Abstract—Matching is a task at the heart of any data integration process, aimed at identifying correspondences among data elements. Matching problems were traditionally solved in a semi-automatic manner, with correspondences being generated by matching algorithms and outcomes subsequently validated by human experts. Human-in-the-loop data integration has been recently challenged by the introduction of big data and recent studies have analyzed obstacles to effective human matching and validation. In this work we characterize human matching experts, those humans whose proposed correspondences can mostly be trusted to be valid. We provide a novel framework for characterizing matching experts that, accompanied with a novel set of features, can be used to identify reliable and valuable human experts. We demonstrate the usefulness of our approach using an extensive empirical evaluation. In particular, we show that our approach can improve matching results by filtering out inexpert matchers.

I. INTRODUCTION

Modern industrial and business processes require intensive use of large-scale data alignment and integration techniques to combine data from multiple heterogeneous data sources into meaningful and valuable information. Such integration is performed on structured and semi-structured data sets from various sources such as SQL and XML schemata, entity-relationship diagrams, ontology descriptions, Web service specifications, interface definitions, process models, and Web forms. Data integration plays a key role in a variety of domains, including data warehouse loading and exchange, data wrangling [23], aligning ontologies for the Semantic Web, Web service composition [25], and business document format merging (e.g., orders and invoices in e-commerce) [33]. As an example, a shopping comparison app that supports queries such as “the cheapest computer among retailers” or “the best medical specialist for Crohn’s disease in Crete” requires integrating and matching several data sources of product purchase orders and medical records.

A major challenge in data integration is a matching task, which creates correspondences between model elements, may they be schema attributes, ontology concepts, model entities, or process activities. Matching research has been a focus for multiple disciplines including Databases [33], Artificial Intelligence [7], Semantic Web [12], Process Management [26], and Data Mining [16]. Most studies have focused on designing high quality matchers, automatic tools for identifying correspondences. Several heuristic attempts (e.g., COMA [9]) were followed by theoretical grounding (e.g., see [3], [15]).

Matching problems have been historically defined as semi-automated tasks in which correspondences are generated by matching algorithms and outcomes are subsequently validated by one or more human experts. The reason for that is twofold. First, automatic matchers were unable to overcome the inherent uncertainty in the matching process due to ambiguity and heterogeneity of data description concepts [15]. Second, there was an inherent assumption that humans “do it better,” leading to the necessity of humans in the loop.

Human-in-the-loop data alignment and integration has been recently challenged by the need to handle large volumes of data, arriving at high velocity from a variety of sources, and demonstrating varying levels of veracity. Existing matching techniques, especially human-intensive methods, become obsolete in the presence of such data. Solutions in the form of crowdsourcing (e.g., [21], [39]) and pay-as-you-go frameworks (e.g., [30], [45]), were therefore proposed to flexibly use human input in the matching process. Such an approach may have its drawbacks [18], and, in turn, requires a deeper understanding on human capabilities when it comes to matching.

Several recent works that study human matching abilities have raised concerns about the existing conception of human superiority in matching. Dragisic et al. have pointed out that schema and ontology matching require domain expertise [10]. Following this insight, Zhang et al. stated that users that match schemata are typically non experts, and may not even know what is a schema [45]. Others, e.g., [35], [40], have observed the diversity among human inputs. Recently, Ackerman et al. have challenged both traditional and new methods for human-in-the-loop matching, showing that humans have cognitive biases decreasing their ability to perform matching tasks effectively [1]. For example, the study shows that over time, human matchers are willing to determine that an element pair matches despite their low confidence in the match, leading to poor performance. Finally, to date there has been little agreement on what makes a human a matching expert, which is the focus of this work.

A. Motivating Example

This work aims to characterize the expertise of human matchers using their behavioral profile.

To motivate the research into seeking matching experts, consider Figure 1, which depicts two archetypes of human matchers based on our experiments (see Section IV-A). For
each matcher, we measure accumulated Precision, Recall, and average confidence ordered sequentially according to the order in which decisions were taken. In addition, we provide a mouse movement heat map.

Figure 1a illustrates the performance of an expert. From the very beginning, Matcher A demonstrates precise decision making with high Precision values. In addition, many decisions are geared towards increasing the coverage of the match, adding more and more correct correspondences and incrementally increasing Recall. The average confidence, in this case, closely follows the aggregated precision values indicating that the matcher is cognitively-aware of decision odds. The heatmap shows Matcher A focuses on three main parts of the screen, the two schemata descriptions at the top and the matching matrix at the bottom.

Matcher B (Figure 1b) represents typical performance of a non-expert. Starting at a low Precision level, Matcher B continues to make wrong matches, reducing Precision without increasing Recall much. As a result, the final performance measures remain fairly low. Matcher B demonstrates a significant over confidence, a well-known established human tendency, e.g., [1], [11]. It is interesting to see that the heatmap reveals that Matcher B has consistently refrained from investigating the metadata of the schema on the top left part of the screen, which may explain some of the poor performance.

B. Contributions

In this work, we aim at characterizing human matching experts, those humans whose proposed correspondences can be trusted to provide valid matches. We do so by offering MExI (Matching Expert Identification), a novel framework that learns matchers’ qualification as experts based on their behavioral profile. Such a profile is composed of state-of-the-art matching predictors, aggregated behavioral features adapted from recent crowd quality assessment literature, and a novel use of neural networks to capture the decision making and mouse movements of human matchers. With such a tool at hand, we enhance the ability of matching systems to fuse appropriate experts and recognize their strengths and weaknesses when incorporating their input. We demonstrate our approach using the task of schema matching and further show in our experiments its usefulness on the related task of ontology alignment. Specifically, the paper provides the following specific contributions.

- We suggest a 4-dimensional expert characterization framework, grounded in matching and metacognition research, to identify matching experts (Section II-B).
- We formulate expert matching identification as a classification problem, utilizing a novel set of features that stem from monitoring human matchers (Section III).
- We provide an extensive empirical evaluation to demonstrate the benefit of our approach. In particular, we show that MExI can identify and characterize matching experts dealing with challenging matching problem and the related problem of ontology alignment. In addition, we show the benefit of MExI in boosting final matching outcomes when identifying experts (Section IV).

