# Quantifying Knowledge Wealth to Reveal Knowledge Gaps: A Case Study of Wikidata

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Abstract

The increasing volume of data has amplified the demand for structured, machine-readable information, making knowledge graphs essential for organizing and storing knowledge. Understanding and ensuring the quality of knowledge graphs are essential to improving their fairness and usability. One key aspect of knowledge graph quality is knowledge wealth, which represents the amount of information contained in the graph. At the entity level, wealth indicates how much information is associated with that entity. When aggregated across entities, it reflects the overall informativeness of the knowledge graph. A higher level of knowledge wealth across the graph suggests a more informative and robust resource, whereas a low wealth level points to limited information availability. However, there is no standardized method to quantify and analyze knowledge wealth. This study introduces a novel framework for quantifying knowledge wealth and assessing knowledge gap within knowledge graphs, and focuses on Wikidata as a case study. The proposed approach formalizes three notions of knowledge wealth, and their combinations, based on property cardinality, property type, and link direction, and employs statistical measures and visualizations such as the Gini coefficient and Lorenz curves, to analyze the distribution of knowledge wealth. We also develop a Python-based implementation that supports analysis facilitates and insight discovery. Through empirical evaluation, we reveal significant knowledge gaps across gender (male vs. female entities) and geographic regions (western vs. non-western entities). We also examine how different definitions of knowledge wealth influence inequality measurements. Another key finding is the structural gap across property types, where certain properties (e.g., object, literal, ID) contribute disproportionately to entity wealth, leading to systemic imbalances. Our findings provide valuable insights into identifying underrepresented entities and support data enrichment efforts aimed at closing knowledge gaps in open KGs.

Keywords

Knowledge graph, knowledge wealth, knowledge gap, data quality, Wikidata

## 1. Introduction

Wealth is the abundance of valuable possessions or money, or the state of having this abundance [1]. In economics, wealth is defined as the current market value of all assets owned by individuals or households, calculated as total assets minus liabilities [2]. When considering individual (human) wealth, the most common measure is net worth. One important application of this measure is in official asset reporting, where many governments require public officials to disclose their financial for transparency and accountability. For instance, the United States of America mandates government officials and political candidates to submit a public financial disclosure report, while the European Union requires a declaration of interests from its commis-
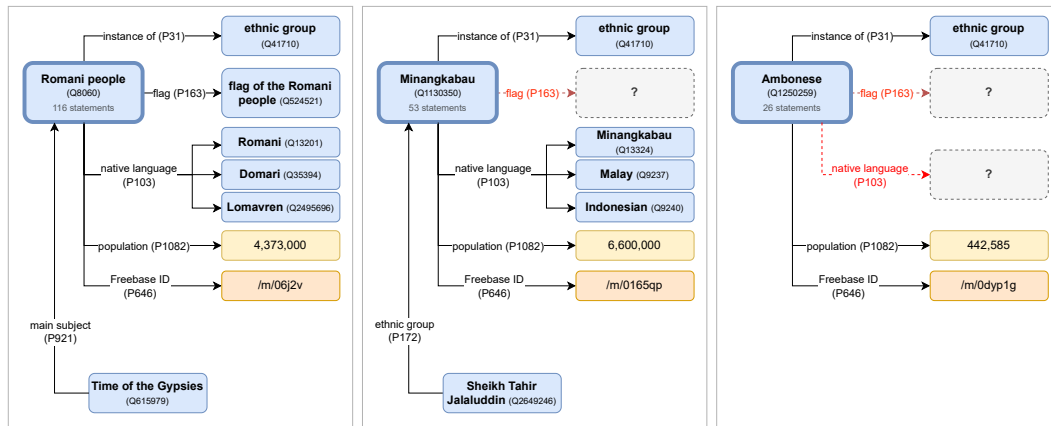
**Figure 1:** Data on Wikidata about the Romani people, the Minangkabau, and the Ambonese retrieved on 17th of February 2025. This figure illustrates how entities of the same class can have variations in their representation, including differences in: *(i)* the properties associated with them, *(ii)* the data types of property values (e.g., objects vs. literals vs. IDs), *(iii)* the cardinality of properties (single vs. multiple values), and *(iv)* the direction of information association (whether entities appear in the subject or object position in RDF triples).

sioners. In Indonesia, this is done through the *Laporan Harta Kekayaan Penyelenggara Negara*[1] (LHKPN), which includes components such as immovable assets (e.g., land and buildings), movable assets (e.g., vehicles), securities, cash and its equivalents, receivables, and liabilities.

On the other hand, in knowledge graphs (KGs), wealth can be defined as the amount of information (in terms of properties or links) an entity possesses. Just like the different components of wealth in LHKPN, the wealth of an entity in a KG can be calculated based on different types of properties or links, and with different notion of calculation model. This concept allows us to compare how richly or poorly entities are described within a KG. To illustrate this idea, we examine several entities from Wikidata and the kinds of information they contain.

Figure 1 shows three Wikidata entities of the type ethnic group: the Romani people, the Minangkabau, and the Ambonese, along with some information about them. For example, the entity Romani people includes information such as its class, flag, native languages, population, and associated Freebase ID. We can observe that a type of information can have a single value, such as the property *flag* for each entity, which is exactly one (or zero, if the information does not exist), or multiple value, such as the property *native language*. Both properties have values that are other Wikidata entities. Additionally, there are other types of properties, such as *population*, which has a static numerical value, and *Freebase ID*, which provides a string used to identify the equivalent entity in the Freebase database.

