FGNET-RH: Fine-Grained Named Entity Typing via Refinement in Hyperbolic Space

Muhammad Asif Ali,¹ Yifang Sun,¹ Bing Li,¹ Wei Wang,²
¹School of Computer Science and Engineering, UNSW, Australia
²The Hong Kong University of Science and Technology, China
{muhammadasif.ali, bing.li, yifangs}@unsw.edu.au, {weiwcs}@ust.hk

ABSTRACT
Fine-Grained Named Entity Typing (FG-NET) aims at classifying the entity mentions into a wide range of entity types (usually hundreds) depending upon a context. While distant supervision is the most common way to acquire supervised training data, it brings in label noise, as it assigns type labels to the entity mentions irrespective of mentions' context. In attempts to deal with the label noise, leading research on the FG-NET assumes that the fine-grained entity typing data possesses a euclidean nature, which restrains the ability of the existing models in combating the label noise. Given the fact that the fine-grained type hierarchy exhibits a hierarchical structure, it makes hyperbolic space a natural choice to model the FG-NET data. In this research, we propose FGNET-RH, a novel framework that benefits from the hyperbolic geometry in combination with the graph structures to perform entity typing in a performance-enhanced fashion. FGNET-RH initially uses LSTM networks to encode the mention in relation with its context, later it forms a graph to distill/refine the mention's encodings in the hyperbolic space. Finally, the refined mention encoding is used for entity typing. Experimentation using different benchmark datasets shows that FGNET-RH improves the performance on FG-NET by up to 3.5% in terms of strict accuracy.

CCS CONCEPTS
• Information Retrieval → FG-NET; Distant Supervision; • Deep Learning → Hyperbolic Geometry.

KEYWORDS
FG-NET, Hyperbolic Geometry, Label noise, Distant Supervision

1 INTRODUCTION
Named Entity Typing (NET) is a fundamental operation in natural language processing, it aims at assigning discrete type labels to the entity mentions in the text. It has immense applications, including: knowledge base construction [7]; information retrieval [12]; question answering [18]; relation extraction [27] etc. Traditional NET systems work with only a coarse set of type labels, e.g., organization, person, location, etc., which severely limit their potential in the down-streaming tasks. In recent past, the idea of NET is extended to Fine-Grained Named Entity Typing (FG-NET) that assigns a wide range of correlated entity types to the entity mentions [13]. Compared to NET, the FG-NET has shown a remarkable improvement in the sub-sequent applications. For example, Ling and Weld, [13] showed that FG-NET can boost the performance of the relation extraction by 93%.

FG-NET encompasses hundreds of correlated entity types with little contextual differences, which makes it labour-intensive and error-prone to acquire manually labeled training data. Therefore, distant supervision is widely used to acquire training data for this task. Distant supervision relies on: (i) automated routines to detect the entity mention, and (ii) using type-hierarchy from existing knowledge-bases, e.g., Probase [24], to assign type labels to the entity mention. However, it assigns type-labels to the entity mention irrespective of the mention’s context, which results in label noise [20]. Examples in this regard are shown in Figure 1, where the distant supervision assigns labels: {person, author, president, actor, politician} to the entity mention: "Donald Trump", whereas, from contextual perspective, it should be labeled as: {person, president, politician} in S1, and {person, actor} in S2. Likewise, the entity mention: "Vladimir Putin" should be labeled as: {person, author} and {person, athlete} in S3 and S4 respectively. This label noise in-turn propagates in the model learning and severely effects/limits the end-performance of the FG-NET systems.

Earlier research on FG-NET either ignored the label noise [13], or applied some heuristics to prune the noisy labels [8]. Ren et al., [19] bifurcated the training data into clean and noisy data samples, and used different set of loss functions to model them. However, the modeling heuristics proposed by these models are not able to cope with the label noise, which limits the end-performance of the FG-NET systems relying on distant supervision. We, moreover, observe that these models are designed assuming a euclidean nature of the problem, which is inappropriate for FG-NET, as the fine-grained type hierarchy exhibit a hierarchical structure. Given that it is not possible to embed hierarchies in euclidean space [15], this assumption, in turn limits the ability of the existing models to: (i)
effectively represent FG-NET data, (ii) cater label noise, and (iii) perform FG-NET classification task in a robust way.