Building blocks of our model are given in Section II-A and related work in schema matching and assessing human expertise is discussed in Section V. We conclude in Section VI.

II. MODEL AND PROBLEM DEFINITION

We present a human matching model and propose a 4-dimension characterization of a matching expert.

A. A Human Matching Model

The schema matching task revolves around providing correspondences among concepts, describing the meaning of data, e.g., database attributes. We present next a human matching model that has a static as well as dynamic components, the former is based on a model, presented by Gal [15].

1) Static Matching Model: Let $S, S'$ be two data sources with elements $\{a_1, a_2, \ldots, a_n\}$ and $\{b_1, b_2, \ldots, b_m\}$, respectively. A matching process matches $S$ and $S'$ by aligning their elements.

Example 1: We illustrate the model using the task of schema matching. Figure 2 presents two simplified purchase order schemata [9]. $PO_1$ has four attributes (foreign keys are ignored for simplicity): purchase order’s number (poCode), timestamp (poDay and poTime) and shipment city (city). $PO_2$ has three attributes: order issuing date (orderDate),
order number (orderNumber), and shipment city (city). A matching process aligns the schemata attributes, where a match is given by double-arrow edges, e.g., orderNumber in PO2 corresponds to poCode in PO1.

A matcher’s output is conceptualized as a matching matrix $M(S, S')$ (or simply $M$), having entry $M_{ij}$ (typically a real number in $[0, 1]$) represent a degree of alignment between $a_i \in S$ and $b_j \in S'$.

A match, denoted $\sigma$, between $S$ and $S'$ is a subset of $M$’s entries, containing of all non-zero entries. In our context we assume the existence of a ground truth as a matrix $M^c$, which represents a reference match such that $M_{ij} = 1$ whenever the pair $(a_i, b_j)$ is part of the reference match and $M_{ij} = 0$ otherwise. Reference matches were created to test matcher performance, typically compiled and refined by domain experts over time.

Matching is a complex decision making process, which involves a series of interrelated tasks [1]. Humans base their decisions on several aspects of the data source, such as attribute names, data-types, etc. Algorithmic matchers typically compute similarity between elements, which can be transformed using additional information (such as domain constraints) to report confidence. For human matchers, we can directly query their confidence level regarding a correspondence. We note, however, that these confidence values may hide judgment biases [43]. An illustration of a matching matrix, using the use-case of Example 1, is given in Figure 3.

A matching matrix (Section II-A1) is created from a matching history by assigning the latest confidence to each matrix entry. Referencing to decision elements as $h.e$ (element pair), $h.c$ (confidence), and $h.t$ (timestamp), we compute a matrix entry as follows:

$$M_{ij} = \begin{cases} \max_{h.t \in H|h.t.e = (a_i, b_j)} (h.t.c) & \text{if } \exists h.t \in H|h.t.e = (a_i, b_j) \\ 0 & \text{otherwise} \end{cases}$$

(1)

B. A Model of a Matching Expert

Human matchers vary in their abilities. Ackerman et al. [1] show that human matchers may be biased in their decision making, which may lead to poor matching. Therefore, we seek a model of a matching expert, one we can rely on to be effective when making matching decisions. We consider
human matchers to be “weak experts” (rather than typical crowd sourcing workers that are assumed to be only “generally knowledgeable”), satisfying some prerequisites such as familiarity with database systems.

Given a pair of data sources, \((S, S')\), we model an expert using measures of her observed performance, as captured by a matching matrix \(M\) and a reference match \(M^c\). We focus on two measure types, namely quantitative (high quality) and cognitive (reliability). Specifically, on the quantitative level, an expert should be precise and thorough, and on the cognitive level she should be correlated and calibrated. These characteristics were chosen as representative of a wide range of requirements of a desirable matching system (see [1], [15]). The proposed model can be extended and tuned to fit various matching system desiderata. For each measure we describe how to compute a matcher’s expertise level, which when accompanied by a threshold (\(\delta\)) can determine expertise. Thresholds can be tailored to different expertise needs compelling differing system requirements.

1) Quantitative Measures: We first describe the two quantitative measures, namely precision and thoroughness, for achieving high-quality matches.

Precision: A matching task involves multiple decisions regarding correspondences between schema elements. Given a limited human attention span, a human expert is not expected to address all subtasks. However, we expect a matching expert to succeed in the subtasks she chose to address. We use the precision measure (Eq. 2, left) and set a threshold \(\delta_P\) to capture a precise expert (Eq. 2, right).

\[
P(H) = \frac{|\sigma \cap M^c|}{|\sigma|}, E_P(H) = \mathbb{I}(P(H) > \delta_P) \tag{2}
\]

Recall that \(\sigma\) is a subset of \(M\)’s entries, \(M^c\) represents the set of non-zero entries of \(M^c\) and \(\mathbb{I}(\cdot)\) denotes an indicator function. \(P(H)\) measures the ratio of correct matching decisions out of all matching decisions. \(\delta_P\) was set to 0.5 in the experiments to define a precise expert to be a matcher that matches correctly more pairs than she matches incorrectly.

Thoroughness: Dealing with a complex task, and given limited span of attention, a human expert has to rely on her intuitions. Thus, human matchers may set a self-imposed time limit [1] and aim at covering more subtasks while sacrificing precision. We use recall (Eq. 3, left) with a \(\delta_R\) threshold to define a thorough expert (Eq. 3, right).

\[
R(H) = \frac{|\sigma \cap M^c|}{|M^c|}, E_R(H) = \mathbb{I}(R(H) > \delta_R) \tag{3}
\]

where \(M^c\), \(\sigma\), and \(\mathbb{I}(\cdot)\) are defined as before. \(R(H)\) measures the number of correct matching decisions from all correct correspondences. Setting \(\delta_R = 0.5\) represents an ability to cover most of the element pairs space as the number of identified correct correspondences exceeds the misidentified.

