The Profiling Machine: Active Generalization over Knowledge

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Abstract
The human mind is a powerful multifunctional knowledge storage and management system that performs generalization, type inference, anomaly detection, stereotyping, and other tasks. A dynamic KR system that appropriately profiles over sparse inputs to provide complete expectations for unknown facets can help with all these tasks. In this paper, we introduce the task of profiling, inspired by theories and findings in social psychology about the potential of profiles for reasoning and information processing. We describe two generic state-of-the-art neural architectures that can be easily instantiated as profiling machines to generate expectations and applied to any kind of knowledge to fill gaps. We evaluate these methods against Wikidata and crowd expectations, and compare the results to gain insight in the nature of knowledge captured by various profiling methods. We make all code and data available to facilitate future research.

Introduction
A key characteristic of intelligent behavior is the use of knowledge. The human mind is a powerful multifunctional knowledge storage and management system that performs generalization, type inference, anomaly detection, profiling, stereotyping, and other tasks. No computational system to date implements all these capabilities together. Traditional databases comprise one or more tables of (usually instantial) facts, coupled to a definitional metadata schema. Declarative AI knowledge bases are essentially multigraph concept networks with explicitly named relations between nodes (each node being a cell in an equivalent database), allowing one to define filler constraints along the edges and perform inference via graph traversal. KR typologies/ontologies encode and organize terminology and definitional information, but seldom include instance data.

Growing amounts of data and the advent of workable neural (deep) models raise the natural question: can one build models that simultaneously encode instance-level knowledge, generalize it to form 'concepts', learn profiles, detect anomalies, provide preferences, etc.? How can one generalize and spot inconsistencies when, unlike in databases or Semantic Web, no explicit ontological schema can be assumed? Can one test such models in applications like natural language QA systems that require various semantic background knowledge exactly because stereotypical information is deliberately left out in people’s communication?

In this paper we focus on an important but unaddressed component of this challenge: profiling. We believe that a representation [learning] system should be able to absorb instances (exemplars) of some multifaceted concept (such as Person) and automatically generate expectations for the unspecified facets. These expectations should of course be conditioned on whatever (partial) information is provided for any test case, and automatically adjusted when any additional information is provided. Further, they should conform to human intuition and experience.

To the best of our knowledge, this quite natural task of profiling has not been addressed widely in the AI or NLP literature. A related challenge, knowledge base completion (KBC), has however been relatively popular: in it, the system is asked to add new concrete instance-level facts given other instantial information. This can be seen as an ‘edge case’ of profiling, but is fundamentally different in that it predicts specific values rather than generating human-like expectations over value classes. We see profiling as a common and potentially more helpful capability for NLU and QA, where knowing preferences or general expectations is often necessary in order to perform reasoning and to direct interpretation on partial and underspecified data. Profiling lies somewhat between the existing tasks of KBC in machine learning and missing value imputation in databases, seeking to fill all missing values (as in the field of databases), albeit with types, where the underlying entities and relations are analogous to those used in KBC.

We summarize the contributions of this paper as follows:
1. We define the task of profiling over knowledge for AI machines, which is especially needed for contextual, long-tail instances, where knowledge is extremely scarce, yet much of what is unknown can be stereotyped. 2. We pose this task as inspired by insights in social psychology, potentially providing another link between cognitive sciences and AI systems. 3. We perform profiling on coarse-grained values to bridge the gap between factual data and human stereotypes. 4. We describe two generic state-of-the-art neural methods that can be easily instantiated into profiling machines for generation of expectations, and applied to any kind of knowledge to fill gaps. 5. We evaluate these methods against Wikidata and crowd expectations, and compare the results to gain insight in the nature of knowledge captured by profiles. 6. We make all code and data available to facilitate future research.
Related Work

Several quite distinct research areas are relevant to profiling. We briefly list some of the most relevant work.

**Data imputation.** Data imputation refers to the procedure of filling in missing values in databases. In its simplest form, this procedure can be performed by mean imputation and hot-deck imputation (Lakshminarayan, Harp, and Samad 1999). Model-based methods are often based on regression techniques or likelihood maximization (Pearson 2006). Gautam and Ravi combine a neural network with a genetic algorithm, while Auylik and Arslan cluster missing values with existing, known values. These efforts focus on guessing numeric and interval-valued data, which is a shared property with the related task of guesstimation (Abourbih, Bundy, and McNeill 2010). In contrast, profiling aims to predict typical classes of values. Moreover, data imputation has no direct cognitive correlate regarding inferred expectations.