The inherent advantage of hyperbolic geometry to embed hierarchies is well-established in literature. It enforces the items on the top of the hierarchy to be placed close to the origin, and the items down in the hierarchy near infinity. This enables the embedding norm to cater to the depth in the hierarchy, and the distance between embeddings represent the similarity between the items. Thus the items sharing a parent node are close to each other in the embeddings space. This makes the hyperbolic space a perfect paradigm for embedding the distantly supervised FG-NET data, as it explicitly allows label-smoothing by sharing the contextual information across noisy entity mentions corresponding to the same type hierarchy, as shown in Figure 2 (b), for a 2D Poincaré Ball. For example, given the type hierarchy: "Person" ← "Leader" ← "Politician" ← "President", the hyperbolic embeddings, on contrary to the euclidean embeddings, offer a perfect geometry for the entity type "President" to share and augments the context of "Politician", which in turn adds to the context of "Leader" and "Person" etc., shown in Figure 2 (a). We hypothesize that such hierarchically-organized contextually similar neighbours provide a robust platform for the end task, i.e., FG-NET over distantly supervised data, also discussed in detail in the section 4.5.2.

Nevertheless, we propose Fine-Grained Entity Typing with Refinement in Hyperbolic space (FGNET-RH), shown in Figure 3. FGNET-RH follows a two-stage process, stage-I: encode the mention along with its context using multiple LSTM networks, stage-II: form a graph to refine mention’s encoding from stage-I by sharing contextual information in the hyperbolic space. In order to maximize the benefits of using the hyperbolic geometry in combination with the graph structure, FGNET-RH maps the mention encodings (from stage-I) to the hyperbolic space. And, performs all the operations: linear transformation, type-specific contextual aggregation etc., in the hyperbolic space, required for appropriate additive context-sharing along the type hierarchy to smoothen the noisy type-labels prior to the entity typing. The major contributions of FGNET-RH are enlisted as follows:

(1) FGNET-RH accommodates the benefits of: the graph structures and the hyperbolic geometry to perform fine-grained entity typing over distantly supervised noisy data in a robust fashion.
(2) FGNET-RH explicitly allows label-smoothing over the noisy training data by using graphs to combine the type-specific contextual information along the type-hierarchy in the hyperbolic space.
(3) Experimentation using two models of the hyperbolic space, i.e., the Hyperboloid and the Poincaré-Ball, shows that FGNET-RH outperforms the existing research by up to 3.5% in terms of strict accuracy.

2 RELATED WORK

Existing research on FG-NET can be bifurcated into two major categories: (i) traditional feature-based systems, and (ii) embedding models.

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**Figure 1**: FG-NET training data acquired by distant supervision. For examples S1:S4, we provide the fine-grained labels acquired by the distant supervision, with erroneous labels struck-through.

**Figure 2**: (a) Illustration of how the entity type "President" shares the context of the entity type "Politician" which in turn shares the context of the entity-type "Leader" and so on; (b) Embedding FG-NET data in 2-D Poincaré Ball, where each disjoint type may potentially be embedded along a different direction
Traditional feature-based systems rely on feature extraction, later using these features to train machine learning models for classification. Amongst them, Ling and Weld [13] developed FGER, that uses hand-crafted features to develop a multi-label, multi-class perceptron classifier. Yosef et al., [29] developed HYENA, i.e., a hierarchical type classification model using hand-crafted features in combination with the SVM classifier. Gillick et al., [8] proposed context-dependent fine-grained typing using hand-crafted features along with logistic regression classifier. Shimaoka et al., [21] developed neural architecture for fine-grained entity typing using a combination of automated and hand-crafted features.

Embedding models use widely available embedding resources with customized loss functions to form classification models. Yoshitaka et al., [28] used embeddings along with Weighted Approximate Rank Pairwise (WARP) loss. Ren et al., [19] proposed AFET that uses different set of loss functions to model the clean and the noisy entity mentions. Abhishek et al., [1] proposed end-to-end architecture to jointly embed the mention and the label embeddings. Xin et al., [25] used language models to compute the compatibility between the context and the entity type prior to entity typing. Choi et al., [4] proposed ultra-fine entity typing encompassing more than 10,000 entity types. They used crowd-sourced data along with the distantly supervised data for model training.

Especially noteworthy amongst the embedding models are the graph convolution networks, introduced in recent past, that extend the concept of convolutions from regular-structured grids to graphs [11]. Ali et al., [2] proposed attentive convolutional network for fine-grained entity typing. Nickel et al., [15] illustrated the benefits of hyperbolic geometry for embedding the graph structured data. Chami et al., [3] combined graph convolutions with the hyperbolic geometry. López et al., [14] used hyperbolic geometry for ultra-fine entity typing. To the best of our knowledge, we are the first to explore the combined benefits of the graph convolution networks in relation with the hyperbolic geometry for FG-NET over distantly supervised noisy data.