Example 1 (continued): Let \(H_{exp}\) be the matcher producing Table I. Projecting a match for Table I we obtain \(\{M_{34}, M_{11}, M_{12}, M_{21}\}\).\(^3\) Let \(M^{c+} = \{M_{11}, M_{12}, M_{23}, M_{34}\}\) be the reference match for the matching problem of Figure 3, then, \(P(H_{exp}) = \frac{5}{3}, E_P(H_{exp}) = 1\), \(R(H_{exp}) = \frac{5}{3}\), and \(E_R(H_{exp}) = 1\), leading to the conclusion that \(H_{exp}\) is both precise and thorough.

| Sequential Decision # | Elapsed Measure |
|----------------------|-----------------|
| 0.0                  | 0.2             |
| 0.4                  | 0.6             |
| 0.8                  | 1.0             |

Recalling the matcher archetypes described in Section I-A, Figure 4 illustrates a third archetype, Matcher C. Similar to Matcher A (Figure 1a), Matcher C maintains a precise performance throughout the decision making process and her average confidence level generally follows the average precision level. However, in contrast to Matcher A, Matcher C fails to improve significantly her recall over time, resulting in an insufficient performance (less than 0.2). Matchers of type C may be extremely confusing for contemporary human-in-the-loop matching systems as they seem (and actually are) very precise. Yet, with a limited timespan, matchers of type C cover only a fraction of the correct match. The heatmap shows that Matcher C mainly focuses on the top part of the right schema. This may indicate that Matcher C failed to reach the nested elements of the schema in the given timespan.

2) Cognitive Measures: To measure expert reliability, we apply state-of-the-art metacognitive measures [1] to matcher’s reported confidence, assessing correlation and calibration. As both measures are computed relative to the entire matcher population, in the experiments we set thresholds with respect to the train set matchers.

Correlation: A correlated expert is a matcher who is more confident when correct than when incorrect. We use resolution (Eq. 4, top) to assess a correlated expert using a threshold \(\delta_{Res}\) (left part of Eq. 4, bottom). In addition, a matcher is considered correlated only if the resolution is statistically significant (right part of Eq. 4, bottom).

\[
Res(H) = \gamma(\sigma, M^{c+}),
\]

\[
E_{Res}(H) = \mathbb{I}(Res(H) > \delta_{Res} \wedge p_{val} < .05) \tag{4}
\]

where \(\gamma(\cdot, \cdot)\) is a Goodman and Kruskal correlation.

Calibration: A calibrated expert is a matcher that can gauge her confidence. We use the calibration measure (Eq. 5) from metacognition research [2], accounting for over/under-

\(^3\)Recall the \(M_{ij}\) represents a correspondence between the \(i\)th element in \(S\) and the \(j\)th element in \(S'\). For example, including \(M_{11}\) in the match means that \(PO_1\) poDay and \(PO_2\) orderDate correspond.
confidence. Noting that better calibration is lower, we set a
threshold $\delta_{Cal}$ to define a calibrated expert.

$$Cal(H) = \overline{H.C} - P(H), E_{Cal}(H) = \mathbb{I}(|Cal(H)| < \delta_{Cal})$$ (5)

where $\overline{H.C}$ is the average confidence reported by the user and $P(H)$ is her precision (Eq. 2).

In the experiments, we set thresholds to correspond to percentiles of the train population, setting $\delta_{Res}$ as the 80th percentile and $\delta_{Cal}$ as the 20th percentile.

Example 1 (continued): Recall the matcher that produced Table I. Based on the table, the calculated resolution is 1.0 with $p_{cal} = 0.5$. Although a resolution value of 1.0 satisfies any $\delta_{Res}$, since $p_{cal} > 0.5$, she is not considered correlated. The matcher’s calibration is $0.67 - 0.75 = -0.12$, which means that she is under confident and given that the 20th percentile in our experiments is 0.205, she is considered calibrated.

As a final note, as suggested by Ipeirotis et al. [22], predictable biased confidence levels, rather than low quality, may be manipulated to achieve much higher quality. For example, having realized that Matcher D is under-confident, a correspondence assigned with a 0.4 confidence may be adjusted to 0.6 and reconsidered as a part of the final outcome.

C. Problem Definition - Expert Identification

Having introduced a matching expert model, we are interested in identifying such experts. Formally, let $Y = \{+1, -1\}^{|L|}$, with $L$ being the expert characteristics space (in our case $|L| = 4$, with precision, thoroughness, correlation and calibration). Specifically, a $+1$ value for property $l \in [1, ..., |L|]$ represents expert ability, and $-1$ represents expert inability. Our problem definition can be expressed as follows.

**Problem 1:** Let $D = (H, G)$ be a human matcher representation and $Y$ be a matcher expert characteristics. We seek a matching expert characterizer $f : D \rightarrow Y$, which is a mapping that maps $D$ into $Y$.

III. IDENTIFYING MATCHING EXPERTS

We now move to the task of Matching Expert Identification (MExI). We position expert identification as a classification problem and utilize novel feature sets to learn a matching expert characterizer (Problem 1). Our approach, different from existing related work (see Section V), advocates no prior knowledge regarding human matchers and focus on their behavior throughout the decision making process. It is worth noting that while casting our problem as a classification problem imitates (binary) expert selection for a real-world system, it can be easily repositioned as a regression problem, estimating expertise level.

A. Human Matching Features

We propose feature encoding of a human matcher, $\Phi : D \rightarrow \mathbb{R}^d$ that maps a pair of decision history $H$ and movement map $G$ (see Section II-A) into a $d$ dimensional feature vector.

In what follows we suggest feature sets that serve at enhancing the ability to predict each of the four decision measures, grounding them in the relevant research areas. When designing the features, we make extensive use of the matching matrix (final decisions), the decision history (decision paths), and movement map (movement patterns). We note that some features may be predictive of more than one decision measure. Figure 7 summarizes the proposed feature sets and full details are given in our repository.