**KBC.** Compared to databases, the sparsity in real-world AI knowledge graphs is typically far greater: e.g., most facet values in both Freebase and Wikidata are missing (Dong et al. 2014). KBC adds new facts to knowledge bases/graphs based on existing ones. Two related tasks are link prediction (with the goal to predict the subject or object of a given triplet, usually within the top 10 results) and triplet completion (a binary task judging whether a given triplet is correct).

In the past decade, KBC predominantly employed deep embedding-based approaches, which can be roughly divided into tensor factorization and neural network models (Ji et al. 2016). TransE (Bordes et al. 2013) and ITransF (Xie et al. 2017) are examples of neural approaches that model the entities and relations in embedding spaces, and use vector projections across planes to complete missing knowledge. Tensor factorization methods like (Guu, Miller, and Liang 2015) regard a knowledge graph as a three-way adjacency tensor. Most similar to our work, Neural Tensor Networks (Socher et al. 2013) also: 1. aim to fill missing values to mimic people’s knowledge; 2. evaluate on structured relations about people; 3. rely on embeddings to abstract from the actual people to profile information.

Universal Schema (US) (Riedel et al. 2013) includes relations extracted from text automatically, which results in larger, but less reliable, initial set of relations and facts. US was designed for the needs of NLP tasks such as fine-grained entity typing (Yao, Riedel, and McCallum 2013).

KBC research, including that by Socher et al., resembles the task of profiling in that it also operates on data about real-world instances and their typed relations. However, the goals of profiling differ from those of KBC: 1. to generate an expectation class for every facet of a category/group, rather than suggesting missing facts; 2. to provide a typical distribution (not a specific value) for the attributes of a specific group; 3. to understand how these profiles shift when additional evidence is provided. These differences make profiling far more useful for reasoning over incomplete data in AI applications, and related to cognitive work on stereotypes.

KnowledgeVault (KV) (Dong et al. 2014) is a probabilistic knowledge base by Google, which fuses priors about each entity with evidence about it extracted from text. Despite using a different method, the priors in KV serve the same purpose as our profiles: they provide expectations for all unknown properties of an instance, learned from factual data on existing instances. Unfortunately, the code, the experiments, and the output of this work are not publicly available, thus preventing further analysis of these priors, the validity of factual data for profiling, and their relation to cognitive/cultural profiling as done by humans.

**Estimation of property values.** Past work in IR attempted to improve the accuracy of retrieval of long-tail entities by estimating their values based on observed head entities. Most similar to profiling, the method by Farid et al. estimates a property of a long-tail entity based on the community/ies it belongs to, assuming that each entity’s property values are shared with others from the same community. Since the goal of this line of research is to improve the accuracy of retrieval, the generalization performed is rather ad-hoc, and the knowledge modeling and management aspects have not been investigated in depth. Moreover, the code, the experiments, and the results of this work are not publicly available for comparison or further investigation.

**Social media analysis.** Community discovery and profiling in social media is a task that clusters the online users which belong to the same community, typically using embeddings representation (Akbari and Chua 2017), without explicitly filling in/representing missing property values.

Local models that infer a specific property (e.g., the tweet user’s location) on other known information, such as her social network (Jurgens 2013) or expressed content (Mahmud, Nichols, and Drews 2012), also address data sparsity. These models target specific facets and data types, thus they are not generalizable to others. Similarly to models in KBC, they lack cognitive support and fill specific instance values rather than typical ranges of values or expectations.

**Probabilistic models.** Prospect Theory (Kahneman and Tversky 1979) proposes human-inspired cognitive heuristics to improve decision making under uncertainty. The Causal Calculus theory (Pearl 2009) allows one to model causal inter-facet dependencies in Bayesian networks. Due to its cognitive background and assumed inter-facet causality, profiling is a natural task for such established probabilistic theories to be applied and tested.

**Stereotypes.** Stereotype creation is enabled by profiling. The practical uses of stereotypes are vast and potentially ethically problematic. For example, Bolukbasi et al. claim that embedding representations of people carry gender stereotypes; they show that the gender bias can be located in a low-dimensional space, and removed when desired. We leave ethical and prescriptive considerations for other venues, and note simply that artificially removing certain kinds of profiling-relevant signals from the data makes embeddings far less useful for application tasks in NLP and IR when evaluated against actual human performance.

Profiles

**Intuitions**

People have no trouble making and using profiles/defaults:

_P1 is male and his native language is Inuktitut. What are his citizenship, political party, and religion? Would knowing_
that he was born in the 19th century change one’s guesses? 

P2 is a member of the American Senate. Where did he get his degree, and what is his native language? 

P3 is an army general based in London. What is P3’s stereotypical gender and nationality? If P3 gets an award “Dame Commander of the Order of the British Empire”, which expectations would change? 

