languages, because some English concepts do not exist (or do not have the same translation) in the target language. Concept sets and categorizations for all languages were made available as part of this submission.

We created language specific sets of input stimuli (as illustrated in Fig-

|      | en  | ar  | ch  | fr  | ge  |
|------|-----|-----|-----|-----|-----|
| concepts | 491 | 394 | 450 | 484 | 482 |
| features | 5,898 | 5,870 | 6,516 | 6,416 | 6,981 |
| stimuli | 418,755 | 86,908 | 147,386 | 258,499 | 233,175 |

Table 2: Datasets obtained from language-specific Wikipedia dumps for Arabic (ar), Chinese (ch), English, (en), French (fr), and German (ge). Number of stimuli (concept mentions in linguistic context), concepts, and features (context word types) are shown.
For each target language we created a corpus as follows: We used a subset of articles from the LinguaTools Wikipedia dump\(^3\) we tokenized, POS-tagged and lemmatized the corpus, and removed stopwords using language-specific lists. From this data set we derived a set of input stimuli as mentions of a concept from the reference set of concepts in sentence context (cf., Figure 1). In order to obtain balanced data sets, we automatically filtered words of low importance to a concept from contexts, using the term-frequency-inverse-document-frequency (tf-idf) metric. After filtering, we only kept stimuli with \(3 \leq n \leq 20\) context words and at most 1,000 stimuli per target concept. Table 2 summarizes the statistics of the resulting data sets. The number of stimuli varies across languages as a function of the number of target concepts, and the size of the respective Wikipedia corpus.

4.2. Comparison Models

We compared BCF against various models explained below. All experiments follow the same experimental protocol, i.e., we train separate instances of the same model on each language.

**Strudel.** Following a pattern-based approach, Strudel automatically extracts features for concepts from text collections. It takes as input a part of speech-tagged corpus, a set of target concepts and a set of 15 hand-crafted rules. Rules encode general, but quite sophisticated linguistic patterns which plausibly connect nouns to descriptive attributes (e.g., *extract an adjective as a property of a target concept mention if the adjective follows the mention, and the set of tokens in between contain some form of the verb ‘to be’.*\(^69\)). Strudel obtains a large set of concept-feature pairs by scanning the context of every occurrence of a target concept in the input corpus, and extracting context words that are linked to the target concept by one of the rules. Each concept-feature pair is subsequently weighted with a log-likelihood ratio expressing the pair’s strength of association. Baroni et al.\(^59\) show that the learnt representations can be used as a basis for various tasks such as typicality rating, categorization, or clustering of features into types. We obtained Strudel representations from the same Wikipedia corpora used for extracting the input stimuli for BCF and BayesCat. Note that Strudel, unlike the two Bayesian models, is not a cognitively motivated *acquisition* model, but

\(^{3}\http://linguatoools.org/tools/corpora/wiki}
a system optimized with the aim of obtaining the best possible features from data.

Co-occurrence Baseline. Strudel relies on manually constructed linguistic patterns, and is consequently not directly applicable across languages. We report a baseline which is constructed to resemble Strudel, but does not rely on linguistic features. It allows us to assess whether pure co-occurrence counts provide a strong enough learning signal for category and feature induction across languages. This model represents each concept $c$ as a vector with dimensions corresponding to its co-occurrence counts with features $f$ (i.e., context words), capped by a minimum number of required observations, approximating the concept-feature association:

$$\text{assoc}(c, f) = N(c, f).$$

We obtained categories by clustering concepts based on their vector representations using $k$-means clustering [70]. Based on these categories, we obtained feature types by (1) collecting all features associated with at least half the concepts in the category; and (2) clustering these features into feature types using $k$-means clustering.