While the previous examples focus on information with outgoing links, we can also consider the opposite perspective by examining incoming links. This approach does not directly show the possessions of an entity but rather indicates its popularity by showing how often it is mentioned

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[1]State Official Wealth Report, a mandatory annual report that requires government officials to report their assets to Indonesia's Corruption Eradication Commission (KPK)

elsewhere, or how other entities declare a sense of ownership or important association with that entity. This is again illustrated by the Romani people being mentioned in *Time of the Gypsies* (through the property *main subject*) and the Minangkabau being associated with Sheikh Tahir Jalaluddin (through the property *ethnic group*).

The example in Figure 1 provides a clear picture of how entities in Wikidata can have different kinds and amounts of information, which may lead to knowledge imbalance. If this issue is left unaddressed, it can be problematic for anyone utilizing open KGs as a data source. Data users may draw invalid inferences and conclusions based on incomplete or imbalanced data, such as mistakenly assuming that the Minangkabau and Ambonese are less important than the Romani. This imbalance becomes even more striking when considering that the Minangkabau population (6.6 million) is larger than the Romani (4.3 million), yet the Minangkabau entry is less developed, as it is missing basic properties like a flag, and having fewer than half the number of statements (53 vs. 116, as shown in Figure 1). If contributors to open KGs cannot identify which entities or classes are lacking information, efforts such as editathons may not be effective, potentially widening the gap between information-rich and information-poor entities. For example, contributors might prioritize enriching the Romani people's data while overlooking gaps in the Minangkabau entry, leaving the *flag* property in the Minangkabau empty despite the well-documented existence of the Marawa flag of Minangkabau which has been existed since 1347[2].

Existing approaches often focus on enriching knowledge graphs through data population efforts, completeness profiling, or gap detection tools, yet they lack a way of quantifying the amount of information contained in KGs. However, quantification of the amount of information is important to ensure more effective effort in tackling the imbalance and incompleteness issue within KGs. From the previous example, we have already seen the wealth of an entity from three different views: wealth based on the cardinality of property, wealth based on types of property, and wealth based on the direction of link. In addressing the aforementioned gap, our study proposes a knowledge wealth framework to define the knowledge wealth in the RDF knowledge graph. Specifically, we focus on three key contributions: *(i)* introducing three notions of quantifying knowledge wealth for knowledge graphs and demonstrating how they can be used to further characterize knowledge wealth; *(ii)* implementing the formal and insight model as a Python library and making it openly accessible for broader use; and *(iii)* conducting a case study and empirical analysis on Wikidata classes to identify knowledge gaps, highlighting how knowledge wealth varies across gender and regional groups, how different definitions of wealth impact inequality measures, and how structural composition of knowledge wealth across entity classes.

The remainder of this paper is organized into the following sections: Section 2 reviews related work on KG population, data completeness, and knowledge gaps in knowledge graphs; Section 3 introduces the proposed knowledge wealth framework, detailing its formal model, insight model, and Python-based library implementation; Section 4 presents a comprehensive knowledge gap analysis on Wikidata; Section 5 discusses the broader implications of the findings, potential improvements, and future research directions; and Sections 6 concludes the study

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[2]See the Wikipedia entry on Marawa, the traditional flag of the Minangkabau people: https://id.wikipedia.org/wiki/Marawa

with a summary of key contributions and outlines opportunities for extending the framework to other knowledge graphs.

## 2. Related Work

In this section, we present related work in knowledge graph (KG) population, KG completeness, and knowledge gaps. KG population concerns adding more information about entities in a KG, thus enriching the knowledge wealth of such entities. KG completeness deals with ensuring whether sufficient information in a KG is available for the task at hand. Intuitively, when a KG possesses more wealth, it has a better chance of being complete for a given task. Knowledge gaps, on the other hand, focus more on measuring whether knowledge wealth in a KG is accumulated in an imbalanced manner.

**KG Population.** Mihindukulasooriya [3] introduced a tool and a method to populate Wikidata with scholarly information from DBLP, particularly co-authors and proceedings. Furthermore, Mihindukulasooriya et al. [4] argued that Wikidata offers a sustainable approach to providing structured scholarly data and that they developed an LLM-based method to populate Wikidata with conference metadata from unstructured sources. They analyzed 105 Semantic Web-related conferences and improved the description of over 6000 Wikidata entities. Bolinches and Garijo [5] made available in Wikidata links between software and their related articles through their SALTbot tool. In addition to creating a new software item in Wikidata (if not there yet), SALTbot will add properties such as "main subject software" and also its inverse, "described by source article". These initiatives demonstrate that improving the quantity in Wikidata is crucial and that measuring how such an improvement makes a difference (by computing the wealth difference of the before-and-after state) is, therefore, a great addition to such efforts.

**KG Completeness.** Wang and Strong [6] devised a conceptual framework of data quality, highlighting related aspects such as completeness and the appropriate amount of data. Similarly, Zaveri et al. [7] conducted a systematic review of Linked Data (LD) quality dimensions, focusing on aspects like relevancy (R2) and completeness. Wisesa et al. [8] contributed by developing a tool to profile attribute completeness in Wikidata, aligning with initiatives aimed at assessing data quality. Issa et al. [9] provided a comprehensive review of knowledge graph completeness research, identifying seven distinct types of completeness. Additionally, Luthfi et al. [10] introduced a SHACL-based method to profile completeness in knowledge graphs, further expanding the methodologies available for evaluating data quality. In [11], Xue and Zou surveyed related work on KG quality management. They discovered that most of the work focused on accuracy and completeness. In contrast, no mention was made about the work in KG gaps/imbalances.