**Precision Features:** Matching predictors were suggested for match evaluation when a reference match is unavailable [38]. A matching predictor is a function that quantifies the quality of a match (given as a matching matrix). For example, a dominants predictor measures the proportion of dominant

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4 Although prior knowledge is not part of the proposed model, we provide a discussion on personal information of our human matchers in Section IV-C.

5 https://github.com/shraga89/MED/blob/master/Featuresets.md
Aggregated Features ($\Phi_{\text{agg}}(H)$)

Sequential Learning ($\Phi_{\text{seq}}(H)$)

Matching Predictors ($\Phi_{\text{LRSM}}(H)$)

Spatial Learning ($\Phi_{\text{spa}}(G)$)

Aggregated Features ($\Phi_{\text{agg}}(G)$)

Mouse Movement

Decision Making

$D$

$G$

Fig. 7: MExI (Matching Expert Identification) Framework. MExI features are composed of five sets extracted from two human matching inputs $D = (H, G)$. MExI uses $H$ to extract behavioral features $\Phi_{\text{Beh}}(H)$ and matching predictors $\Phi_{\text{LRSM}}(H)$ and $G$ to extract aggregated movement-based features $\Phi_{\text{Mou}}(G)$. During training, MExI trains two sets of neural models using $H$ and $G$, which are fused as features during testing.

Element pairs, i.e., having highest value in their respective row and column. Matching predictors study yield observations regarding their varying usability towards precision or recall. Recently, matching predictors were suggested as features in learning to rerank schema matches (LRSM) [16]. We use the matching matrix (computed from the history $H$, see Section II-A2) to generate matching predictors features, denoted as $\Phi_{\text{LRSM}}(H)$. We rely on Sagi et al. [38] when choosing precision-oriented predictors.

**Thoroughness Features:** Similarly to precision features, we use matching predictors to encode thoroughness features, focusing on predictors that were shown in the literature to lean towards higher recall. Specifically, predictors that capture negative characteristics such as uncertainty, diversity, and variability were shown to correlate with recall (and negatively correlate with precision). For example, matrix norm predictors [16] are used to quantify the amount of error in the matching matrix, which can be attributed to uncertainty.

**Correlation Features:** Match consistency quantifies the extent to which a human matcher produces consistent matches [1], highlighting human biases in the matching process. We create correlation features based on two consistency dimensions, namely, temporal and consensuality, which were shown to be predictive in terms of confidence and quality. The temporal dimension measures matching time and consensuality assesses the agreement among matchers. The predictive power of consistency analysis concerning confidence makes it effective for correlation features.

**Calibration Features:** Calibration aims at qualifying matchers as experts by observing the dynamics of their matching. Therefore, calibration features naturally relate to the decision history $H$ and movement map $M$. Calibration features are grouped into three feature groups, as follows.

**Aggregated features** are extracted from the matching decision history ($\Phi_{\text{Beh}}(H)$) and the movement map ($\Phi_{\text{Mou}}(G)$). $\Phi_{\text{Beh}}(H)$ contains aggregations over confidence, decision times, and the number of changed matching decisions. For $\Phi_{\text{Mou}}(G)$, we follow [19], [37], [44] to extract features.

**Sequential features** ($\Phi_{\text{Seq}}(H)$) examine the sequential decision making of a matcher through her declared confidence levels, the time spent until reaching a decision, and the extent of agreement with other matchers. Sequential processing of the matching process aims to capture development (decline) in the matchers behavior.

**Spatial features** ($\Phi_{\text{spa}}(G)$) capture human matcher move-
B. Learning a Matching Expert Characterizer

Equipped with a feature encoding for human matchers, we aim to find a "good" matching expert characterizer (Definition 1). We cast the problem as a multi-class multi-label classification problem. Following Read et al. [34], we transform the multi-label problem into a set of binary problems, one for each label. Hence, we train $|L|$ binary classifiers (one for each expert ability) using $\Phi(\cdot)$, where classifier $L_i$ is responsible for predicting $i$'s expert ability. The expert characterizer, $f$, returns $|L|$ binary labels, corresponding to the $|L|$ binary classifiers. Finally, given a (new) human matcher $D = (H, G)$, we extract $\Phi(H, G)$ and use the trained $f$ to characterize her, possibly identifying a new (unseen) expert.

The learning process is illustrated in Figure 7 and is applied as follows. First, we capture the aggregated features, which can be calculated offline. Then, we employ neural networks to process the matching history $H$ sequentially with a recurrent neural network and the movement map $G$ spatially with a convolutional neural network.

Recurrent neural networks, and specifically long short-term memory (LSTMs), serve as a natural choice when processing the matching history sequentially. LSTMs use a gating system to control the amount of information to preserve at each timestamp using a hidden state. $\Phi_{Seq}(H)$ encodes the sequential decision making of a human matcher using her confidence levels $(h_1.c, \ldots, h_T.c)$, the time spent on a decision $(h_2.t - h_1.t, \ldots, h_T.t - h_{T-1}.t)$, and the level of agreement on a decision, $\pi_1, \ldots, \pi_T$, with $\pi_i$ calculated as the number of human matchers in the training set that selected $h_{1.e}$ as part of their final matching matrix.

Given a human movement map, we seek a spatial analysis using a convolutional neural network (CNN), which was originally used for image processing, and apply convolution and pooling layers to extract filters over an input. $\Phi_{Spat}(G)$ encodes spatial matcher patterns of behavior through analysis of the main areas visited on the screen. We train four networks based on the movement heat maps $G_0$ (move over), $G_1$ (left click), $G_r$ (right click), and $G_s$ (scrolling). Since our dataset size is limited, we fine-tuned a CNN model, which was pretrained on an image classification task [20], with our dataset.

Finally, the set of trained models are fused as additional features to $MExI$. Specifically, in this work, we adapt a late fusion strategy [32]. During training, we first train the aforementioned networks on the training set of matchers. Then, we add label coefficients predicted by the networks as additional features ($\Phi_{Seq}(H)$ and $\Phi_{Spat}(G)$) to $\Phi(D)$ to train $MExI$. During testing, we extract $\Phi_{Seq}(H)$ and $\Phi_{Spat}(G)$ using the trained networks, which are then added to $\Phi_{Beh}(H), \Phi_{Mou}(G)$ and $\Phi_{LRSU}(H)$ to construct $\Phi(D)$ and apply the trained $MExI$ to predict the labels.