BayesCat. Similar to BCF, BayesCat is a knowledge-lean acquisition model which can be straightforwardly applied to input from different languages. It induces categories $z$ which are represented through a distribution over target concepts $c$, $p(c|z)$, and a distribution over features $f$ (i.e., individual context words), $p(f|z)$. BayesCat, like BCF, is a Bayesian model and its parameters are inferred using approximate MCMC inference, in the form of a Gibbs sampler. Unlike BCF, however, BayesCat does not induce structured feature representations, and comparing it to BCF allows us to evaluate the advantage of joint category and feature learning. BayesCat induces categories represented through unstructured bags-of-features. As such, the model structure of BayesCat is closely related to topic models such as Latent Dirichlet Allocation (LDA; [58]). Comparing our proposed model against BayesCat allows us to shed light on the benefit of more sophisticated model structure which allows to learn features jointly with categories, compared to the information that can be captured in vanilla topic models. For our human evaluation in Section 7 we construct feature types from BayesCat features as follows. First we represent each feature $f$ as its probability under each
category $p(z|f)$. Based on this representation, we again employ $k$-means clustering to group features into $G$ global feature types $g$. Finally, we compute category-featuretype associations as:

$$p(g|z) = \sum_{f \in g} p(f|z),$$

where $p(f|z)$ is learnt by BayesCat.

While BCF induces a hard assignment of concepts to categories, BayesCat learns a soft categorization. Soft assignments can be converted into hard assignments by assigning each concept $c$ to its most probable category $z$,

$$z(c) = \max_z p(c|z)p(z|c).$$

**Model Parameters.** Across all simulations we trained BCF to induce $K = 40$ categories and $G = 50$ feature types which are shared across categories. We ran the Gibbs sampler for 1,000 iterations, and report the final most likely representation. We trained BayesCat on the same input stimuli as BCF, with the following parameters: the number of categories was set to $K = 40$, and the hyperparameters to $\alpha = 0.7$, $\beta = 0.1$, and $\gamma = 0.1$. From the learnt representations, we induced $G = 50$ global feature types as described above. Again results are reported as averages over 10 runs of 1,000 iterations of the Gibbs sampler. The co-occurrence model induces $K = 40$ categories, and, subsequently, $G = 5$ feature types for each category.

5. **Experiment 1: Category Quality**

In this simulation, we evaluate the extent to which model-induced categories resemble the human created reference categorization. We report results on cluster quality for BCF, BayesCat, and the frequency baseline for our five target languages. For English, we additionally report results for Strudel. We also lower-bound the performance of all models with a random clustering baseline (random), which randomly assigns all concepts to $K = 40$ categories.

5.1. **Method**

The output clusters of an unsupervised learner do not have a natural interpretation. Cluster evaluation in this case involves mapping the induced clusters to a gold standard and measuring to what extent the two clusterings
(induced and gold) agree [74]. Purity \((pu)\) measures the extent to which each induced category contains concepts that share the same gold category. Let \(G_j\) denote the set of concepts belonging to the \(j\)-th gold category and \(C_i\) the set of concepts belonging to the \(i\)-th cluster. Purity is calculated as the member overlap between an induced category and its mapped gold category. The scores are aggregated across all induced categories \(i\), and normalized by the total number of category members \(N\):

\[
pu = \frac{1}{N} \sum_i \max_j |C_i \cap G_j| \tag{11}
\]

Inversely, collocation \((co)\) measures the extent to which all members of a gold category are present in an induced category. For each gold category we determine the induced category with the highest concept overlap and then compute the number of shared concepts. Overlap scores are aggregated over all gold categories \(j\), and normalized by the total number of category members \(N\):

\[
co = \frac{1}{N} \sum_j \max_i |C_i \cap G_j| \tag{12}
\]

Finally, the harmonic mean of purity and collocation can be used to report a single measure of clustering quality. If \(\beta\) is greater than 1, purity is weighted more strongly in the calculation, if \(\beta\) is less than 1, collocation is weighted more strongly:

\[
F_\beta = \frac{(1 + \beta) \cdot pu \cdot co}{(\beta \cdot pu) + co} \tag{13}
\]