3 PROPOSED APPROACH

3.1 Problem Definition

In this paper, we present a multi-class, multi-label entity typing system using distantly supervised data to classify an entity mention into a set of fine-grained entity types. Specifically, we propose attentive type-specific contextual aggregation in the hyperbolic space to fine-tune the mention’s encodings learnt over noisy data prior to entity typing. We assume the availability of training corpus $C_{train}$ acquired via distant supervision, and manually labeled test corpus $C_{test}$. Each corpus $C$ (train/test) encompasses a set of sentences. For each sentence, the contextual token $(c_i)_{i=1}^N$, the mention spans $(m_j)_{j=1}^N$ (corresponding to the entity mentions), and the candidate type labels $(t_i)_{i=1}^N \in \{0,1\}^T$ ($T$-dimensional vector with $t_{ix} = 1$ if $x^{th}$ type corresponds to the true label and zero otherwise) have been inferred. The type labels are inferred from type hierarchies in the knowledge base $\psi$ with the schema $T_\psi$. Similar to Ren et al., [19], we bifurcate the training data $D_{tr}$ into clean $D_{tr-clean}$ and noisy $D_{tr-noisy}$, if the corresponding mention’s type-path follows a single path in the type-hierarchy $T_\psi$ or otherwise. Following the type-path in Figure 1 (ii), a mention with labels $\{person, author\}$ will be considered as clean, whereas, a mention with labels $\{person, president, author\}$ will be considered as noisy.

3.2 Overview

Our proposed model, FGNET-RH, follows a two-step approach, labeled as stage-I and stage-II in the Figure 3. Stage-I follows text encoding pipeline to generate mention’s encoding in relation with its context. Stage-II is focused on label noise reduction, for this, we map the mention’s encoding (from stage-I) in the hyperbolic space and use a graph to share aggregated type-specific contextual information along the type-hierarchy in order to refine the mention encoding. Finally, the refined mention encoding is embedded along with the label encodings in the hyperbolic space for entity typing.

Details of each stage are given in the following sub-sections.

3.3 Stage-II (Fine-tuning the Mention Encodings)

Stage-I follows a standard text processing pipeline using multiple LSTM networks [9] to encode the entity mention in relation with its context. Individual components of stage-I are explained as follows:

- **Mention Encoding**: We use LSTM network to encode the character sequence corresponding to the mention tokens. We use $\phi_c = [\phi c] \in \mathbb{R}^c$ to represent the encoded mention’s tokens.

- **Context Encoding**: For context encoding, we use multiple Bi-LSTM networks to encode the tokens corresponding to the left and the right context of the entity mention. We use $\phi_{c_l} = [\phi c_l] \in \mathbb{R}^c$ and $\phi_{c_r} = [\phi c_r] \in \mathbb{R}^c$ to represent the encoded left and the right context respectively.

- **Position Encoding**: For position encoding, we use LSTM network to encode the positions of the left and the right contextual tokens. We use $\phi_{p_l} = [\phi p_l] \in \mathbb{R}^p$ and $\phi_{p_r} = [\phi p_r] \in \mathbb{R}^p$ to represent the encoded position corresponding to the mention's left and the right context.

- **Mention Encodings**: Finally, we concatenate all the mention-specific encodings to get $L$-dimensional context-dependent noisy mention encoding: $x_m \in \mathbb{R}^L$, where $L = e + 2 * e + 2 + p$.

\[
x_m = [\phi_{p_l}; \phi_{c_l}; \phi_c; \phi_{c_r}; \phi_{p_r}]
\]  

(1)

3.4 Stage-II (Fine-tuning the Mention Encodings)

Stage-II is focused on alleviating the label noise. Underlying assumption in combating the label noise is that the contextually similar mentions should get similar type labels. For this, we form a graph to cluster contextually-similar mentions and employ hyperbolic geometry to share the contextual information along the type-hierarchy. As shown in Figure 3, the stage-II follows the following pipeline:

1. Construct a graph $G$ such that contextually and semantically similar mentions end-up being the neighbors in the graph.
2. Use exponential map to project the noisy mention encodings from stage-I to the hyperbolic space.
In the hyperbolic space, use the corresponding exponential and logarithmic transformations to perform the core operations, i.e., (i) linear transformation, and (ii) contextual aggregation, required to fine-tune the encodings learnt in stage-I prior to entity typing.

We analyze the performance of FGNET-RH using two different models in the hyperbolic space, i.e., the Hyperboloid ($\mathbb{H}^d$) and the Poincaré-Ball ($\mathbb{D}^d$). In the following subsections, we provide the mathematical formulation for the Hyperboloid model of the hyperbolic space. Similar formulation can be designed for the Poincaré-Ball model.