**Knowledge Gaps.** Ramadhana et al. [12] designed a tool for analyzing knowledge imbalances. The tool featured property quantification for classes and Gini index analysis. Nevertheless, the tool focused only on Wikidata and did not offer fine-grained measures for wealth and imbalances.

Ramadizsa et al. [13] introduced the concept of gap properties that helps to characterize class-level knowledge gaps within knowledge graphs. The framework adapts association rule mining and empirically analyzes property gaps among various Wikidata classes. Our work complements both of the work with more general yet more detailed wealth analysis over KGs, including Wikidata. Furthermore, in [14], Abián et al. examined gaps in Wikidata content, analyzing edit metrics (contributions to Wikidata) in relation to corresponding Wikipedia pageviews (user needs). Their findings suggest that gaps in gender and recency are not driven by internal factors within Wikidata. However, gaps related to socio-economic factors may be partially endogenous to Wikidata.

## 3. Knowledge Wealth Framework

In this section, we define the formal framework for measuring knowledge wealth in knowledge graphs (KGs). We start by introducing the underlying data model based on RDF structure and how entities are represented through triples. Then, we formalize different notions of knowledge wealth using property-based metrics. Lastly, we present an insight model that supports both quantitative analysis and qualitative interpretation of wealth distributions across entity classes.

### 3.1. Wealth Formal Model

Knowledge graphs follow Resource Description Framework (RDF) [15] as a means of data organization. Without loss of generality of how the form of the URIs is, data is stored in the form of triple $(s, p, o)$; a combination of a subject $s$, a predicate $p$, and an object $o$ which can be visualized as nodes and directed-arc diagrams. For example, the statement "William Shakespeare's notable work is Romeo and Juliet" in human-readable URIs is mapped to the triple (*WilliamShakespeare*, *notableWork*, *RomeoAndJuliet*). Likewise, the statement in Wikidata, which uses ID-based URIs, is mapped to (*Q692*, *P800*, *Q83186*).

There are 2 kinds of nodes: IRIs and literals. A triple is in the form of $(s, p, o) \in I \times I \times (I \cup L)$ where $I$ is the node with type IRI and $L$ is the node with type literal. A knowledge graph is a finite set of triples $(s, p, o)$.

### 3.1.1. Entity-Level Wealth: Knowledge Wealth Type and Definition

Let $e \in I$ be an entity in a knowledge graph $G$. We quantify the wealth of entity $e$ in $G$ as the amount of information about $e$ available in $G$. Thus, we define the knowledge wealth of an entity as the number of properties associated/linked to it. For example, the wealth of *William Shakespeare* (*Q692*) in Wikidata counts all triples describing *Q692* in Wikidata, including those detailing his family, occupation, image, and so on.

As motivated in Section 1, there are three key dimensions to consider when alculating the knowledge wealth of an entity: (1) wealth based on the (non-)uniqueness or multiplicity of individual property; (2) wealth based on type of property; and (3) wealth based on the direction of the link. We denote the knowledge wealth of an entity $e$ in graph $G$ using the general form:

$$W_{mult,[prop],[dir]}(e, G)$$

where:

$$mult \in \{bag, set\}$$

$$prop \subseteq \{obj, ltr, id\}$$

$$dir \subseteq \{out, in\}$$

This formalization provides a flexible and expressive way to define and compute knowledge wealth under different configurations.
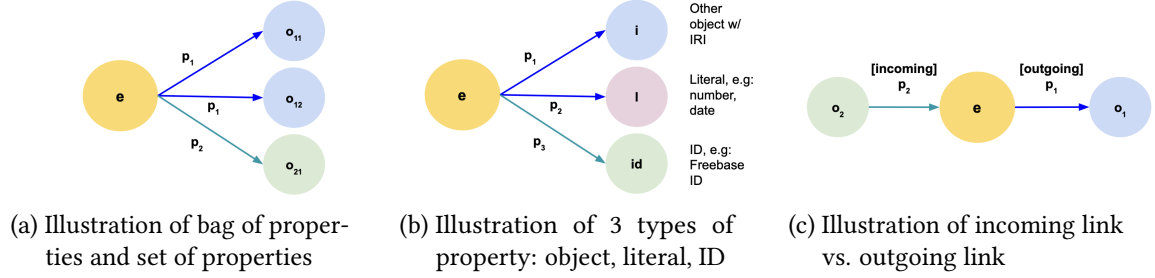


(a) Illustration of bag of properties and set of properties

(b) Illustration of 3 types of property: object, literal, ID

(c) Illustration of incoming link vs. outgoing link

**Figure 2:** Three simple graphs

**Wealth based on the (non-)uniqueness of individual properties.** The first aspect of knowledge wealth concerns how we regard the multiplicity or the (non-)uniqueness or the properties. Specifically, if an entity $e$ has a property $p_1$ that links it to a finite set of $n$ distinct objects $o_1, o_2, ..., o_n$, we may choose whether to account for the total number of objects associated with it (which is $n$), or to consider only the existence of $p_1$. We refer to the former as the bag of properties, and the latter as the set of properties approach.