Presumable answers to the above questions are as follows. P1 is a citizen of Canada, votes for the Conservative Party of Canada, and is Catholic. However, P1’s 19th century equivalent belongs to a different party. P2 speaks English as main language and graduated at Harvard or Yale University. Finally, the initial expectation on P3 of a male Englishman switches to a female after the award evidence is revealed. 

Most of us would agree with the suggested answers. Why/how!? What is it about the Inuititut language that associates it to the Conservative Party? Why is the expectation about the same person in different time periods different? Why does the sole change of political party change the expectation of one’s work position or cause of death? Despite the vast set of possibilities, these kinds of knowledge gaps are easily filled by people based on knowledge about associations among facet values, and give rise to a continuously evolving and changing collection of cognitive expectations and stereotypical profiles. Further, people assume that they are entitled to fill knowledge gaps with their expectations unless contradictory evidence is explicitly presented; if the truth differs from the profile, pragmatics requires (as reflected in Grice’s Maxim of Quantity) that this truth will be explicitly stated.1 

AI systems such as NLU and QA engines require such human-like expectations. As this information tends to be deliberately absent from (or implicit in) human communication, information harvesting systems cannot simply distill it directly from available material. Knowledge missing during AI system processing is traditionally injected from knowledge bases, which attempt to mimic the world knowledge possessed and applied by humans. However, current knowledge bases are notoriously sparse (Dong et al. 2014), and do not contain implicit expectations nor provide inference mechanisms that can generate such expectations. AI systems face an apparently insurmountable obstacle, most notable for long-tail instances with little to no accessible facts.2 

Aspects of Profiles 

Following (Ashmore and Del Boca 1981) we define a profile as a set of beliefs about the attributes of members of some group. A stereotypical profile is a type of schema, an organized knowledge structure that is built from experience and carries predictive relations, thus providing a theory about how the social world operates (Kunda 1999). Stereotypical profiles shared by a culture/sample are named consensual. 

Functions. As a fast cognitive process, profiling gives basis for acting in uncertain/unforeseen circumstances (Dijker and Koomen 1996). Profiles are “shortcuts to thinking”, that provide people with rich and distinctive information about unseen individuals. Moreover, they are efficient, thus preserving our cognitive resources for more pressing concerns. 

Accuracy. Profile accuracy reflects the extent to which beliefs about groups correspond to the actual characteristics of those groups (Jussim, Crawford, and Rubinstein 2015). Consensual ones have been empirically shown to be highly accurate, especially the demographic (race, gender, ethnicity, etc.) and other societal profiles (like occupations or education), and somewhat less the political ones (Jussim, Crawford, and Rubinstein 2015). This effect has been called the “wisdom of the crowds” (Surowiecki 2004). 

This high accuracy does not mean that profiles will correctly describe any group individual; they are a statistical phenomenon. In that sense, the findings by Jussim, Crawford, and Rubinstein that most profiles are justified empirically are of great importance for AI machines: it means that they can be reliably inferred from individual facts, which (unlike many profiles themselves) are readily available. 

Granularity. Profiles exist at various levels of specificity for facets and their combinations. A profile of 20th century French people differs from a profile of 20th century people in general, with more specificity in what kind of food they eat and what movies they watch, or from the profile of French people across all ages. Added information usually causes the initial expectations to change (“shift”), gradually narrowing the denotation group in a transition toward ultimately an individual. The shift may be to a more accurate profile (what in (Stone, Gage, and Leavitt 1957) is called an “accurately shifted item”), or the opposite (“inaccurately shifted item”). 

Formal Definition of a Profile 

Given a finite set of \( n \) facets, each group \( g \) is defined through a set of \( k \) known attribute values, namely: 

\[
g(x, y, K) = \bigcup_{i=1}^{k} (x_i, y_{ij}) \mid x_i \in X \land y_{ij} \in Y_i
\]

\( X = x_1, \ldots, x_n \) is the set of all facets, \( Y_i = y_{i1}, \ldots \) is the set of possible values for the attribute \( x_i \), as found in the background knowledge \( K \). Concrete groups can be easily instantiated from this definition: \{‘religion’, ‘Buddhism’\} is a group of all Buddhists, \{‘religion’, ‘Buddhism’, ‘citizenship’, ‘USA’\} is a group of all American Buddhists, etc. 