### 3.4.1 Hyperboloid Model

$d$-dimensional hyperboloid model of the hyperbolic space (denoted by $\mathbb{H}^d$) is a space of constant negative curvature $-1/K$, with $\mathbb{T}_p\mathbb{H}^d$ as the euclidean tangent space at point $p$, such that:

$$\mathbb{H}^d = \{ p \in \mathbb{R}^{d+1} : \langle p, p \rangle = -K, p_0 > 0 \}$$

$$\mathbb{T}_p\mathbb{H}^d = r \in \mathbb{R}^{d+1} : \langle r, p \rangle_L = 0$$

where $\langle \cdot, \cdot \rangle_L : \mathbb{R}^{d+1} \times \mathbb{R}^{d+1} \to \mathbb{R}$ denotes the Minkowski inner product, with $\langle p, q \rangle_L = -p_0q_0 + p_1q_1 + \ldots + p_dq_d$.

**Geodesics and Distances:** For two points $p, q \in \mathbb{H}^d$, the distance function between them is given by:

$$d^d_L(p, q) = \sqrt{K} \arccosh(-\langle p, q \rangle_L / K)$$

**Exponential and Logarithmic maps:** We use exponential and logarithmic maps for mapping to and from the hyperbolic and the tangent space respectively. Formally, given a point $p \in \mathbb{H}^d$ and tangent vector $t \in \mathbb{T}_p\mathbb{H}^d$, the exponential map $\exp_p : \mathbb{T}_p\mathbb{H}^d \to \mathbb{H}^d$ assigns a point to $t$ such that $\exp_p(t) = \gamma(1)$, where $\gamma$ is the geodesic curve that satisfies $\gamma(0) = p$ and $\dot{\gamma} = t$.

The logarithmic map ($\log_p^K$) being the bijective inverse maps a point in hyperbolic space to the tangent space at $p$. We use the following equations for the exponential and the logarithmic maps:

$$\exp_p^K(v) = \cosh\left(\frac{|v|_L}{\sqrt{K}}\right)p + \sqrt{K} \sinh\left(\frac{|v|_L}{\sqrt{K}}\right)\frac{v}{|v|_L}$$

$$\log^K_p(q) = d^K_L(p, q) \left(q + \frac{1}{\sqrt{K}}p, q < L \frac{p}{|q| + \frac{1}{\sqrt{K}}} \frac{q}{|q| + \frac{1}{\sqrt{K}}} \frac{p}{|q| + \frac{1}{\sqrt{K}}} \frac{p}{|q| + \frac{1}{\sqrt{K}}} \right)$$

### 3.4.2 Graph Construction

The end-goal of graph construction is to group the entity mentions in such a way that contextually similar mentions end up being neighbours in the graph by forming edges. Given the fact, the euclidean embeddings are better at capturing the semantic aspects of the text data [6], we opt to use deep contextualized embeddings in the euclidean domain [17] for the graph construction. For each entity type, we average out corresponding 1024d embeddings for all the mentions in the training corpus $C_{train}$, to learn prototype vectors for each entity type, i.e., $(\text{prototype}_t)_{t \in T}$. Later, for each entity type $t$, we capture type-specific confident entity mention candidates $\text{cand}_t$, following the criterion: $\text{cand}_t = \text{cand}_{t \cup \text{men}}$ if $(\cos(\text{men}, \text{Prototype}_t)) \geq \delta$ $\forall \text{men} \in C, t \in T$, where $\delta$ is a threshold. Finally, we form pairwise edges for all the mention candidates corresponding to each entity-type, i.e., $(\text{cand})_{t \in T}$, to construct the graph $G$, with adjacency matrix $A$. Formulating the graph in this particular manner allows similar mentions (i.e., sharing similar context) to be clustered around each other by forming edges in the graph, which facilitates the information passing across the noisy entity mentions. The granularity of the information shared may be controlled by edge weights.

### 3.4.3 Mapping Noisy Mention Encodings to the Hyperbolic space

The mention encodings learnt in the stage-I are noisy, as they...
are learnt over distantly supervised data. These encodings lie in the euclidean space, and in order to refine them, we first map them to the hyperbolic space, where we may best exploit the fine-grained type hierarchy in relation to the type-specific contextual clues (using $G$) to fine-tune these encodings as an aggregate of contextually-similar neighbours.