We additionally report results in terms of V-Measure \((VM, \[72]\)) which is an information-theoretic measure. VM is analogous to F-measure, in that it is defined as the weighted harmonic mean of two values, homogeneity \((VH, \text{the precision analogue})\) and completeness \((VC, \text{the recall analogue})\):

\[
VH = 1 - \frac{H(G|C)}{H(G)} \tag{14}
\]

\[
VC = 1 - \frac{H(C|G)}{H(C)} \tag{15}
\]

\[
VM = 1 - \frac{(1 + \beta) \cdot VH \cdot VC}{(\beta \cdot VH) + VC} \tag{16}
\]
where $H(\cdot)$ is the entropy function; $H(C|G)$ denotes the conditional entropy of the induced class $C$ given the gold standard class $G$ and quantifies the amount of additional information contained in $C$ with respect to $G$. The various entropy values involve the estimation of the joint probability of classes $C$ and $G$:

$$\hat{p}(C, G) = \frac{\mu(C \cap G)}{N} \quad (17)$$

5.2. Results

| model     | PU  | CO  | F1  | VH  | VC  | VM  |
|-----------|-----|-----|-----|-----|-----|-----|
| **English** |     |     |     |     |     |     |
| BCF       | 0.552 | 0.432 | 0.484 | 0.652 | 0.598 | 0.623 |
| BayesCat  | 0.551 | 0.429 | 0.482 | 0.646 | 0.577 | 0.609 |
| Strudel   | 0.572 | 0.442 | 0.499 | 0.662 | 0.590 | 0.624 |
| co-occ    | 0.550 | 0.394 | 0.459 | 0.626 | 0.559 | 0.591 |
| random    | 0.193 | 0.135 | 0.159 | 0.317 | 0.282 | 0.298 |
| **German** |     |     |     |     |     |     |
| BCF       | 0.454 | 0.400 | 0.425 | 0.545 | 0.523 | 0.534 |
| BayesCat  | 0.458 | 0.378 | 0.414 | 0.563 | 0.513 | 0.537 |
| co-occ    | 0.338 | 0.387 | 0.361 | 0.408 | 0.435 | 0.421 |
| random    | 0.194 | 0.134 | 0.158 | 0.316 | 0.280 | 0.297 |
| **French** |     |     |     |     |     |     |
| BCF       | 0.534 | 0.441 | 0.483 | 0.632 | 0.585 | 0.608 |
| BayesCat  | 0.507 | 0.415 | 0.457 | 0.609 | 0.558 | 0.582 |
| co-occ    | 0.459 | 0.365 | 0.407 | 0.544 | 0.509 | 0.526 |
| random    | 0.197 | 0.134 | 0.158 | 0.319 | 0.283 | 0.300 |
| **Chinese** |     |     |     |     |     |     |
| BCF       | 0.441 | 0.349 | 0.389 | 0.510 | 0.497 | 0.503 |
| BayesCat  | 0.430 | 0.320 | 0.367 | 0.532 | 0.493 | 0.512 |
| co-occ    | 0.367 | 0.327 | 0.345 | 0.408 | 0.422 | 0.415 |
| random    | 0.208 | 0.135 | 0.164 | 0.325 | 0.291 | 0.307 |
| **Arabic**  |     |     |     |     |     |     |
| BCF       | 0.408 | 0.327 | 0.363 | 0.444 | 0.446 | 0.445 |
| BayesCat  | 0.394 | 0.298 | 0.339 | 0.491 | 0.462 | 0.476 |
| co-occ    | 0.261 | 0.308 | 0.283 | 0.312 | 0.344 | 0.327 |
| random    | 0.214 | 0.125 | 0.158 | 0.329 | 0.296 | 0.312 |

Table 3: Quality of induced categories for BCF (this work), BayesCat, a co-occurrence baseline, Strudel (for English only), and a random baseline. Results are reported for English, German, French, Chinese and Arabic.
Table 3 displays the results for all five languages. BCF learns categories which most closely resemble the human gold standard, and both BCF and the co-occurrence model clearly outperform the random baseline. The Bayesian models, BCF and BayesCat, outperform the co-occurrence model across metrics and languages. For English, Strudel slightly outperforms BCF. Note, however, that, BCF learns the categories from data, whereas for Strudel we construct the categories post-hoc after a highly informed feature extraction process (relying on syntactic patterns). It is therefore not surprising that Strudel performs well, and it is encouraging to see that BCF learns categories of comparable quality.