The profile \( pr \) for a group \( g = (x_1, y_{i1}), \ldots, (x_k, y_{kj}) \) can be defined as a distribution of expected values (probabilities) for each of the remaining \( (n - k) \) properties, namely: 

\[
pr(g, x, y, K) = g(x, y, K) \cup \{(x_{k+1}, d_{k+1}), \ldots, (x_n, d_n)\}
\]

where \( d_{k+1}, \ldots, d_n \) are distributions of expected values for the properties \( x_{k+1}, \ldots, x_n \) given the known property values in the group \( g \). For a given group, a profile is chosen to be optimal when its property-value pairs have the highest probability given the background knowledge used for training. 

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1We would typically only state the native language of an American citizen if it is not English, unless that could be inferred from his/her name or other extant information.

2e.g. (Esquivel et al. 2017) reports that around 50% of the people mentioned in news documents are not represented in Wikipedia.
Profiling Methods and Implementation

In this section we describe two neural architectures for computing profiles at large scale, and baselines for comparison.

Autoencoder (AE)\textsuperscript{4}

An autoencoder is a neural network that is trained to copy its input to its output (Goodfellow, Bengio, and Courville 2016). Our AE contains a single densely connected hidden layer. Its input $x$ consists of $n$ discrete facets $x_1, \ldots, x_n$, where each $x_i$ is encoded with an embedding of size $N_e$. Moreover, for each input the entity Angela Merkel, we concatenate $n$ embeddings for its $n$ individual features (nationality: German, political party: CDU, etc.). The total size of the embedding input layer is then $|x| = n \times N_e$.

We denote the corresponding output for an input sequence $x$ with $z = g(f(x))$, where $f$ is the encoding and $g$ is the decoding function. The output layer of the AE assigns probabilities to the entire vocabulary for each of the $n$ features. The size of the output layer is a sum over the variable vocabulary sizes of the individual inputs $e_i$: $|z| = \sum_{i=1}^{n} |e_i|$. The AE aims to maximize the probability of the correct class for each feature given inputs $x$, i.e., it is trained to minimize the cross-entropy loss $L$ that measures the discrepancy between the output and the input sequence:

$$L(x, z) = -\sum_{i=1}^{n} [x_i \log z_i + (1 - x_i) \log(1 - z_i)]$$

Due to the sparse input, it is crucial that AE can handle missing values. We aid this in two ways: 1. we deterministically mask all non-existing input values; 2. we apply a probability $p$ of dropouts to the input layer, i.e., in each iteration we randomly remove a subset of the inputs (any existing input is dropped with a probability $p$) and train the model to still predict these correctly. Although we apply the dropout method to the input layer rather than the hidden layer, we share the motivation with Srivastava et al. to make the model robust and able to capture subtle dependencies between the inputs. Such dropout helps the AE reconstruct missing data.

Embedding-based Neural Predictor (EMB)

In our second architecture each input is a single embedding vector $e$ rather than a concatenation of $n$ facet-embeddings. For example, the input for the entity Angela Merkel is its fully-trained entity embedding. The size of the input is the size of that embedding: $|e| = N_e$. In the current version of EMB, we use pre-trained embeddings as inputs and we fix their values (these were trained in a previous project). Future work can investigate the benefits of further training/tuning, or even training from scratch for cases where pre-trained embeddings are not available.

Like the AE, EMB has one densely connected hidden layer. For an input $x$ and its embedding representation $e$, the corresponding output is $z = g(h(e))$. The output layer of the embedding-based predictor has the same format as the one of the AE, and the same cross-entropy loss function $L(x, z)$.\textsuperscript{5

Baselines

We evaluate the methods against two baselines:

Most frequent value baseline (MFV) chooses the most frequent value in the training data for each attribute, e.g., since 14.26% of all politicians are based in the USA, MFV’s accuracy for profiling politicians’ citizenship is 14.26%. This baseline indicates for which facets and to which extent our methods can learn dependencies that transcend MFV.

Naive Bayes classifier (NB) applies Bayes’ theorem with strong independence assumptions between the features. We represent the inputs for this classifier as one-hot vectors. Naive Bayes classifiers consider the individual contribution of each input to an output class probability. However, the independence assumption prevents it from adequately handling complex inter-feature correlations.

Model Implementation Details

Both neural models use a single dense hidden layer with 128 neurons. For the AE model, we pick an attribute embedding size of $N_e = 30$. These vectors are initialized randomly and trained as part of the network. We set the dropout probability to $p = 0.5$. The inputs to the EMB are 1000-dimensional vectors that were previously trained on Freebase.\textsuperscript{5}

Both models were implemented in Theano (Bergstra et al. 2010). We used the ADAM (Kingma and Ba 2014) optimization algorithm. We train for a maximum of 100 epochs with early stopping after 10 consecutive no-improvement iterations, to select the best model on a held-out validation data. We fix the batch size to 64. When an attribute has no value in an entire minibatch, we apply oversampling: we randomly pick an exemplar that has a value for that attribute from another minibatch and append it to the current one.