Under the bag of properties, an entity's knowledge wealth is defined as the cardinality of the set of triples in which it appears (either in the subject or object position, depending on the assumed link direction). For example, assuming an outgoing link direction, the triples $(e, p_1, o_1)$ and $(e, p_1, o_2)$ account for a wealth of 1 each, thus both have a total of 2. Formally, the knowledge wealth of an entity $e$ under the bag of properties approach when no filtering is applied to the property type and using outgoing link direction, is denoted as $W_{bag,*,[out]}(e, G)$ and is defined as:

$$W_{bag,*,[out]}(e, G) = |\{(p, o)|(e, p, o) \in G\}|$$

In the set of properties, knowledge wealth is measured by counting the number of distinct properties that describe the entity. By this way, we are capturing the variety of information about an entity. In contrast to bag of properties, in set of properties (with an assumption of outgoing link direction), $(e, p_1, o_1)$ and $(e, p_1, o_2)$ would be regarded as the "same" information because of the identical property $p_1$, thus they only account for a total wealth of 1. Formally, the knowledge wealth of an entity $e$ under the set of properties approach when no filtering is applied to the property type and using outgoing link direction, is denoted as $W_{set,*,[out]}(e, G)$ and is defined as:

$$W_{set,*,[out]}(e, G) = |\{p|(e, p, o) \in G\}|$$

**Wealth based on type of property.** There are two main categories of properties in RDF: object properties, which link IRIs (on subject position) to IRIs (on object position), and datatype properties, which link IRIs (on subject position) to data literals (on object position) [15]. The idea of knowledge wealth based on property type is inspired by how human wealth is assessed across different types of possessions (e.g., real estate, vehicles, financial assets). Similarly, in knowledge graphs, property types can be seen as categories of informational assets that contribute to an entity's overall wealth.

This formulation allows us to evaluate not just how much information an entity has, but what kind of information it possesses. For instance, one entity may be rich in object links (e.g., affiliations or relationships to other entities), while another may be rich in literal facts (e.g., birth date, height). Segmenting wealth by property type thus provides a more nuanced view of an entity's informational profile.

Since each property $p \in I$, we define the set of object properties as $I_{objProp}$. Therefore, the knowledge wealth of an entity $e$, based solely on object properties and using the bag of properties approach (assuming outgoing link direction) is defined as:

$$W_{bag,[obj],[out]}(e, G) = |\{(p, o)|((e, p, o) \in G) \cap (p \in I_{objProp})\}|$$

The handling for datatype properties is special. Among literal values, we see that there are two categories: pure literals, which are values that behave like constants or factual attributes (e.g., date of birth, height, population), and (external) IDs, which are string-based values that are used as identifier for the entity in external systems or databases (e.g., Freebase ID, IMDb ID). Based on this distinction, we define two corresponding subsets of datatype properties. The first one is $I_{ltrProp}$ for the set of pure literals properties, and $I_{idProp}$ for the set of IDs properties. Then, the knowledge wealth of an entity $e$ under the bag of properties approach, using outgoing links, can be separately defined for each category as:

$$W_{bag,[ltr],[out]}(e, G) = |\{(p, o)|((e, p, o) \in G) \cap (p \in I_{ltrProp})\}|$$

$$W_{bag,[id],[out]}(e, G) = |\{(p, o)|((e, p, o) \in G) \cap (p \in I_{idProp})\}|$$

The sets $I_{objProp}$, $I_{ltrProp}$, and $I_{idProp}$ are all mutually exclusive. We define their union as $I_{Prop}$, the set of IRIs that function as properties (i.e., those used in the predicate position of RDF triples but not act as entity subjects or objects). Formally, this set is defined as:

$$I_{Prop} = (I_{objProp} \cup I_{ltrProp} \cup I_{idProp})$$

When measuring the knowledge wealth of an entity $e$, we may choose to filter by a specific property type or take a combination of them. For instance, in the previously defined measure $W_{bag,*,[out]}(e, G)$, the assumption is that all property types are included (i.e., $p \in I_{Prop}$), while $W_{bag,[obj,ltr],[out]}(e, G)$ includes only object and literal properties (i.e., $p \in (I_{objProp} \cup I_{ltrProp})$)

**Wealth based on the direction of the link.** In the previous definitions of knowledge wealth, we assumed that links originate from the entity $e$; that is, $e$ appears as the subject in the set of triples in graph $G$. However, wealth can also be defined from the opposite perspective, where

links point toward the entity. In this incoming link formulation, the properties contributing to the wealth of an entity $e$ are derived from triples in which $e$ appears as the object.

Under the bag of properties approach, in contrast to the outgoing link formulation where we count the pairs $p, o$ from triples $e, p, o$, in the incoming link case we count the pairs $s, p$ from triples $s, p, e$. In this definition, the triples $(s_1, p_1, e)$ and $(s_2, p_1, e)$ each contribute a wealth of 1 since the pairs $s_1, p_1$ and $s_2, p_1$ are treated as distinct. This results in a total wealth of 2 for the entity $e$. Formally, the knowledge wealth of an entity $e$ in this case is denoted as $W_{bag,*,[in]}(e, G)$, and is defined as:

$$W_{bag,*,[in]}(e, G) = |\{(s,p)|(s,p,e) \in G\}|$$

Likewise, under the set of properties approach and incoming link direction, the triples $(s_1, p_1, e)$ and $(s_2, p_1, e)$ are treated as identical since they share the same property $p_1$, and collectively count as a single contribution to the entity's wealth. The corresponding formal definition for this case is denoted as $W_{set,*,[in]}(e, G)$, and is defined as:

$$W_{set,*,[in]}(e, G) = |\{(p)|(s,p,e) \in G\}|$$

It is important to note that, for the incoming link formulation, we always assume that $p \in I_{objProp}$. This is because the object position in the triples is taken by the entity $e$, and $e \in I$ ($e$ is not a literal/ID).