We conducted an extensive set of experiments to test the ability of $MExI$ to identify matching experts and its impact on matching quality. We describe the experimental setup in Section IV-B, followed by an analysis of human matcher characteristics (Section IV-C). When experimenting with $MExI$ we focus on the behavioral aspects, demonstrating the following four properties of our proposed approach:

- **Expert Identification**: Using a challenging matching task, we demonstrate that $MExI$ identifies expert matchers better than state-of-the-art methods (Section IV-D, Table IIa).
- **Generalizability**: Using a related problem of ontology alignment, we show that a trained $MExI$ can generalize to identify experts in other similar tasks (Section IV-D, Table IIb).
- **Human Matcher Representation**: Using an ablation study we analyze the suggested feature representations of human matchers and their effect of the identification quality of $MExI$ (Section IV-E).
- **Matching Outcome Improvement**: Using $MExI$'s identified matching experts, we generate better matching results (Section IV-F).

A. Human Matching Dataset

The dataset contains 7716 match decisions of 140 human matchers, all Science/Engineering undergraduates who studied database management courses. The study was approved by the institutional review board and four pilot participants completed the task prior to the study to ensure its coherence and instruction legibility. Participants were briefed in matching prior to the task, after which they were trained on a pair of short schemata (9-12 attributes) from the Thalia dataset prior to performing the main tasks.

The human matchers that participated in the experiments were asked to self-report personal information before the experiment. The gathered information includes gender, age, psychometrics exam score, English level (scale of 1-5), knowledge in the domain (scale of 1-5) and basic database management education (binary). The human matchers that participated in the experiments reported on psychometrics exam scores that are higher than the general population. While the general population’s mean score is 533, participants average is 678. In addition, 88% of human matchers consider their English level to be at least 4 out of 5 and only 14% claim their knowledge in the domain is above 1. To sum, the participating human matchers represent academically oriented audience with a proper English level, yet with lack of any significant knowledge in the domain of the task.

The main matching tasks were chosen from two domains. The first is a *Purchase Order* (PO) dataset [9] with schemata of medium size, with 142 and 46 attributes, and with high information content (labels, data types, and instance examples).

6$\Phi_{Seq}(H)$ and $\Phi_{Spat}(G)$ are described in more details in the context of the algorithm in the next section.

7www.cise.ufl.edu/research/dbintegrate/thalia/howto.html

8https://en.wikipedia.org/wiki/Psychometric_Entrance_Test

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IV. EMPIRICAL EVALUATION
The second domain is taken from an ontology alignment [12] task introduced in the OAEI 2011 and 2016 competitions,9 containing ontologies with 121 and 109 elements with high information content. The two tasks offer different challenges, where ontology elements differ in their characteristics from schemata attributes. Element pairs vary in their difficulty level, introducing a mix of both easy and complex matches.

Match confidence was inserted by participants as a value in [0, 1] to construct a history. We record the matcher mouse usage (clicks, moves, scrolls), accompanied by a timestamp and screen coordinates using Ghost-Mouse.10 Some preprocessing of the data was required to ensure the correctness of the results. This included removing the first three correspondences per participant, assuming a warm-up period is needed before response times are comparable. Of the 148 participants, 8 were discarded due to technical faults, leaving 140 valid participants. Finally, elapsed time outliers (over 2 standard deviations from the mean of each participant) were removed due to the sensitivity of our measures to outliers. These outliers may be the result of methodical pauses by the participant, unrelated to the specific target term or revisiting a target term after time.

The interface that was used in the experiments is an up-graded version of the Ontobuilder research prototype [29], which is open source.11 An illustration of the user interface is given in a technical report12. Schemata are presented as foldable trees of terms (attributes). When selecting an attribute from the target schema, the match table presents a list of candidate attributes synchronized with the candidate schema tree. Selecting a term reveals additional information about it in a properties box. Terms that have sub-terms are highlighted. When a matcher selects an attribute, time until reaching a decision is recorded.

B. Experimental Setup

Evaluation was performed on a GPU server that contains two Nvidia gtx 2080 Ti and a CentOS 6.4 operating system. For the classifiers we used scikit-learn13 implementation and the networks were implemented using Keras14 with a tensor-flow backend. Adam [24] (\(\eta = 0.001, \beta_1 = 0.9, \beta_2 = 0.999\)) was used for optimization and cross entropy was used as a loss function. The code repository is available online.15

1) Methodology: For the sequential feature extraction (\(\Phi_{Seq}(H)\)), following an LSTM hidden layer of 64 nodes, we perform a 0.5 dropout and a 100 nodes fully connected layer with a ReLU activation. We fine-tuned a pre-trained ResNet [20] to extract spatial features (\(\Phi_{Sp}(G)\)). Finally, we add the label coefficients of each trained network to the feature-set (see Section III-B for details).16

We present the results of two experiments. The first aims to quantify the ability of MExI to identify experts in a schema matching task. The second aims at emphasizing the generalization abilities of MExI using a related problem of ontology alignment. The experiments were conducted as follows:

**Expert Identification experiment:** 106 human matchers performed a schema matching task over the PO task (see Section IV-A), for which, we randomly split the matchers into 5 folds and repeat an experiment 5 times. For each experiment we use 4 folds for training (84 matchers) and the remainder fold (22 matchers) for testing. In tables IIa and III we report on the average performance over the 5 experiments.

**Generalizability experiment:** We use the 106 PO task human matchers as a training set and the 34 OAEI task (see dataset description above) human matchers as a test set.

For each experiment, we trained a set of state-of-the-art classifiers (e.g., SVM and Random Forest) for classification and selected the top performing classifier to be used for testing.