We observe a slight drop in performance for languages other than English which is likely due to smaller stimuli sets (see Table 2). BCF, nevertheless, achieves purity scores of 0.4 or higher for all languages, meaning that on average at least 40% of the members of a gold standard category are clustered together by BCF (purity rises to 58% for English). This indicates that meaningful categories emerge throughout. Qualitative model output shown in Figures 2 (English) and 4 (all languages) corroborates this result. The categories shown are intuitively meaningful; in particular VEGETABLE and CLOTHING (Figure 4) are interpretable, and thematically consistent across languages.

A few interesting idiosyncrasies emerge from our cross-lingual experimental setup, and the ambiguities inherent in language. For example, the English concepts *tongue* and *bookcase* were translated into French words *langue* and *bibliothèque*, respectively. The French BCF model induced a category consisting of only these two concepts with highly associated feature types \{story, author, publish, work, novel\} and \{meaning, language, Latin, German, form\}. Although this category does not exist in the gold standard, it is arguably a plausible inference. Another example concerns the concept *barrel*, which in the English BCF output, is grouped together with concepts *cannon*, *bayonet*, *bomb* and features like \{kill, fire, attack\}. In French, on the other hand, it is grouped with *stove*, *oven* and the features \{oil, production, ton, gas\}.

We showed that BCF learns meaningful categories across languages which are quantitatively better than those inferred by a simpler co-occurrence model. Although generally consistent, categories are sometimes influenced by characteristics of the respective training and test language. While the literature confirms an influence of language on categorization [5, 6], this effect is undoubtedly amplified through our experimental framework.
### 6. Experiment 2: Feature Quality

We next investigate the quality of the features our model learns. We do this by letting the model predict the right concept solely from a set of features.

| Category: Clothing | Category: Vegetables |
|--------------------|----------------------|
| blouse slipper jacket shaved dress | tomato garlic cauliflower zucchini pepper cucumber lettuce radish cab-
| women dress white shirt skirt hat jacket | onion sauce vegetable diy pepper meat tomato potato garlic |
| shirt skirt hat jacket | crop potato vegetable grow bean wheat fruit tomatoes corn |
| white blue shirt uniform | oil seed juice water grow vegetable produce vegetable fruit vitamin sugar |
| form | plant family leaf grow flower flowering root wild fruit |
| short skirt | cake milk cream sugar chocolate broad cheese swiss |
| tie face olive scarf coat | cauliflower zucchini pepper |}

Figure 4: Categories CLOTHING (a) and VEGETABLES (b) (light red), and their five most highly associated feature types (light blue) for English (en), German (de), French (fr), Arabic (ar), and Chinese (ch). Model output of languages other than English was translated into English by native speakers.
|      | pr@1 | pr@10 | pr@20 | avg rank |
|------|------|-------|-------|----------|
| BCF  | 0.07 | 0.34  | 0.48  | 61.9     |
| BayesCat | 0.05 | 0.31  | 0.44  | 63.6     |
| Strudel | 0.04 | 0.31  | 0.45  | 76.1     |
| co-occ baseline | 0.013 | 0.210 | 0.370 | 97.4 |
| random baseline | 0.002 | 0.020 | 0.040 | –       |

|      | pr@1 | pr@10 | pr@20 | avg rank |
|------|------|-------|-------|----------|
| BCF  | 0.07 | 0.31  | 0.42  | 90.5     |
| BayesCat | 0.07 | 0.32  | 0.41  | 66.3     |
| co-occ baseline | 0.007 | 0.110 | 0.137 | 177.6 |
| random baseline | 0.002 | 0.021 | 0.041 | –       |