Table 1: Wealth Formal Definitions

| No | Formal Notation | Multiplicity | Property Type | Link Direction | Formal Definition | Notes |
|---|---|---|---|---|---|---|
| 1 | $W_{bag,*,[out]}(e,G)$ | Bag | * | Out | $|\{(p,o)|(e,p,o) \in G\}|$ | |
| 2 | $W_{bag,[obj],[out]}(e,G)$ | Bag | Object | Out | $|\{(p,o)|((e,p,o) \in G) \cap (p \in I_{objProp})\}|$ | |
| 3 | $W_{bag,[ltr],[out]}(e,G)$ | Bag | Literal | Out | $|\{(p,o)|((e,p,o) \in G) \cap (p \in I_{ltrProp})\}|$ | |
| 4 | $W_{bag,[id],[out]}(e,G)$ | Bag | ID | Out | $|\{(p,o)|((e,p,o) \in G) \cap (p \in I_{idProp})\}|$ | |
| 5 | $W_{bag,[obj,ltr],[out]}(e,G)$ | Bag | Object, literal | Out | $|\{(p,o)|((e,p,o) \in G) \cap (p \in (I_{objProp} \cup I_{ltrProp}))\}|$ | |
| 6 | $W_{bag,[obj,id],[out]}(e,G)$ | Bag | Object, ID | Out | $|\{(p,o)|((e,p,o) \in G) \cap (p \in (I_{objProp} \cup I_{idProp}))\}|$ | |
| 7 | $W_{bag,[ltr,id],[out]}(e,G)$ | Bag | Literal, ID | Out | $|\{(p,o)|((e,p,o) \in G) \cap (p \in (I_{ltrProp} \cup I_{idProp}))\}|$ | |
| 8 | $W_{bag,*,[in]}(e,G)$ | Bag | * | In | $|\{(s,p)|(s,p,e) \in G\}|$ | |
| 9 | $W_{bag,[obj],[in]}(e,G)$ | Bag | Object | In | $|\{(s,p)|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | |
| 10 | $W_{bag,[ltr],[in]}(e,G)$ | Bag | Literal | In | $|\emptyset| = 0$ | $p \in I_{objProp}$ because $e \in I$ |
| 11 | $W_{bag,[id],[in]}(e,G)$ | Bag | ID | In | $|\emptyset| = 0$ | $p \in I_{objProp}$ because $e \in I$ |
| 12 | $W_{bag,[obj,ltr],[in]}(e,G)$ | Bag | Object, literal | In | $|\{(s,p)|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | $p \in I_{objProp}$ because $e \in I$ |
| 13 | $W_{bag,[obj,id],[in]}(e,G)$ | Bag | Object, ID | In | $|\{(s,p)|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | $p \in I_{objProp}$ because $e \in I$ |
| 14 | $W_{bag,[ltr,id],[in]}(e,G)$ | Bag | Literal, ID | In | $|\emptyset| = 0$ | $p \in I_{objProp}$ because $e \in I$ |
| 15 | $W_{bag,*,*}(e,G)$ | Bag | * | * | $|\{(p,o)|(e,p,o) \in G\}| + |\{(s,p)|(s,p,e) \in G\}|$ | Aggregation of #1 and #8 |
| 16 | $W_{bag,[obj],*}(e,G)$ | Bag | Object | * | $|\{(p,o)|((e,p,o) \in G) \cap (p \in I_{objProp})\}|$ $+|\{(s,p)|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | Aggregation of #2 and #9 |
| 17 | $W_{bag,[ltr],*}(e,G)$ | Bag | Literal | * | $|\{(p,o)|((e,p,o) \in G) \cap (p \in I_{ltrProp})\}|$ | Aggregation of #3 and #10 |
| 18 | $W_{bag,[id],*}(e,G)$ | Bag | ID | * | $|\{(p,o)|((e,p,o) \in G) \cap (p \in I_{idProp})\}|$ | Aggregation of #4 and #11 |
| 19 | $W_{bag,[obj,ltr],*}(e,G)$ | Bag | Object, literal | * | $|\{(p,o)|((e,p,o) \in G) \cap (p \in (I_{objProp} \cup I_{ltrProp}))\}|$ $+|\{(s,p)|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | Aggregation of #5 and #12 |
| 20 | $W_{bag,[obj,id],*}(e,G)$ | Bag | Object, ID | * | $|\{(p,o)|((e,p,o) \in G) \cap (p \in (I_{objProp} \cup I_{idProp}))\}|$ $+|\{(s,p)|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | Aggregation of #6 and #13 |
| 21 | $W_{bag,[ltr,id],*}(e,G)$ | Bag | Literal, ID | * | $|\{(p,o)|((e,p,o) \in G) \cap (p \in (I_{ltrProp} \cup I_{idProp}))\}|$ | Aggregation of #7 and #14 |
| 22 | $W_{set,*,[out]}(e,G)$ | Set | * | Out | $|\{p|(e,p,o) \in G\}|$ | |
| 23 | $W_{set,[obj],[out]}(e,G)$ | Set | Object | Out | $|\{p|((e,p,o) \in G) \cap (p \in I_{objProp})\}|$ | |
| 24 | $W_{set,[ltr],[out]}(e,G)$ | Set | Literal | Out | $|\{p|((e,p,o) \in G) \cap (p \in I_{ltrProp})\}|$ | |
| 25 | $W_{set,[id],[out]}(e,G)$ | Set | ID | Out | $|\{p|((e,p,o) \in G) \cap (p \in I_{idProp})\}|$ | |
| 26 | $W_{set,[obj,ltr],[out]}(e,G)$ | Set | Object, literal | Out | $|\{p|((e,p,o) \in G) \cap (p \in (I_{objProp} \cup I_{ltrProp}))\}|$ | |
| 27 | $W_{set,[obj,id],[out]}(e,G)$ | Set | Object, ID | Out | $|\{p|((e,p,o) \in G) \cap (p \in (I_{objProp} \cup I_{idProp}))\}|$ | |
| 28 | $W_{set,[ltr,id],[out]}(e,G)$ | Set | Literal, ID | Out | $|\{p|((e,p,o) \in G) \cap (p \in (I_{ltrProp} \cup I_{idProp}))\}|$ | |
| 29 | $W_{set,*,[in]}(e,G)$ | Set | * | In | $|\{p|(s,p,e) \in G\}|$ | |
| 30 | $W_{set,[obj],[in]}(e,G)$ | Set | Object | In | $|\{p|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | |
| 31 | $W_{set,[ltr],[in]}(e,G)$ | Set | Literal | In | $|\emptyset| = 0$ | $p \in I_{objProp}$ because $e \in I$ |
| 32 | $W_{set,[id],[in]}(e,G)$ | Set | ID | In | $|\emptyset| = 0$ | $p \in I_{objProp}$ because $e \in I$ |
| 33 | $W_{set,[obj,ltr],[in]}(e,G)$ | Set | Object, literal | In | $|\{p|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | $p \in I_{objProp}$ because $e \in I$ |
| 34 | $W_{set,[obj,id],[in]}(e,G)$ | Set | Object, ID | In | $|\{p|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | $p \in I_{objProp}$ because $e \in I$ |
| 35 | $W_{set,[ltr,id],[in]}(e,G)$ | Set | Literal, ID | In | $|\emptyset| = 0$ | $p \in I_{objProp}$ because $e \in I$ |
| 36 | $W_{set,*,*}(e,G)$ | Set | * | * | $|\{p|(e,p,o) \in G\}| + |\{p|(s,p,e) \in G\}|$ | Aggregation of #22 and #29 |
| 37 | $W_{set,[obj],[out]}(e,G)$ | Set | Object | Out | $|\{p|((e,p,o) \in G) \cap (p \in I_{objProp})\}|$ $+|\{p|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | Aggregation of #23 and #30 |
| 38 | $W_{set,[ltr],[out]}(e,G)$ | Set | Literal | Out | $|\{p|((e,p,o) \in G) \cap (p \in I_{ltrProp})\}|$ | Aggregation of #24 and #31 |
| 39 | $W_{set,[id],[out]}(e,G)$ | Set | ID | Out | $|\{p|((e,p,o) \in G) \cap (p \in I_{idProp})\}|$ | Aggregation of #25 and #32 |
| 40 | $W_{set,[obj,ltr],[out]}(e,G)$ | Set | Object, literal | Out | $|\{p|((e,p,o) \in G) \cap (p \in (I_{objProp} \cup I_{ltrProp}))\}|$ $+|\{p|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | Aggregation of #26 and #33 |
| 41 | $W_{set,[obj,id],[out]}(e,G)$ | Set | Object, ID | Out | $|\{p|((e,p,o) \in G) \cap (p \in (I_{objProp} \cup I_{idProp}))\}|$ $+|\{p|((s,p,e) \in G) \cap (p \in I_{objProp})\}|$ | Aggregation of #27 and #34 |
| 42 | $W_{set,[ltr,id],[out]}(e,G)$ | Set | Literal, ID | Out | $|\{p|((e,p,o) \in G) \cap (p \in (I_{ltrProp} \cup I_{idProp}))\}|$ | Aggregation of #28 and #35 |