Evaluation on Wikidata Instances

Data

No existing dataset is directly suitable to evaluate profiling. We therefore chose People, since data is plentiful, people are multifaceted, and it is easy to spot problematic generalizations. We defined three typed datasets: people, politicians, and actors, each with the same stereotypical facets, such as nationality, religion, and political party, that largely correspond to some facets central in social psychology research. We created data tables by extracting facets of people from Wikidata. Table 1 lists all attributes, each with its number of examples and categories. The largest dataset describes 3.2 million people, followed by the data on politicians and actors, each with the same set of 14 facets in each dataset. We evaluate on multiple datasets to test the sensitivity of our models to the number of examples and categories. The largest dataset describes 3.2 million people, followed by the data on politicians and actors, smaller by an order of magnitude. As pre-trained embeddings are only available for a subset of all people in Wikidata (cf. Model Implementation Details), we cannot

\textsuperscript{4}Demo at <anonymizedlink>

\textsuperscript{5}These vectors are available at code.google.com/archive/p/word2vec/. They correspond and can be mapped to only a subset of all Wikidata entities.
Table 1: Numbers of examples ($n_{ex}$), categories ($v_i$), and entropy ($H_i$ and $H_{i/t}$) per facet of People in our training data. We limit $v_i$ to 3,000 to restrict the complexity of the value space, but also to mimic the simplification aspect of cognitive profiling.

| attribute                | $n_{ex}$ | $v_i$ | $H_i$ | $H_{i/t}$ | $n_{ex}$ | $v_i$ | $H_i$ | $H_{i/t}$ | $n_{ex}$ | $v_i$ | $H_i$ | $H_{i/t}$ |
|--------------------------|----------|-------|-------|-----------|----------|-------|-------|-----------|----------|-------|-------|-----------|
| educated at              | 273,096  | 3,000 | 9.28  | 0.80      | 22,461   | 3,000 | 9.73  | 0.84      | 5,047    | 883   | 7.56  | 0.77      |
| sex or gender            | 2,453,980| 11    | 0.64  | 0.18      | 168,758  | 5     | 0.50  | 0.25      | 75,980   | 5     | 1.00  | 0.50      |
| citizenship              | 1,546,757| 995   | 5.28  | 0.53      | 152,131  | 335   | 5.07  | 0.61      | 57,570   | 187   | 5.12  | 0.68      |
| native language          | 41,760   | 141   | 1.70  | 0.24      | 16,818   | 33    | 1.08  | 0.21      | 4,273    | 29    | 0.41  | 0.08      |
| position held            | 177,302  | 3,000 | 7.44  | 0.64      | 101,766  | 1,701 | 7.08  | 0.66      | 244      | 25    | 0.96  | 0.21      |
| award received           | 154,275  | 3,000 | 7.97  | 0.69      | 10,588   | 546   | 6.82  | 0.75      | 2,880    | 297   | 6.60  | 0.80      |
| religion                 | 32,311   | 341   | 3.24  | 0.38      | 2,414    | 127   | 3.99  | 0.58      | 350,720  | 3,000 | 7.93  | 0.68      |
| political party          | 158,105  | 3,000 | 7.28  | 0.63      | 82,617   | 2,456 | 7.26  | 0.64      | 273,096  | 3,000 | 9.28  | 0.80      |
| work location            | 68,602   | 1,989 | 6.25  | 0.57      | 30,320   | 272   | 5.07  | 0.63      | 152,131  | 3,000 | 7.97  | 0.69      |
| place of death           | 350,720  | 3,000 | 7.93  | 0.68      | 29,071   | 3,000 | 8.39  | 0.73      | 350,720  | 3,000 | 9.28  | 0.80      |
| place of birth           | 927,089  | 3,000 | 7.64  | 0.66      | 59,627   | 3,000 | 7.27  | 0.63      | 39,694   | 3,000 | 8.55  | 0.74      |
| cause of death           | 21,926   | 499   | 5.35  | 0.60      | 1,408    | 115   | 4.75  | 0.69      | 1,546,757| 995   | 5.28  | 0.53      |
| lifespan range           | 922,634  | 55    | 1.89  | 0.33      | 79,346   | 39    | 1.68  | 0.32      | 273,096  | 3,000 | 9.28  | 0.80      |
| century of birth         | 1,975,197| 43    | 1.36  | 0.25      | 140,087  | 22    | 1.48  | 0.33      | 164      | 24    | 2.47  | 0.56      |

Quantification of the Data Space

We quantify aspects of profiling through the set of possible outcomes and its relation to the distribution of values.