|      | pr@1 | pr@10 | pr@20 | avg rank |
|------|------|-------|-------|----------|
| BCF  | 0.07 | 0.31  | 0.44  | 73.2     |
| BayesCat | 0.04 | 0.28  | 0.45  | 64.2     |
| co-occ baseline | 0.017 | 0.153 | 0.227 | 136.6 |
| random baseline | 0.002 | 0.021 | 0.041 | –       |

|      | pr@1 | pr@10 | pr@20 | avg rank |
|------|------|-------|-------|----------|
| BCF  | 0.09 | 0.37  | 0.49  | 66.0     |
| BayesCat | 0.09 | 0.38  | 0.53  | 41.7     |
| co-occ baseline | 0.033 | 0.157 | 0.187 | 139.1 |
| random baseline | 0.002 | 0.022 | 0.044 | –       |

|      | pr@1 | pr@10 | pr@20 | avg rank |
|------|------|-------|-------|----------|
| BCF  | 0.13 | 0.49  | 0.61  | 54.9     |
| BayesCat | 0.14 | 0.54  | 0.65  | 27.5     |
| co-occ baseline | 0.012 | 0.110 | 0.139 | 154.8 |
| random baseline | 0.003 | 0.025 | 0.050 | –       |

Table 4: Model performance on the concept prediction task in terms of precision at rank 1, 10, 20, and average rank assigned. We compare BCF (this work), BayesCat, a co-occurrence baseline, Strudel (for English only), and a random baseline. Results are reported for English, German, French, Chinese and Arabic.

If the model has acquired informative features, they will be predictive of the unknown concept. Specifically, the model is presented with a set of previously unseen test stimuli with the target concept removed. For each stimulus, the model predicts the missing concept based on the features \( f \) (i.e., context words).

6.1. Method

Like in the category evaluation above, we compare the ranking performance of BCF, BayesCat, the co-occurrence based model, and Strudel for
English. For the Bayesian models, we directly exploit the learnt distributions. For BCF, we compute the score of a target concept \( c \) given a set of features as:

\[
\text{Score}(c|f) = \sum_{g} P(g|c)P(f|g).
\]  

(18)

Similarly, for BayesCat we compute the score of a concept \( c \) given a set of features as follows:

\[
\text{Score}(c|f) = \sum_{k} P(c|k)P(f|k).
\]  

(19)

For both Strudel and the co-occurrence model, we rank concepts according to the cumulative association over all observed features for a particular concept \( c \). For Strudel, association corresponds to log-likelihood ratio-based association scores, while for the co-occurrence model it corresponds to co-occurrence counts, concept \( c \):

\[
\text{Score}(c|f) = \sum_{f \in f} \text{association}(c, f).
\]  

(20)

We also report a baseline which randomly selects target concepts from the full set of concepts.

We report precision at rank 1, 10, and 20. We also report the average rank assigned to the correct concept. All results are based on a random test set of previously unseen stimuli.

6.2. Results

Figure 5 depicts three English stimuli, together with concept predictions from BCF and the co-occurrence model. Table 4 shows quantitative results of the three models averaged over a corpus of 300 test stimuli for all languages. Both BCF and the co-occurrence model outperform the random baseline by a large margin, and BCF achieves consistently highest scores. Both Bayesian models (BCF and BayesCat) outperform the co-occurrence model across all metrics and conditions. We assume that plain concept-feature co-occurrence information might be too sparse to provide a strong signal of concept relevance given a set of features. The Bayesian models, on the other hand, learn complex correspondences between features and all concepts in a category. BayesCat and BCF perform comparably given that they
exploit local co-occurrence relations in similar ways. BCF learns feature associations which discriminate concepts more accurately, suggesting that the joint learning objective and \textit{structured} feature information is beneficial. The example predictions in Figure 5 corroborate this.

Cross-lingual comparisons reveal that, compared to BCF, the performance of the co-occurrence model degrades more severely for languages other than English. This suggests that BCF can leverage information more efficiently from smaller learning corpora (see Table 2). The number of concepts (i.e., target items to be ranked) differs across languages so that absolute numbers are not directly comparable.