This table summarizes the 30 formal definitions of knowledge wealth used in this study. Each row represents a variant of wealth based on three key dimensions: (1) multiplicity: bag or set; (2) property type: object, literal, ID, or any of their combinations; and (3) link direction: in, out, or any of their combinations. In the notation used in the table, $G$ denotes the RDF knowledge graph, $e$ is an entity (instance) in that graph. Each triple in the graph is composed of a subject $s$, a property $p$, and an object $o$. $I$ the set of all IRIs in the graph, $I_{objProp}$ is the set of IRIs used as object properties, $I_{ltrProp}$ is the set of IRIs used as pure literal properties, and $I_{idProp}$ is the set of IRIs used as identifier properties. $I_{Prop} = (I_{objProp} \cup I_{ltrProp} \cup I_{idProp})$ is the set of all valid property IRIs.

### 3.1.2. Class-Level Wealth

In this study, we re-use the class model defined by Ramadizsa et al. [13]. A class is a group of entities that are the subject of the study. *Human*, *film*, and *taxon* are some examples of class. In general, entity $s$ is an instance of class $C$ is expressed by the triple ($s$, *instanceOf*, $C$) or ($s$, *type*, $C$). We can get a more narrow class inside the defined class by specifying additional conditions, each consisting of a particular property and value associated with it. Example of such conditions for human class is *gender* with associated value *male*, while example for a country would be *continent* with value *Asia*. For instance, the class of human with gender male that lived during English Renaissance is queried using ($?s$, {($?s$, *instanceOf, human*), ($?s$, *gender, male*), ($?s$, *timePeriod, EnglishRenaissance*)}).