Formally, let $\mathbf{p}^E = X_m \in \mathbb{R}^{N \times L}$ be the matrix corresponding to the noisy mentions’ encodings in the euclidean domain. We consider $\sigma = \{\sqrt{K}, 0, ..., 0\}$ as a reference point (origin) in a $d$-dimensional Hyperboloid with curvature $-1/K$ ($\mathbb{H}^d, K$); $(0, \mathbf{p}^E)$ as a point in the tangent space ($\mathbb{T}^d, K$), and map it to $\mathbf{p}^H \in \mathbb{H}^d$ using the exponential map given in Equation (4), as follows:

$$
\mathbf{p}^H = \exp^K ((0, \mathbf{p}^E))
$$

$$
\exp^K ((0, \mathbf{p}^E)) = \left( \sqrt{K} \cos \left( \frac{||\mathbf{p}^E||_2}{\sqrt{K}} \right), \sqrt{K} \sinh \left( \frac{||\mathbf{p}^E||_2}{\sqrt{K}} \right) \right)
$$

3.4.4 Linear Transformation. In order to perform linear transformation operation on the noisy mention encodings, i.e., (i) multiplication by weight matrix $W$, and (ii) addition of bias vector $b$, we rely on the exponential and the logarithmic maps. For multiplication with the weight matrix, firstly, we apply logarithmic map on the encodings in the hyperbolic space, i.e., $\mathbf{p}^H \in \mathbb{H}^d$, in order to project them to $\mathbb{T}^d, K$. This projection is then multiplied by the weight matrix $W$, and the resultant vectors are projected back to the manifold using the exponential map. For a manifold with curvature constant $K$, these operations can be summarized in the equation, given below:

$$
W \odot \mathbf{p}^H = \exp^K (W \log^K (\mathbf{p}^H))
$$

For bias addition, we rely on parallel transport, let $\mathbf{b}$ be the bias vector in $\mathbb{T}^d, K$, we parallel transport $\mathbf{b}$ along the tangent space and finally map it to the manifold. Formally, let $T^{K}_{0 \rightarrow p} b$ represent the parallel transport of a vector from $T^d_{0} H$ to $T^d_{p} H$, we use the following equation for the bias addition:

$$
\mathbf{p}^H \oplus \mathbf{b} = \exp^K_{X^d}(T^{K}_{0 \rightarrow p} b))
$$

3.4.5 Type-Specific Contextual Aggregation. Aggregation is a crucial step for noise reduction in FG-NET, it helps to smoothen the type-label by refining/fine-tuning the noisy mention encodings by accumulating information from contextually similar neighbours lying at multiple hops. Given the graph $G$, with nodes ($V$) being the entity mentions, we use the pairwise embedding vectors along the edges of the graph to compute the attention weights $\eta_{ij} = \cos(||\mathbf{m}^n||, ||\mathbf{m}^n||) \forall (i, j) \in V$. In order to perform the aggregation operation, we first use the logarithmic map to project the results of the linear transformation from hyperbolic space to the tangent space. Later, we use the neighbouring information contained in $G$ to compute the refined mention encoding as attentive aggregate of the neighbouring mentions. Finally, we map these results back to the manifold using the exponential map $\exp^K$. Our methodology for contextual aggregation is summarized in the following equation:

$$
\text{AGG}_{\text{ctx}}(\mathbf{p}^H)_i = \exp^K_{X^d_j}(\sum_{j \in N(i)} (\eta_{ij} \odot A) \log^K (\mathbf{p}^H_j))
$$

where $\eta_{ij} \odot A$ is the Hadamard product of the attention weights and the adjacency matrix $A$. It accommodates the degree of contextual similarity among the mention pairs in $G$.

3.4.6 Non-Linear Activation. Contextually aggregated mention’s encoding is finally passed through a non-linear activation function $\sigma$ (ReLU in our case). For this, we follow similar steps, i.e., (i) map the encodings to the tangent space, (ii) apply the activation function in the tangent space, (iii) map the results back to the hyperbolic space using exponential map. These steps are summarized in the following equation:

$$
\sigma(\mathbf{p}^H) = \exp^K (\sigma(\log^K (\mathbf{p}^H)))
$$

3.5 Complete Model

We combine the above-mentioned steps to get the refined mention encodings at $l$th-layer $\mathbf{z}^H_{out}$ as follows:

$$
\mathbf{p}^{l,H} = W^l \odot \mathbf{p}^{l-1,H} \oplus \mathbf{b}^l;
$$

$$
\mathbf{y}^{l,H} = \text{AGG}_{\text{ctx}}(\mathbf{p}^{l,H}); \quad \mathbf{z}^H_{out} = \sigma(\mathbf{y}^{l,H})
$$

Let $\mathbf{z}^H_{out} \in \mathbb{H}^d, K$ correspond to the refined mentions’ encodings hierarchically organized in the hyperbolic space. We embed them along with the fine-grained type label encodings $\{\phi_t\}_{t=1}^{N_t}$ in $\mathbb{H}^d$. For that we learn a function $f(\mathbf{z}^H_{out}, \phi_t) = \mathbf{a}^T \times \mathbf{z}^H_{out} + \mathbf{b}^t$, and separately learn the loss functions for the clean and the noisy mentions.