Figures 2 and 4 qualitatively support the claim that BCF learns meaningful features across languages, which are overall coherent and relevant to their associated category. Some interesting cultural differences emerge, for exam-
language German is the only language for which a measurement feature type is induced for vegetables (Figure 4b; de, 4th from left), while for clothing, a fashion industry feature emerges in French (Figure 4a; fr, 3rd from left). For the same category, a feature type pertaining to colour emerges for all five languages (4a, bold margins). In addition, some features in other languages were not straightforwardly translatable into English. For example, the 3rd feature type for vegetables in Chinese (Figure 4b) includes the word 分 which refers to the extent to which food is cooked and 烂 which is the stage when food starts to fall apart after cooking (stewing). In addition, the feature types induced for the Chinese clothing category include two words which both translate to the English word wear, but in Chinese are specific to wearing small items (e.g., jewelery; 戴), and wearing clothes (穿), respectively.

Language-specific features are meaningful, and at the same time category-feature associations across languages reflect culture-driven differences.

7. Experiment 3: Feature Relevance and Coherence

Given that our aim is to induce cognitive representations of the world, the ultimate assessment of the model’s representations is their meaningfulness to humans, i.e., speakers of our target languages. To this end, we elicited judgments of feature quality from native speakers using the crowd sourcing platforms CrowdFlower\(^5\) and Amazon Mechanical Turk\(^6\). Specifically, we are interested in two questions: (1) Do induced feature types have a single co-
Figure 7: An example task for our feature relevance study. The example task involves categories and features induced by BCF from the English Wikipedia.

herent underlying theme such as color or function (feature coherence); (2) Do feature types associated with a category relate to that category (feature relevance)?

We compared the feature types learnt by BCF against the co-occurrence model as well as BayesCat. For English we also include Strudel. We omitted the random baseline from this evaluation since it was clearly inferior in previous simulations.

7.1. Method

We adopted the topic intrusion experimental paradigm [73] for assessing the induced features in two ways. Firstly, we examined whether the feature types our model learns are thematically coherent. Participants were presented features types (as lists of words), which were augmented with a random ‘intruder’ feature, and their task was to correctly identify the intruder feature. Figure 6 displays an example task. If the feature types are internally coherent we expect annotators to identify the intruder with high accuracy. We evaluated all 50 feature types as induced by BCF and the co-occurrence model.

Secondly, we assessed the relevance of feature types assigned to any category. An example task is shown in Figure 7. We presented participants with a category and five feature types (each as a list of words), one of which was randomly added and was not associated with the category in the model output. Again, they needed to select the correct intruder. If category-feature type associations induced by the model are generally relevant, annotators will be able to identify the intruder with high accuracy. We evaluated all 40 induced categories and their associated features for BCF and the co-occurrence model.

29
For both elicitation studies, we obtained 10 responses per task (see Figures 6 and 7); participants judged a single concept and its features per task. All participants were required to be native speakers of the language they were evaluating, and we filtered crowdworkers through their location of residence and self-reported native language (using the functionality provided by the crowdsourcing platforms). We additionally included test questions among tasks for which the true answer was known, and discarded the data from participants who failed to achieve high accuracy on these test questions. Overall, we obtained 50×10 responses for the feature coherence study and 40×10 responses for feature relevance.

We report the average accuracy across participants of selecting the correct intruder feature and intruder feature type, respectively. In addition we report inter annotator agreement (IAA) using Fleiss Kappa [74]. The extent to which annotators agree in their judgments allows us to evaluate the difficulty of the task, as well as the reliability of the results.

7.2. Results

Table 5 displays the results for the feature relevance study and Table 6 the feature coherence study. Table 5 shows that humans are able to detect intruder feature types with higher accuracy in the context of BCF-induced representations, compared with all comparison models. Additionally, inter annotator agreement (IAA) is consistently higher for BCF, indicating that participants more frequently agreed on their selections and that selecting intruders in the BCF output was an easier task for them compared to the comparison models. Similar to the previous simulations, we observe that both Bayesian models (BayesCat and BCF) outperform the count-based models. In this evaluation, however, we also observe a clear advantage of BCF compared to BayesCat, which does not learn structured feature types inherently. BCF learns to associate relevant features to categories.