Let $C$ be a class that consists of $m$ distinct entities $s_1$, $s_2$, ... $s_m$ in graph $G$. We define $T_C$ a multiset consists of the wealth of each entity of $C$, i.e.,

$$T_{C,G} = \{W(s_1), G, W(s_2, G), W(s_3, G), ..., W(s_m, G)\}$$

We denote the overall wealth of class $C$ as $\mathcal{W}(C)$. It can be quantified using its constituent entities and be expressed as a function of $T_C$, denoted as $f(T_C)$, where $f$ may represent statistical summaries such as the cardinality (i.e., entity count), sum, mean, median, mode, or percentile of its entities's wealth.

$$\mathcal{W}(C, G) = f(T_{C,G})$$

As an example, consider a class $C$ consisting of of 4 entities $s_1$, $s_2$, $s_3$, and $s_4$ from Figure 3. If we use cardinality as the function $f$, then $\mathcal{W}(C) = 4$, corresponding to the number of entities it contains.

It is important to note that not all statistical functions are suitable for this purpose. The previously mentioned functions provide interpretable measures of central tendency or overall volume, thus they are considered valid to be used as $f$ to represent the level of wealth of a class. On the contrary, inequality metrics such as the Gini coefficient or standard deviation are designed to capture distributional imbalance rather than the actual level of wealth, and therefore are not appropriate as definitions of $\mathcal{W}(C)$, which aims to describe how rich a class is, and not how unequal the wealth distribution is within it.

### 3.2. Insight Model

**Exploratory Data Analysis (EDA): Descriptive Statistics Measures.** Descriptive statistics is concerned with the description and summarization of data. It is a summary of a dataset that helps to describe features of data quantitatively (Ross, 2019). To have a general view of wealth distribution of a class, we use the following measures:

- measures of central tendency: mean, median, mode
- measures of frequency: count, cumulative frequency/percentage
- measures of position: quartile, percentile
- measures of dispersion: minimum, maximum, range, interquartile range, standard deviation, coefficient of variation, kurtosis
- measures of symmetry: skewness

**Gini Coefficient.** Gini coefficient is a metric used to measure the economic wealth gaps between countries. A study by Akbar (2020) utilized the Gini coefficient to measure the level of knowledge imbalance in knowledge graphs, particularly Wikidata classes. To calculate the imbalance level of a Wikidata class using Gini coefficient, the researcher started by calculating the number of properties of each entity of that particular class and storing them in an array. The array will then be sorted in descending order, from the smallest to the largest i.e., $y_i \geq y_{i+1} \forall i \in \{1, 2, ..., n\}$. The Gini coefficient will be calculated from the sorted array using the Gini coefficient formula below [16].

$$G = 1 - \frac{1}{n^2 \mu} \sum_{i=1}^{n} \sum_{j=1}^{n} Min(y_i, y_j)$$

$$G = 1 + \frac{1}{n} - \frac{1}{n^2 \mu} - (y_1 + 2y_2 + ... + ny_n)$$

In economics context, $n$ is the size of population of a country, $\mu$ is the average income, and $y$ is an array containing data of each country's income. However, in the context of knowledge graph, $n$ is the number of entities in the class, $\mu$ is the average knowledge wealth of the entities, and $y$ is an array containing data of each entity's wealth, sorted in descending order.

For example, let's say we have a class that consists of 10 entities. After counting the number of properties of each entities (using the notion of bag of properties for wealth) and sorting them in descending order, we will have an array of $y = [10, 8, 8, 7, 4, 2, 2, 1, 1, 1]$. The length of the array is $n = 10$ and the average wealth is $\mu = 4.4$. Then, apply the Gini coefficient formula and we get $G = 1 + \frac{1}{10} - \frac{2}{10^2 \times 4.4}(1 \times 10 + 2 \times 8 + ... + 10 \times 1) = 0.414$

For another another example, let's say we have another array of 10 entities $z = [10, 9, 9, 9, 9, 9, 9, 9, 9, 5]$. By applying the same formula to z, we get a Gini coefficient value of 0.052.

The Gini coefficient has a value between 0 and 1. The higher the coefficient value, the greater the imbalance level. The value of 0 is achieved when all observed entities have the same amount of wealth. The value of 1 occurs when all income is owned solely by one entity and this phenomenon expresses full inequality.

**Lorenz Curve.** Lorenz curve is a graphical representation of wealth distribution and its inequality [17]. It shows how the wealth is cumulatively distributed, with data points sorted in ascending order from the poorest to the richest. In Lorenz curve, the horizontal axis represents the fraction of the population, and the vertical axis represents the cumulative wealth. Therefore, if the point (x, y) = (30, 15) lies on the curve, then we can interpret that the bottom 30% of the population account for 15% of the total wealth in that population. The Lorenz curve is usually drawn along with a straight diagonal line with a slope of 1. This straight line represents perfect equality in wealth distribution, i.e., each individual in the observed population has equal wealth. The Lorenz curve itself is drawn below the straight line. The ratio of the area between the Lorenz curve and the straight line of perfect equality to the triangular area below the straight line, is the Gini coefficient.