Loss for clean mentions: In order to model the clean entity mentions $D_{\text{clean}}$, we use a margin-based loss to embed the refined mention encodings close to the true type labels ($T_y$), and push it away from the false type labels ($T'_y$). The loss function is summarized as follows:

$$
\mathcal{L}_{\text{clean}} = \sum_{t \in T_y} \text{ReLU}(1 - f(\mathbf{z}^H_{out}, \phi_t)) + \sum_{t' \in T'_y} \text{ReLU}(1 + f(\mathbf{z}^H_{out}, \phi_t'))
$$

Loss for noisy mentions: In order to model the noisy entity mentions $D_{\text{noisy}}$, we use a variant of above-mentioned loss function to embed the mention close to most relevant type label $t^*$, where $t^* = \arg \max_{t \in T_y} f(\mathbf{z}^H_{out}, \phi_t)$, among the set of noisy type labels ($T_y$) and push it away from the irrelevant type labels ($T'_y$). The loss function is mentioned as follows:

$$
\mathcal{L}_{\text{noisy}} = \text{ReLU}(1 - f(\mathbf{z}^H_{out}, \phi_{t^*})) + \sum_{t' \in T'_y} \text{ReLU}(1 + f(\mathbf{z}^H_{out}, \phi_{t'}))
$$

Finally, we minimize $\mathcal{L}_{\text{clean}} + \mathcal{L}_{\text{noisy}}$ as the final loss function of the FGNET-RH.
We evaluate FGNET-RH against the following baseline models:
(i) Figer [13]; (ii) Hyena [29]; (iii) AFET, AFET-NoCo and AFET-NoPa [19]; (iv) Attentive [21]; (v) FNET [1]; (vi) NFGEC + LME [25]; and (vii) FGET-RR [2]. For performance comparison, we use the scores reported in the original papers, as they are computed using a similar data settings as that of ours.

Note that we do not compare our model against [4, 14] because these models use crowd-sourced data in addition to the distantly supervised data for model training. Likewise, we exclude [26] from evaluation because Xu and Barbosa changed the fine-grained problem definition from multi-label to single-label classification problem.

This makes their problem settings different from that of ours and the end results are no longer comparable.

4.4 Main Results

The results of the proposed model are shown in Table 2. For each data set, we boldface the best scores with the existing state-of-the-art underlined. These results show that FGNET-RH outperforms the existing state-of-the-art models by a significant margin. For the BBN data, FGNET-RH achieves 3.5%, 1.2% and 1.5% improvement in strict accuracy, mac-F1 and micro-F1 respectively, compared to the previous best, i.e., FGET-RR. For OntoNotes, FGNET-RH improves the mac-F1 and micro-F1 scores by 1.2% and 1.6%.

These results show that FGNET-RH offers multi-faceted benefits, i.e., using hyperbolic space in combination with the graphs to encode the fine-grained type hierarchy, while at the same time catering to noise in the best possible way. This setting is best suited for FGNET over distantly supervised data, especially because it allows FGNET-RH to perform augmented context sharing along the type hierarchy which plays a vital role for label smoothing at different levels of granularity.

4.5 Ablation Study

In the following sub-sections, we perform in-depth analysis of FGNET-RH, including: (i) Role of adjacency graph (G); (ii) Effectiveness of hyperbolic geometry; (iii) Impact of stage-II; (iv) Analysis of label vectors; and (v) Error cases.

4.5.1 Role of adjacency graph (G). We analyze the performance of FGNET-RH using variants of the adjacency graph, including: (i) randomly generated adjacency graph of approximately the same size as G: FGNET-RH (R), (ii) unweighted adjacency graph: FGNET-RH (A), and (iii) pairwise contextual similarity as the attention weights FGNET-RH (η ⊕ A). The results in Table 3 show that for the given model architecture, the performance improvement (correspondingly noise-reduction) can be attributed to using the appropriate adjacency graph.

A drastic reduction in the model performance for FGNET-RH (R) shows that once the contextual similarity structure of the adjacency graph is lost, the label-smoothing is no longer effective to combat the label-noise. This is also evident from a relatively higher performance by the models: FGNET-RH (A), and FGNET-RH (η ⊕ A) using unweighted adjacency graph (A) and attention weights (η ⊕ A) respectively.