The total size of the data value space is $d_{size} = \prod_{i=1}^{n} v_i$, where $n$ is the number of attributes and $v_i$ is the size of the category vocabulary for an attribute $x_i$ (e.g., $v_i = |\{'Swiss', 'Dutch', \ldots\}|$). For $x_i = \text{nationality}$, we define the average training density as the ratio of the total data value size to the overall number of training examples $n_{ex}$: $d_{avg-d} = d_{size}/n_{ex}$. As an illustration, we note that the full dataset on People has $d_{size} = 10^{39}$ and $d_{avg-d} = 10^{32}$.

For the $i$-th attribute $x_i$, the entropy $H_i$ of its values is their ‘dispersion’ across its $v_i$ different categories. The entropy for each category $j$ of $x_i$ is computed as $-p_{i,j} \log p_{i,j}$, where $p_{i,j} = n_{ex}(i,j)/n_{ex}(i)$. The entropy of $x_i$ is then a sum of the individual category entropies: $H_i = -\sum_{j=1}^{v_i} p_{i,j} \log p_{i,j}$, whereas its normalized entropy is limited to $[0, 1]: H_{i/t} = H_i/\log_2(n_{ex}(i))$. Entropy is a measure of informativeness; when $H_{i/t} = 0$ there is only one value for $x_i$; when all values are equally spread the entropy is maximal, $H_{i/t} = 1$ (with no MVF).

Of course, we do not know the true distribution but only that of the sparse input data. Here we assume our sample is unbiased. Table 1 shows that, e.g., educated at consistently has less instance values and a ‘flatter’ value distribution (= higher $H_{i/t}$) than sex or gender, where the category male is dominant on any dataset, except for actors. The entropy and the categories size together can be seen as an indicator for the relevance of a facet for a dataset, e.g., $H_{i/t}$ and $v_i$ of position held are notably the lowest for actors. We expect MVF to already perform well on facets with low entropy, whereas higher entropy to require more complex dependencies.

Results

We evaluate by measuring the correctness of predicted (i.e., top-scoring) attribute values against their (not provided) true values, evaluated only on exemplars that were not included in the training data.

Table 2 provides the results of our methods and baselines on the three smaller datasets that contain embeddings (the full datasets yielded similar results for MVF, NB, and AE). We observe that AE and EMB outperform the baselines on almost all cases. As expected, we see lower (or no) improvement over the baselines for cases with low entropy (e.g., sex or gender and lifespan range) compared to attributes with high entropy (e.g., award received). We also note that the accuracy of profiling per facet correlates inversely with its vocabulary size $v_i$.

The superiority of the neural models over the baselines means that capturing complex inter-facet dependencies improves the profiling ability of machines. Moreover, although the two neural methods perform comparably on average, there are differences between their accuracy on individual facets (e.g., compare award received and native language on any dataset). This might be due to the main architectural difference between these two methods: EMB’s input embedding contains much more information (both signal and noise) than what is captured by the 14 facets in the AE.

How does a profile improve (or not) with increasing input? We analyze both top-1 and top-3 accuracies of AE for
predicting a facet value against the number of other known facets provided at test time. Figure 1 shows examples of all three possible correlations (positive, negative, and none) for politicians. These findings are in line with conclusions from social psychology (cf. Profiles): knowing more facets of an instance might trigger a shift of the original profile, and it might be correct or incorrect, as defined in (Stone, Gage, and Leavitt 1957). Generally, we expect that attributes with large $v_i$, like place of birth, will suffer as input exemplars become more specified and granularity becomes tighter, while facets with small $v_i$ would benefit from additional input. Figure 1 follows that reasoning, except for sex or gender, whose behavior is additionally influenced by low entropy (0.25) and strong frequency bias to the male class.

### Human Evaluation

In order to collaborate with humans, or understand human language and behavior, both humans and AI machines are required to fill knowledge gaps with assumed world expectations (cf. Introduction). Given that in most AI applications information is created for humans, a profiler has to be able to mimic human expectations. We thus compare our neural profiles to profiles generated by crowd workers.

### Data

We evaluate on 10 well-understood facets describing American citizens. For each facet, we generated a list of 10 most frequent values among American citizens in Wikidata, and postprocessed them to improve their comprehensibility. We collected 15 judgments for 305 incomplete profiles with the Figure Eight crowdsourcing platform. The workers were instructed to choose ‘None of the above’ when no choice seemed appropriate, and ‘I can not decide’ when all values seemed equally intuitive. We picked reliable, US-based workers, and ensured US minimum wage ($7.25) payment.