We evaluated three variations of the model. The first uses the set of human matchers as is (MExI_\(\emptyset\)). As part of the training phase (see Section IV-B1), we use sub-matchers to ensure sufficient data for a deep network. The sub-matchers were generated as a subset of consecutive decisions made by matchers in the training set and were used only during training. Specifically, we trained two additional models, MExI_50 contains sub-matchers with 50 decisions each and MExI_70 contains sub-matchers of 30, 40, ..., 70 decisions (average decisions per expert is 55).

2) Baselines: We compared MExI to seven baselines, using various methodologies for selecting high-quality individuals for a task. The first two baselines are fairly simple, Rand randomly assigns labels and Rand_Freq assigns labels by frequencies in the training set. Then, we introduce three baselines based on common practice quality control in crowdsourcing [6]. Conf uses the reported confidence to determine expertise [31], Qual. Test uses the warmup phase as a qualification test to estimate crowd’s accuracy following Zhang et al. [45] which is used to determine expertise and Self-Assess applies a pre-selection rule following Gadiraju et al. [14], where matchers with \(|Cal| < 0.2\) and \(P > 0.6\) during the warmup phase are classified as experts. Finally, we examine two learning-based baselines, which classify experts using matching predictors (LRSM [16]) and behavioral features as suggested by Goyal et al. [19] (BEH).

3) Evaluation Measures: In our experiments we use two types of evaluation measures. First, we measure matching performance (Section IV-F) using precision, recall, resolution, and calibration (see Section II-B). Second, to assess expert identification quality (Section IV-D), we quantify accuracy

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9http://oaei.ontologymatching.org/2011/benchmarks/
10https://www.ghost-mouse.com/
11https://github.com/shraga89/Ontobuilder-Research-Environment
12https://github.com/shraga89/MED/blob/master/MExI.pdf
13https://scikit-learn.org/stable/
14https://keras.io/
15https://github.com/shraga89/MED
16Networks implementation is available at https://github.com/shraga89/MED/blob/master/utils.py
17Details in https://github.com/shraga89/MED/blob/master/Classifiers.md
with respect to a single characteristic (binary classification, Eq. 6) and all characteristics (multi-label classification, Eq. 7). Let $\hat{Y}(D)$ and $Y(D)$ be the predicted and real characterization of $D$ respectively. Recall that $|\hat{Y}(D)| = |Y(D)| = |L|$; thus, we denote the $c$'th class (e.g., precise) as $Y_c(D)$ and $\hat{Y}_c(D)$. Then, accuracy for a single characteristic and all characteristics are defined as follows.

$$A_c = \frac{1}{K} \sum_{k=1}^{K} (Y_c(D_k) = \hat{Y}_c(D_k))$$ (6)

$$A_{ML} = \frac{1}{K} \sum_{k=1}^{K} \frac{Y(D_k) \cap \hat{Y}(D_k)}{Y(D_k) \cup \hat{Y}(D_k)}$$ (7)

C. Human Matcher Characterization

We start with an analysis of the overall population of matchers. Figure 8 presents the mean performance of matchers using each of the four expertise measures (recall Section II-B).

As illustrated, matchers are generally better in precision than recall (average of 0.55 compared to 0.33, respectively), which suggests that human matchers are geared towards correctness rather than coverage. Cognitively, the average resolution is relatively low in absolute value. However, when focusing on matchers with positive resolution (those that are more confident when correct), the average value is significantly higher (0.61 compared to 0.37) indicating that positively correlated matchers offer better end result. Similarly, the average (absolute) calibration is deficient, i.e., the calibration is fairly high (0.33). Yet, focusing on under confident matchers, i.e., those with negative calibration, we obtain a much better average absolute calibration of 0.11 indicating that under confident matchers are more likely to be calibrated.

Fig. 8: Average performance of matchers by measure. Resolution ($Res$) and Calibration ($Cal$) are given in absolute value.

The proportion of matching experts by expertise type is illustrated in Figure 9. Overall, more than half of the matchers are precise and only ~15% of matchers are thorough. This indicates again that human matchers aim to provide correct answers and are concerned less with the amount of responses they provide. 33% of the matchers are correlated and 42% of matchers are calibrated. Yet, as discussed above, positively correlated and under confident matchers are superior and 57% of the former are correlated and 80% of the latter are calibrated. Interestingly, 84% of the under confident matchers are precise and 40% are thorough (compared to 53% and 15%, respectively, over all matchers). This demonstrates the impact of cognitive measures on quantitative performance.

D. Characterizing Matching Experts

Now, we turn our efforts to analyze the ability of $MExl$ to identify matching experts. Table II compares accuracy (eqs. 6-7) results of $MExl$ to the baselines. An asterisk denotes statistical significant differences in performance using a two-sample bootstrap hypothesis test over the top performing baseline, LRSM ($p$-value < .05).

Primarily, using submatchers ($MExl_{50}$) boosts results, improving the PO task results (Table IIa) on $Ap$, $Ar$, $A_{Res}$, $A_{Cal}$, $A_{ML}$ by 11%, 5%, 14%, 9%, and 48% over $MExl_{0}$, respectively, indicating that using sub-matchers is a valuable approach. Yet, using it too aggressively, lowers accuracy, suggesting that reusing subsets with different sizes (as in $MExl_{70}$) is likely to overfit.
TABLE II: MExI’s accuracy compared to the baselines, using Eq. 6 for \( A_P \), \( A_R \), \( A_{Res} \) and \( A_{Cal} \) and Eq. 7 for \( A_{ML} \)

(a) Schema Matching (PO)

| Method   | \( A_P \) | \( A_R \) | \( A_{Res} \) | \( A_{Cal} \) | \( A_{ML} \) |
|----------|------------|------------|---------------|---------------|---------------|
| Rand     | .31        | .18        | .65           | null          | .50           |
| Rand_eq  | .56        | .88        | .64           | .40           | .12           |
| Conf     | .35        | .70        | .57           | .40           | .18           |
| Qual. Test | .58       | .69        | .59           | .61           | .26           |
| Self-Assess | .51      | .80        | .66           | .64           | .28           |
| LRSM     | .80        | .93        | .71           | .73           | .33           |
| BEH      | .81        | .88        | .64           | .70           | .30           |
| MExI_0   | .88        | .88        | .71           | .80           | .46           |
| MExI_50  | .98*       | .93        | .81           | .87*          | .68*          |
| MExI_70  | .93*       | .92        | .79           | .82           | .66*          |