Especially noteworthy is the impact of the attention weights (η ⊕ A), which strongly indicates that, for label de-noising within each type-specific contextual cluster, each mention has a different impact on its neighbouring mentions in G depending upon the degree of their contextual similarities. It, moreover, confirms that FGNET-RH (η ⊕ A) indeed incorporates the required type-specific contextual clusters at the needed level of granularity to effectively smoothen the noisy labels prior to the entity typing.

4.5.2 Effectiveness of hyperbolic geometry. In order to verify the effectiveness of refining the mention encodings in the hyperbolic space (stage-II), we perform label-wise performance analysis for the dominant labels in the BBN dataset. Corresponding results for the Hyperboloid and the Poincaré-Ball model (in Table 4) show that...
FGNET-RH outperforms the existing state-of-the-art, i.e., FGET-RR by Ali et al., [2], achieving higher F1-scores across all the labels. Note that FGNET-RH can achieve higher performance for the base type labels: e.g., "Person", "Organization", "GPE" etc., as well as other type labels down in the hierarchy, e.g., "Organization/Corporation", "GPE/City" etc.,. For {"Organization" and "Corporation"} FGNET-RH achieves a higher F1=0.896 and F1=0.855 respectively, compared to the F1=0.881 and F1=0.844 by FGET-RR. This is made possible because embedding in the hyperbolic space enables type-specific context sharing at each level of the type hierarchy by appropriately adjusting the norm of the label vector.

To further strengthen our claims regarding the effectiveness of using hyperbolic space for FG-NET, we analyzed the context of the entity types along the type-hierarchy. We observed, for the fine-grained type labels: {e.g., "/Person", "/Organization", "/GPE" etc., }, for {"Organization/Corporation", "/GPE/City" etc.,}, For {"Organization" and "Corporation"} FGNET-RH adds tokens similar to {"family, patient, kidney, stone, infection etc.,"} to the context of "Organization". Likewise, "Hospital" adds tokens similar to {"bill, treasury, deficit, fiscal, senate etc.,"} to the context of "Organization".

4.5.3 Impact of stage-II. We also analyzed the entity mentions corrected especially by the label-smoothing process, i.e., the stage-II of FGNET-RH. For this, we examined the model performance with and without the label-smoothing, i.e., we perform entity typing solely based on the noisy mention encodings learnt in stage-I.

For the BBN data, the stage-II corrects approximately 18% of the mis-classifications made by stage-I. For example in the sentence: "CNW Corp. said the final step in the acquisition of the company has been completed with the merger of CNW with a subsidiary of Chicago & amp," the bold-faced entity mention CNW is labeled {"/GPE"} by stage-I. However, after label-smoothing in stage-II, the label predicted by FGNET-RH is {"/Organization/Corporation"}, which indeed is the correct label. A similar trend was observed for the OntoNotes data set.

This analysis concludes that the FGNET-RH using a blend of the contextual graphs and the hyperbolic space incorporates the right geometry to embed the noisy FG-NET data with lowest possible distortion. Compared to the euclidean space, the hyperbolic space

\[
\text{Table 2: FG-NET performance comparison against baseline models}
\]

| Labels | Ontonotes | BBN | F1 | Pre | Rec | F1 | Pre | Rec | F1 |
|--------|-----------|-----|----|-----|-----|----|-----|-----|----|
| \text{FGET-RR} [2] | 0.829 | 0.855 | 0.844 |
| \text{FGET-RR (Glove)} | 0.806 | 0.777 | 0.774 |
| \text{FGET-RR (ELMO)} | 0.896 | 0.829 | 0.833 |

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\text{Table 3: FGNET-RH performance comparison using different adjacency matrices and Glove Embeddings}
\]

| Model | OntoNotes | BBN | F1 | Pre | Rec | F1 | Pre | Rec | F1 |
|-------|-----------|-----|----|-----|-----|----|-----|-----|----|
| \text{FGNET-RH (Hyperboloid + Glove)} | 0.738 | 0.685 | 0.828 | 0.835 |
| \text{FGNET-RH (Hyperboloid + ELMO)} | 0.752 | 0.696 | 0.824 | 0.823 |
| \text{FGNET-RH (Poincaré-Ball + Glove)} | 0.741 | 0.684 | 0.829 | 0.833 |
| \text{FGNET-RH (Poincaré-Ball + ELMO)} | 0.740 | 0.685 | 0.828 | 0.830 |
being a non-euclidean space allows the graph volume (number of nodes within a fixed radius) to grow exponentially along the hierarchy, which enables the FGNET-RH to perform label-smoothing by forming type-specific contextual clusters across noisy mentions along the type hierarchy.