Given that there is no ‘correct’ answer for a profile and our annotators’ guesses are influenced by their subjective experiences, it is reasonable that they have a different intuition in some cases. Hence, the relatively low mean Krippendorff (1980) alpha agreement per property (0.203) is not entirely surprising. We note that the agreement on the high-entropy facets is lower than expected.

### Table 2: Top-1 accuracies for the both neural methods and the two baselines on the smaller datasets. For each dataset-facet pair, we emphasize the best result. Our neural methods, especially EMB, outperform the baselines. Entropy and vocabulary sizes can partially explain deltas in accuracies on individual facets.

| attribute            | MFV  | NB  | AE  | EMB | MFV  | NB  | AE  | EMB |
|----------------------|------|-----|-----|-----|------|-----|-----|-----|
| educated at          | 4.41 | 9.22| 13.20| 22.45| 2.57 | 6.88| 13.14| 9.47 |
| sex or gender        | 82.61| 81.76| 82.37| 95.83| 85.15| 84.10| 83.23| 94.79 |
| citizenship          | 29.10| 57.36| 66.49| 78.49| 18.27| 46.75| 72.94| 77.96 |
| native language      | 44.70| 69.44| 87.63| 33.33| 46.67| 88.89| 93.33| 83.33 |
| position held        | 4.98 | 15.95| 21.56| 37.50| 3.85 | 10.58| 18.27| 26.09 |
| award received       | 27.52| 40.83| 45.48| 71.43| 27.08| 42.71| 52.08| 56.52 |
| religion             | 13.18| 29.67| 42.08| 47.06| 9.41 | 22.78| 34.28| 37.59 |
| political party      | 22.47| 57.18| 64.49| 60.00| 22.22| 69.90| 83.09| 60.77 |
| place of death       | 4.09 | 25.09| 28.20| 36.84| 2.81 | 8.03 | 17.27| 25.81 |
| place of birth       | 2.85 | 33.01| 32.07| 49.04| 1.88 | 18.87| 32.76| 25.81 |
| cause of death       | 23.80| 24.13| 24.32| 15.39| 32.76| 37.93| 24.14| 71.43 |
| lifespan range       | 41.76| 43.56| 41.69| 42.03| 41.30| 40.68| 38.51| 48.75 |
| century of birth     | 82.04| 85.45| 84.94| 89.53| 76.13| 80.13| 83.14| 85.79 |
| political party      | 13.18| 29.67| 42.08| 47.06| 9.41 | 22.78| 34.28| 37.59 |
| work location        | 22.47| 57.18| 64.49| 60.00| 22.22| 69.90| 83.09| 60.77 |
| place of death       | 4.09 | 25.09| 28.20| 36.84| 2.81 | 8.03 | 17.27| 25.81 |
| place of birth       | 2.85 | 33.01| 32.07| 49.04| 1.88 | 18.87| 32.76| 25.81 |
| cause of death       | 23.80| 24.13| 24.32| 15.39| 32.76| 37.93| 24.14| 71.43 |
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| cause of death       | 23.80| 24.13| 24.32| 15.39| 32.76| 37.93| 24.14| 71.43 |
| lifespan range       | 41.76| 43.56| 41.69| 42.03| 41.30| 40.68| 38.51| 48.75 |
| century of birth     | 82.04| 85.45| 84.94| 89.53| 76.13| 80.13| 83.14| 85.79 |

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Figure 1: Dependency of the accuracy of profiling politicians on the number of known facets: a positive correlation for country of citizenship (left Figure), no correlation for sex or gender (center), and a slightly negative one for place of birth (right).
Table 3: Human evaluation results per attribute: number of values ($v_i$), entropy ($H_i$), normalized entropy ($H_i/N$), mean judgments entropy ($J_i$), divergences of: MFV, NB, and AE.

| attribute          | $v_i$ | $H_i$ | $H_i/N$ | $J_i$ | MFV | NB | AE |
|--------------------|-------|-------|---------|-------|-----|----|----|
| cent. of birth     | 5     | 0.40  | 0.92    | 10^{-8}| 0.13| 0.12| 0.12|
| religion           | 4     | 0.63  | 1.26    | 10^{-10}| 0.05| 0.09| 0.06|
| sex or gender      | 2     | 0.70  | 0.70    | 10^{-14}| 0.04| 0.02| 0.02|
| place of death     | 8     | 0.80  | 2.40    | 0.05  | 0.51| 0.20| 0.16|
| lifespan range     | 10    | 0.81  | 2.68    | 0.02  | 0.29| 0.09| 0.09|
| place of birth     | 8     | 0.83  | 2.48    | 0.01  | 0.39| 0.26| 0.24|
| work location      | 10    | 0.84  | 2.80    | 0.03  | 0.49| 0.28| 0.30|
| occupation         | 9     | 0.92  | 2.90    | 0.06  | 0.37| 0.36| 0.32|
| educated at        | 9     | 0.92  | 2.91    | 0.06  | 0.39| 0.25| 0.23|
| political party    | 2     | 1.00  | 1.00    | 0.02  | 0.17| 0.06| 0.06|

attributes is typically lower, but tends to increase as more facets were provided. Overall, the annotators chose a concrete value rather than being indecisive (‘I can not decide’) for the low-entropy more often than the high-entropy facets. When more properties were provided, the frequency of indecisiveness on the high-entropy facets declined.