(b) Ontology Alignment (OAEI)

| Method   | \( A_P \) | \( A_R \) | \( A_{Res} \) | \( A_{Cal} \) | \( A_{ML} \) |
|----------|------------|------------|---------------|---------------|---------------|
| Rand     | .39        | .24        | .27           | .45           | .04           |
| Rand_eq  | .60        | .75        | .27           | .55           | .18           |
| Conf     | .58        | .73        | .39           | .58           | .17           |
| Qual. Test | .62       | .73        | .42           | .52           | .17           |
| Self-Assess | .61      | .76        | .43           | .55           | .17           |
| LRSM     | .61        | .76        | .65           | .52           | .23           |
| BEH      | .55        | .70        | .70           | .55           | .24           |
| MExI_0   | .61        | .74        | .70           | .57           | .31           |
| MExI_50  | .70        | .83        | .74           | .61           | .43*          |
| MExI_70  | .61        | .76        | .73           | .61           | .35*          |

MExI_50 outperformed all baselines (statistically significant for \( A_P \), \( A_{Cal} \), and \( A_{ML} \)), suggesting that its ability to identify matching experts is superior to naïve approaches (Rand and Rand_Freq), trusting human judgment (Conf), using a qualification test (Qual. Test), self-assessment based pre-selection (Self-Assess), and recent literature (LRSM and BEH).

Evaluating the generalizability of MExI (OAEI task, Table Iib), we observe a relatively smaller improvement over the baselines. Nevertheless, both MExI_50 and MExI_70 achieved a statistically significant improvement over the top performing baseline. Thus, as a proof-of-concept, we show that even when applying a trained MExI over a new domain, it can still achieve high quality results improving the state-of-the-art.

E. Feature Importance via Ablation Study

Using MExI_50 results over the PO dataset, we performed an ablation study to examine feature-sets influence. Table III reports on accuracy, comparing MExI_50 to: 1) using each feature-set by itself (include) and 2) removing a feature-set one at a time (exclude). Boldface entries indicate the eminent feature-set with respect to an expert measure. For include (exclude), higher (lower) quality means higher importance.

TABLE III: MExI ablation study over the feature-sets. include refers to training using only one feature set while exclude refers to the exclusion of a single feature set at a time.

| Method | \( \Phi_{LRSM} \) | \( \Phi_{Mou} \) | \( \Phi_{BCH} \) | \( \Phi_{SEQ} \) | \( \Phi_{SPA} \) |
|--------|-----------------|-----------------|-----------------|-----------------|-----------------|
| include | \( \Phi_{LRSM} \) | .80             | .93             | .81             | .87             | .68             |
|         | \( \Phi_{Mou} \) | .68             | .88             | .56             | .52             | .32             |
|         | \( \Phi_{BCH} \) | .69             | .86             | .50             | .57             | .31             |
|         | \( \Phi_{SEQ} \) | .77             | .78             | .66             | .74             | .37             |
|         | \( \Phi_{SPA} \) | .53             | .78             | .53             | .53             | .28             |
| exclude | \( \Phi_{LRSM} \) | .81             | .85             | .72             | .68             | .54             |
|         | \( \Phi_{Mou} \) | .86             | .87             | .55             | .72             | .58             |
|         | \( \Phi_{BCH} \) | .86             | .92             | .66             | .75             | .62             |
|         | \( \Phi_{SEQ} \) | .83             | .88             | .66             | .60             | .53             |
|         | \( \Phi_{SPA} \) | .83             | .91             | .56             | .68             | .61             |

In terms of quantitative measures, \( \Phi_{LRSM} \) is most important. For cognitive measures, mouse movement (mainly \( \Phi_{Mou} \) and low accuracy without \( \Phi_{SPA} \)) and sequential decision process (\( \Phi_{SEQ} \)) were predominant. This suggests that mouse movement implies whether an expert discriminates between the correct and incorrect decisions (correlation). Sequential decision process is mainly important to detect over-confidence (calibration). Finally, examining multi-label accuracy, results suggest that using LSTM to capture the expert sequential decision process (\( \Phi_{SEQ} \)) is worthwhile and results in favorable performance even as a standalone feature-set.

Next, we analyzed feature importance within each feature-set\(^\text{18}\) using SHAP [27]. The two most important features in a feature set are given in Table IV with the following main insights for each group\(^\text{19}\). For \( \Phi_{LRSM} \), Dominance and PCA features were in the lead, supporting the feature analysis reported by Gal et al. [16], emphasizing uncertainty and diversity for expert identification. For aggregated features (\( \Phi_{Mou} \) and \( \Phi_{BCH} \)), time and confidence are important along with the average screen position and the number of decisions and changed decisions, indicating that the main location (similar to “on focus” [37]) is important in determining expertise. In terms of sequential learning (\( \Phi_{SEQ} \)), the consensus features (which were computed on the training set) were dominant across measures and the time and confidence features play a notable role as well. Finally, the scrolling features (SMouse), which may indicate uncertain behavior, were the most dominant for spatial learning (\( \Phi_{SPA} \)).

F. Utilizing Matching Experts

Finally, we analyze the impact on the identification of matching experts has on matching quality.

We begin by analyzing the average matching performance (in terms of \( P \), \( R \), \( Res \), and \( Cal \), see Section II-B) of the human matchers. We compare the performance of experts identified by MExI (i.e., those that were identified as precise, thorough, correlated, and calibrated) to the full population of human matchers (no filter) and the crowdsourcing quality assessment baselines (Conf, Qual. Test and Self-Assess, see Section IV-B1.)