4.5.4 Analysis of label vectors. In order to verify our claims that the hyperbolic space is an optimal choice for fine-grained entity typing with highly correlated entity types, we analyse the distance among the neighbouring label vectors to explore the orientation of these label vectors in the hyperbolic space.

We report the nearest neighbours w.r.t the hyperbolic distance for the labels: {"/Location" and "/Organization"} in the hyperboloid model of the hyperbolic space in Table 5. The nearest neighbours of the label {"/Location"} include labels hierarchically derived from the base type label: {"/Location/River", "/Location/Lake_Sea_Ocean"}, and labels semantically related to the base type label: {"/GPE/State_Province"}. Likewise, the nearest neighbours for the label {"/Organization"} also encompasses a blend of derived labels: {"/Organization/Hospital", "/Organization/Hotel"} and related labels: {"/GPE/State_Province"}.

This illustrates that within the hyperbolic space, semantically related and hierarchically-organized label vectors are oriented in one particular direction away from other irrelevant type labels. At the same time exponential growth of the volume in hyperbolic space, as we move along the radius, makes it more favourable to place these hierarchically organized type labels along a hierarchy, thus allowing customized context sharing for each entity type at a much finer level of granularity.

These findings also correlate with the norm of the label vectors, shown in Table 6 for the Poincaré-Ball model. The vector norm of the entity types deep in the hierarchy [e.g., "/Facility/Building", "/Facility/Bridge", "/Facility/Highway" etc.] is greater than that of the base entity type ["/Facility"]. A similar trend is observed for the fine-grained types: {"/Organization/Government", "/Organization/Political" etc..} compared to the base type: {"/Organization"}. It justifies that FGNET-RH adjusts the norm of the label vector according to the depth of the type-label in the label-hierarchy, which allows the model to consequently cluster the type-specific context along the hierarchy in an augmented fashion.

4.5.5 Error Cases. Finally, we analyzed the prediction errors of FGNET-RH and attribute them to the following factors:

Inadequate Context: For these error cases, type-labels are dictated entirely by the mention tokens, with very little information contained in the context. For example, in the sentence: "The IRS recently won part of its long-running battle against John.,” the entity mention "IRS" is labeled as ["/Organization/Corporation"] irrespective of any information contained in the mention’s context. Limited information contained in the mention’s context in turn limits the end-performance of FGNET-RH in predicting all possible fine-grained labels thus effecting the recall. We observed, for the BBN data set, roughly 30% of the errors were caused by the inadequate mention’s context.

Correlated Context: A particular problem associated with the FG-NET is the lack of pre-defined set of type labels. For each data set, the fine-grained type hierarchy encompass a blend of semantically correlated type labels with convoluted/in-distinguishable context, also observed in section 4.5.4.

For the BBN data set, we observed: {"Actor" vs "Artist"}; {"Actor" vs "Director"}; {"Organization" vs "Corporation"}; {"Ship" vs "Spacecraft"}; {"Coach" vs "Athlete"} etc., as some of the correlated entity types with highly convoluted context. For example, the context of the entity types {"Actor"} and {"Artist"} is extremely overlapping, as some of the semantically-related tokens like: [direct, dialogue, dance, acting, etc.,] appear in the context of each of these entity types. Such excessive contextual overlap makes it hard for the FGNET-RH to delineate the decision boundary across these correlated entity types. It leads to false predictions by the model thus effecting the precision. For the BBN data set, more than 35% errors may be attributed to the correlated context.

Label Bias: Label bias originating from the training data automatically acquired via distant supervision may result in the label-smoothing (stage-II of FGNET-RH) to be in-effective. This occurs, specifically, if all the labels originating from the distant supervision are incorrect. For the BBN data set, roughly 35% of the errors may be attributed to the label bias.

The rest of the errors may be attributed to the inability of the FGNET-RH to explicitly deal with different word senses, in-depth syntactic analysis, in-adequacy of underlying embedding models to handle semantics, etc. We plan to accommodate these aspects in the future work.

5 CONCLUSIONS
In this paper, we introduced FGNET-RH, a novel approach that combines the benefits of graph structures and hyperbolic geometry to perform entity typing in a robust fashion. FGNET-RH initially learns noisy mention encodings using LSTM networks and constructs a graph to cluster contextually similar mentions using embeddings in euclidean domain, later it performs label-smoothing in hyperbolic domain to refine the noisy encodings prior to the entity-typing. Performance evaluation using the benchmark datasets shows...
that the FGNET-RH offers a perfect geometry for context sharing across distantly supervised data, and in turn outperforms the existing research on FG-NET by a significant margin.

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