Results

When evaluating, ‘None of the above’ was equalized to any value outside of the most frequent 10, and ‘I can not decide’ to a (1/N)-th vote for each of the values. The human judgments per profile were combined in a single distribution, and then compared to the system distribution by using Jansen-Shannon divergence ($JS$-divergence). \(^6\) We evaluate the profiles generated by our AE and the baselines; EMB could not be tested on this data since most inputs do not have a corresponding Wikipedia page and pre-trained embeddings.

The divergence between our AE system and the human judgments was mostly lower than that of the baselines (Table 3). The divergences for any system have a strong correlation with (normalized) entropy, confirming our previous observation that high-entropy attributes pose a greater challenge. We also computed precision, recall, and F1-score between the classes suggested by our system and the annotators, and observed that it correlates inversely with the entropy in the data ($H_i$), as well as the entropy of the human judgments ($J_i$). We refer the reader to our next work (anonymized, in preparation) for further details on the obtained results.

The results show that our AE can capture human-like expectations better than the two baselines, and that mimicking human profiling is more difficult when the entropy is higher. While parameter tuning and algorithmic inventions might improve the profiling accuracy further, it is improbable that profiles learned on factual data would ever equal human performance. Some human expectations are rather culturally projected, and do not correspond to episodic facts. Future work should seek novel solutions for this challenge.

Limitations of Profiling by NNs

Our experiments show the natural power of neural networks to generalize over knowledge and generate profiles from data independent of schema availability. Techniques like dropout and oversampling further boost their ability to deal with missing or underrepresented values. Ideally these profiling machines can be included in an online active representation system to create profiles on the fly, while their modularity allows easy retraining in the background when needed.

Still, it is essential to look critically beyond the accuracy numbers, and identify the strengths and weaknesses of the proposed profiling methods. Limitations include: 1. **continuous values**, such as numbers (e.g., age) or dates (e.g., birth date), need to be categorized before being used in an AE;\(^7\) 2. AE cannot natively handle **multiple values** (e.g., people with dual nationality). We currently pick a single value from a set based on frequency; 3. as noted, we applied dropout and oversampling mechanisms to reinforce **sparse attributes**, but these remain problematic; 4. it remains unclear which **aspects of the knowledge** are captured by our neural methods, especially by the EMB model whose embeddings abstract over the bits of knowledge. More insight is required to explain some differences we observed on individual facets.

Conclusion and Future Work

Inspired by the functions of profiles in human cognition, in this paper we defined the task of profiling over incomplete knowledge in the belief that AI systems that include an accessible profiling component can naturally fill knowledge gaps with assumed expectations. KBC and other existing tasks can not be used for this purpose, since they focus on predicting concrete missing facts (exact age or location) rather than distributions over ranges of values. We described two profiling machines based on state-of-the-art neural network techniques. We demonstrated their skills in comparison to human judgments as well as existing instantial data.

Data scarcity is (unfortunately) a rather prevalent phenomenon, with most instances being part of the Zipfian long tail. Applications in NLP and IR suffer from hunger for knowledge, i.e. a lack of information on the tail instances in knowledge bases and in communication. We envision a shift in the process of creation of AI knowledge bases to incorporate human skills such as profiling, type inference, etc. Knowledge bases built on cognitive grounds would be able to natively address (at least) three standing problem areas: 1. **scarcity of episodic knowledge**, prominent both in knowledge bases and in communication; 2. **unresolved ambiguity** in communication, when the available knowledge is not necessarily scarce, yet prior expectations could lead to more reliable disambiguation; 3. **anomaly detection**, when a seemingly reliable machine interpretation is counter-intuitive and anomalous with respect to our expectations.

\(^6\) We considered the following metrics: JS-divergence, JS-distance, KL-divergence, KL-divergence-avg, KL-divergence-max, and cosine distance (Mohammad and Hirst 2012). The agreement was very high, the lowest Spearman correlation being 0.894.

\(^7\) We obtained lifespan and century of birth from birth and death dates, see our github page <anonymizedlink> for details.
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