Table 6 shows the results of the feature coherence study, where the overall pattern of results is similar as above. We can see that participants are able to detect intruder features from the types learnt by BCF more reliably than from those learnt by all comparison models. Again, both Bayesian models outperform the count-based baselines both in terms of accuracy and inter annotator agreement. The superior performance of BCF compared to BayesCat indicates that its ability to learn structured features jointly with categories in a single process leads to higher quality feature representations. In particular, in addition to associating relevant feature types with categories, the feature
types themselves are internally coherent, pertaining to different aspects or properties of the reference category.

Comparing results across languages we observe that scores for English exceed scores for all other languages. At the same time, for almost all models and languages the IAA scores fall under the category of ‘fair agreement’ ($0.20 < \kappa < 0.40$) indicating that the elicitation task was feasible for crowdworkers. This applies to both evaluations (Tables 5 and 6). We observed a similar pattern in the results of Experiment 1 (Table 3). We believe there are two reasons for this drop. Firstly, in order to perform cross-linguistic experiments, we translated English categories into other languages. As mentioned in Sections 5.2 and 6.2, such a direct correspondence may not always exist. Consequently, annotators for languages other than English are faced with a noisier (and potentially harder) task. Secondly, while it is straightforward to recruit English native speakers on crowd sourcing platforms, it has proven more challenging for the other languages. We suspect that our effort to re-

| model          | accuracy | IAA  |
|---------------|----------|------|
| BCF           | 0.752    | 0.700|
| BayesCat      | 0.605    | 0.456|
| strudel       | 0.435    | 0.364|
| co-occ baseline | 0.302   | 0.220|
| BCF           | 0.530    | 0.361|
| BayesCat      | 0.370    | 0.206|
| co-occ baseline | 0.340   | 0.201|
| BCF           | 0.555    | 0.427|
| BayesCat      | 0.468    | 0.294|
| co-occ baseline | 0.278   | 0.216|
| BCF           | 0.468    | 0.419|
| BayesCat      | 0.261    | 0.108|
| co-occ baseline | 0.390   | 0.310|
| BCF           | 0.385    | 0.278|
| BayesCat      | 0.385    | 0.215|
| co-occ baseline | 0.278   | 0.155|

Table 5: Results of our feature relevance study for BCF (this work), BayesCat, the co-occurrence model (co-occ), and Strudel (for English only) in terms of accuracy (the proportion of intruders identified correctly) and inter-annotator agreement (IAA; Fleiss Kappa [74]) for five target languages.
Table 6: Results from our feature coherence study for BCF (this work), BayesCat, the co-occurrence model (co-occ), and Strudel (for English only) in terms of accuracy (the proportion of intruders identified correctly) and inter-annotator agreement (IAA; Fleiss Kappa [74]) for five target languages.

| Language | Model       | Accuracy | IAA  |
|----------|-------------|----------|------|
| English  | BCF         | 0.814    | 0.710|
|          | BayesCat    | 0.642    | 0.529|
|          | strudel     | 0.260    | 0.294|
|          | co-occ baseline | 0.266 | 0.296|
| German   | BCF         | 0.760    | 0.639|
|          | BayesCat    | 0.465    | 0.341|
|          | co-occ baseline | 0.220 | 0.210|
| French   | BCF         | 0.690    | 0.527|
|          | BayesCat    | 0.557    | 0.409|
|          | co-occ baseline | 0.224 | 0.227|
| Chinese  | BCF         | 0.574    | 0.723|
|          | BayesCat    | 0.269    | 0.234|
|          | co-occ baseline | 0.228 | 0.227|
| Arabic   | BCF         | 0.594    | 0.444|
|          | BayesCat    | 0.416    | 0.423|
|          | co-occ baseline | 0.236 | 0.195|

cruit native speakers, might not have been entirely fail-safe for languages other than English, and that the language competence of those crowdworkers might have impacted the quality of their judgments.