Figure 10 shows the quality of the identified experts obtained by the different methodologies. MExI’s experts clearly

\(^{18}\)recall that the full list of features is given in https://github.com/shraga89/MED/blob/master/Featuresets.md

\(^{19}\)Top 5 most important features for each feature set is given in a technical report: https://github.com/shraga89/MED/blob/master/MExI.pdf
TABLE IV: Top 2 informative features for each feature set.\textsuperscript{18}

| Characteristic | Feature Set | \textsuperscript{1}F \textsubscript{i} | \textsuperscript{2}F \textsubscript{i} | \textsuperscript{1}F \textsubscript{i} | \textsuperscript{2}F \textsubscript{i} | \textsuperscript{1}F \textsubscript{i} | \textsuperscript{2}F \textsubscript{i} |
|----------------|-------------|----------------|----------------|----------------|----------------|----------------|
| \textsubscript{F} \textsubscript{Dom} | \textsubscript{bim} | \textsubscript{pca2} | \textsubscript{norm} | \textsubscript{bpm} | \textsubscript{totalLength} | \textsubscript{avgTime} |
| \textsubscript{F} \textsubscript{Mouse} | \textsubscript{dom} | \textsubscript{pca2} | \textsubscript{norm} | \textsubscript{bpm} | \textsubscript{totalLength} | \textsubscript{avgTime} |
| \textsubscript{F} \textsubscript{Time} | \textsubscript{dom} | \textsubscript{pca2} | \textsubscript{norm} | \textsubscript{bpm} | \textsubscript{totalLength} | \textsubscript{avgTime} |

Fig. 10: Performance (with error bars representing variance) of those identified experts by \textit{MExI} compared to the full population of matchers (no \textit{filter}) and crowdsourcing quality assessment baselines (Conf, Qual. Test and Self-Assess), recalling that lower calibration is better.

outperform all baselines in terms of matching performance. Compared to no \textit{filter}, \textit{MExI} improved average precision by 42\% (from .55 to .78), average recall by 90\% (from .29 to .55), average correlation by 78\% (from .41 to .73) and average calibration by 218\% (from .35 to .11, recalling that lower calibration is better). In a technical report\textsuperscript{20}, we show that even when using an expert geared towards a different measure, \textit{MExI} generates superior results with respect to using all human matchers. For example, thorough experts improve average precision by 53\% (from .55 to .84).

Human-in-the-loop systems can benefit from early identification, discharging non-experts sooner and preserving financial resources for future use. Therefore, we next analyze whether \textit{MExI} can assist in improving the final matching result using early detection of matches as experts. We utilize \textit{MExI} to identify experts midway their decision process, and only use the identified experts. We note that applying \textit{MExI} for early identification does not require labels for those decisions.

Figure 11 compares \textit{MExI}’s experts, determined using the first half of the median number of decisions per matcher (30), to the ones identified by crowdsourcing quality assessment methods and the full population of matchers. As illustrated, although the experts identified early achieve slightly inferior results than the ones identified at the end of the matching process (Figure 10), they still improve over all of the baselines.

\textsuperscript{20}https://github.com/shraga89/MED/blob/master/MExI.pdf

V. RELATED WORK

We now position the work with respect to related literature in schema matching, ontology alignment, and quality and assessment of humans. Matching works over the years assume superiority of humans over algorithmic matchers. Using humans for matching validation was first proposed by McCann \textit{et al.} [28] and was later extended [30] by using \textit{crowd sourcing} to reduce uncertainty. Recently, Zhang \textit{et al.} [45] assessed human matching quality by associating probabilities to answers based on question hardness and worker’s trustworthiness. In this work, we model human matchers by extracting features and applying learning to infer quality. Some of these features use reported confidence, which Dragisic \textit{et al.} [10], who specified matching expertise types, proposed as future work. Moreover, we specify expertise characterization, enabling a matching system to choose a human resource that fits its need.

Assessing human expertise and quality has been researched in the scope of identifying low quality crowd workers [4], [22], computer user skill identification [17], performance analysis and visualization [36], [37], and more. With most applications relying on gold questions to infer quality in practice [6], we utilize a learned model, relinquishing the need for ground truth during inference. Rzeszotarski and Kittur [37] suggested feature engineering over human behavior to assess quality, which was later expanded by others, e.g., [19], [44], to include a richer representation of workers. Others use information retrieval techniques, ranking workers for a task using a scoring function calculated based on user personal information (and
social media activity) respecting the task description [8]. Finally, a recent paper detected human cognitive biases affecting matching quality [1]. We formally define a set of characteristics to assess human expertise and suggest novel feature sets addressing the challenge.

VI. Conclusion and Future Work

We presented MExI, a novel framework to identify experts for Human-in-the-loop data integration. Using four-way expertize characterization, drawing on insights from both matching and metacognition, we provided a novel feature-set to represent a human matcher for the task. We empirically showed the superiority of MExI over several state-of-the-art methods. To the best of our knowledge, this work is the first to analyze human expert decision making and mouse movements with LSTMs and CNNs, respectively. Finally, we believe that any human-in-the-loop process may benefit from our framework.

Throughout this work, we illustrated our approach using a task of schema matching. In our experiments, we also demonstrated how expert identification training on one task (schema matching) can be useful for other tasks as well, demonstrating it using the closely related area of ontology alignment. We believe that the model and methods we proposed in this work can be extended to other matching tasks in data integration. For example, the task of entity resolution aims at identifying duplicate tuples, either within a single “dirty” dataset or when merging two “clean” (with no duplicates) datasets. Entity resolution is similar to schema matching in many ways. In both, human experts determine whether multiple elements are equal, similar heuristics are applied to identify commonalities among elements, and common 2-step approaches are applied.

This work focused on matcher performance as a whole. In future work, we aim to extend quality assessment to handle varying scales and platforms. Specifically, a common way to assess a subset of the problem is by using crowdsourcing (e.g., using [42]), where several additional aspects, such as the heterogeneity of crowd workers [35], need to be considered. Additionally, we aim to explore more facets of behavioral change in the context of crowdsourcing. Another interesting direction involves experimenting with additional matching tools (e.g., using instances [13], embeddings [5] and deep learning [41]) possibly providing better algorithmic suggestions to enhance expert performance. In this direction it is also intriguing to look at aspects relating to the tendency of people to accept algorithmic advice.

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