Overall, we conclude that *jointly* inducing structured features together with categories from natural language corpora in different languages enables BCF to learn feature types which are (1) internally coherent, referring to a single underlying theme; and (2) informative about the categories with which they are associated.

8. General Discussion

We presented the first large-scale, cross-linguistic analysis of categorization using naturally occurring data. We showed that rational Bayesian models of categorization can learn meaningful categories and their features from
complex environments resembling the natural world more closely than limited laboratory settings.

We developed BCF, a cognitively motivated Bayesian model, and investigated its ability to learn categories (for hundreds of concepts) and their structured features from corpora in five languages. Like humans ‘in the wild’, our model learns categories and relevant features jointly\(^{29, 30}\), and induces structured representations of categories\(^{31, 32, 33}\). Compared to a simpler co-occurrence model and a Bayesian model with no access to these mechanisms BCF learns better categories and features which are rated as more relevant and coherent by humans. BCF models category acquisition as a general, language-independent process. It neither utilizes language-specific knowledge nor requires language-specific tuning, and as such paves the way for future investigations involving more languages, or different kinds of corpora.

Our study sheds light on the acquisition of concrete concepts and their features from text, and as such adopts a constrained view of both the learning environment and the learning target. It suggests a number of interesting suggestions for future research. First, this article considered natural language input as an approximation of the environment from which categories and their representations are learnt. While we showed that the linguistic environment is a useful approximation of the full multimodal input a learner has access to, it is clear that language cannot capture this multimodal environment is not captured in its entirety. Computational models of word learning have been trained on multimodal input data (albeit on smaller-scale problems;\(^{75, 76}\)). Advantageously, Bayesian models are flexible with respect to the input data they receive, so we expect the application of our model to multimodal data to be a feasible avenue for future work. Applying our models to such data sets would allow to compare the category acquisition process as well as the acquired representations from multimodal input against those emerging from language data alone.

A second direction for future work concerns the cognitive assumptions underlying the learning setup. The models discussed in this article learn from collections of natural language stimuli consisting of a target concept mention and its surrounding context. This input is based on the rather bold assumption that the learner already has substantial linguistic prior knowledge prior to concept and feature learning: she has successfully mapped each target concept to a word. As supported by an extensive literature\(^{5, 6, 4}\), word learning, itself a fundamental challenge for young infants, and concept learn-
ing exhibit a mutual influence. Our work remains agnostic about the fact that the meaning of words itself needs to be acquired, and that knowledge about concepts and categories will help tackle the word learning problem. A fully faithful model would consider the problems of word and concept or category learning jointly. Extending BCF to account for this joint optimization, and investigating emerging acquisition patterns across different languages, will be a very interesting avenue for future research.

Humans not only categorize the physical world around them, but also infer complex representations of abstract categories and concepts such as POLITICAL (e.g., parliament, socialist), LEGAL (e.g., law, trial), or FEELINGS (e.g., mirth or embarrassment). Lacking any physical realization, and hence perceivable properties, there is evidence that language plays a particularly important role in acquiring the meaning of such abstract concepts [77]. A data-driven study across languages would be particularly interesting in the context of abstract categories, whose representations are expected to be more sensitive to the cultural environment.

In conclusion, our investigations into category and feature learning from text across languages corroborate prior results [21] that the non-linguistic learning environment is to some extent encoded in language. They additionally provide evidence for the stronger statement that the structure of the world which affords rich mental categorical representations is encoded in language. We envision scalable testbeds which combine naturally occurring data from multiple modalities, for example combining text data with images or video. Our work exemplifies the potential of interpretable statistical models for gaining insights into the mechanisms which are at play in human cognition. We demonstrated the potential of large naturalistic datasets for the development and testing of computational models, and are confident that computational cognitive models together with large naturally occurring data set will open up novel opportunities for investigating human cognition at scale.

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