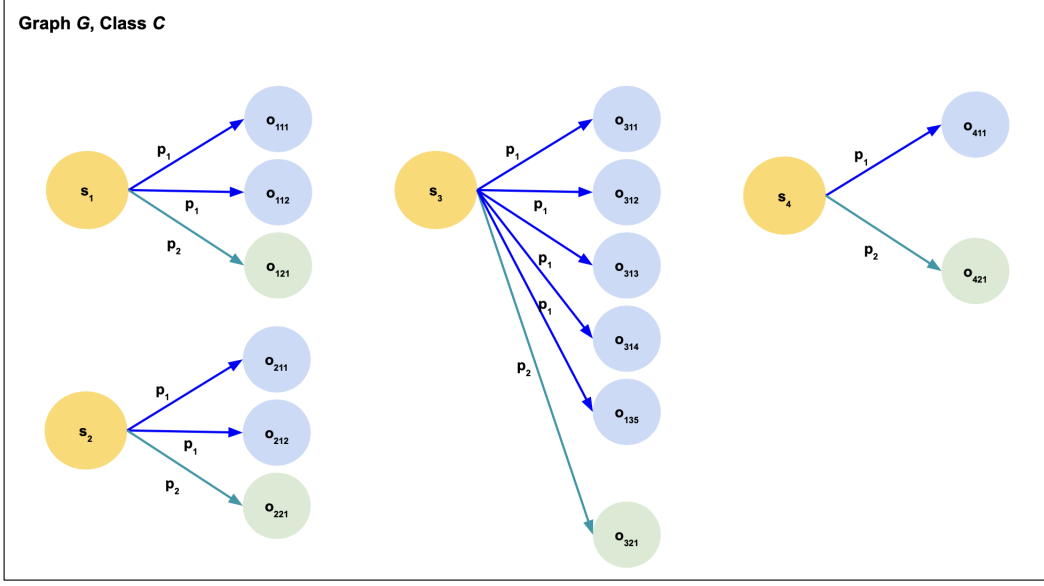### 3.3. Sample Application of Formal and Insight Model



**Figure 3:** Sample knowledge graph $G$ that contains class $C$ with 4 entities ($s_1$-$s_4$), represented as yellow nodes (subjects in RDF triples). Edges represent properties: blue edges correspond to property $p_1$ and green edges to property $p_2$. Object nodes are color-coded to match their associated property: blue circles indicate objects linked via $p_1$, and green circles indicate objects linked via $p2$.

We provide small case in Figure 3 to illustrate how both models can be applied in quantifying knowledge wealth. In this example, we will focus on the notion using bag of properties with outgoing direction of link to quantify the wealth.

A graph $G$ has a class $C$, which consists of four entities $s_1$, $s_2$, $s_3$, and $s_4$. Each entity has two distinct properties $p_1$ and $p_2$. For example, entity $s_1$ is linked by property $p_1$ to objects $o_{111}$ and $o_{112}$, and by property $p_2$ to object $o_{121}$. Using the bag of properties and outgoing link direction, the wealth of entity $s_1$ is 3 (2 accounted for by $p_1$ and 1 by $p_2$). Similarly, the wealth of entities $s_2$, $s_3$, and $s_4$ is 3, 6, and 2, respectively. Table 2 provides a statistical summary describing the wealth of class $C$. Entities in class $C$ have a mean wealth of 3.5, a median wealth of 3, a mode wealth of 3, a minimum wealth of 2, and a maximum wealth of 6. Based on each individual entity's wealth, the imbalance measure of class $C$ is quantified using the Gini coefficient, which has a value of 0.21.

Table 2: Statistical Summary of Wealth of Class $C$

| Measure | Entity Count | Mean | Median | Mode | Minimum | Maximum | Gini |
|---------|--------------|------|--------|------|---------|---------|------|
| Value | 4 | 3.5 | 3 | 3 | 2 | 6 | 0.21 |

This table shows some statistical measures to quantify the wealth of class $C$.

In addition to the Gini coefficient, the Lorenz curve for the wealth of entities in class $C$ is shown in Figure 4. This figure illustrates that the wealth distribution within class $C$ is very
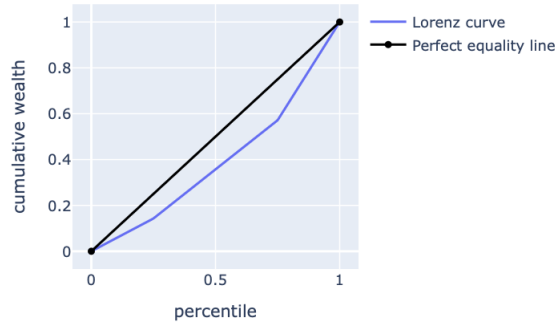
**Figure 4:** Lorenz curve of class $C$

close to the diagonal line of perfect equality, which aligns with the small Gini coefficient value of 0.21.

### 3.4. Python-Based Model Implementation

Our study provides a Python-based implementation library for both the formal model and the insight model. The library incorporates the three notions of knowledge wealth discussed in Subsection 3.1, as well as the insight model outlined in Subsection 3.2. While the model is platform-agnostic, i.e., it can be applied to any KG, we focus its implementation on Wikidata for demonstrating its use cases. Wikidata is specifically chosen because of the availability of Wikidata Query Service which facilitates structured queries over its data.

The notions of wealth are implemented at the query level, meaning that the filters and aggregations based on each wealth definition are directly embedded in SPARQL queries. The flow begins with defining class filters to specify the entities of interest. Next, SPARQL querying is performed using Wikidata Query Service to retrieve RDF triples matching the specified criteria and aggregate them according to the selected notion of wealth. The extracted data is then structured into pandas DataFrames, enabling further analysis through the insight model using Python libraries[3].

In our implementation, we only consider direct properties and exclude blank nodes to reduce complexity and maintain data quality. The complete flow of the formal model and insight model usage is illustrated in Figure 5.

## 4. Knowledge Gap Analysis and Evaluation

In this section, we present the analysis and evaluation of knowledge gaps using real-world use cases. The analyses focus on identifying disparities in knowledge representation. All data were obtained from Wikidata via the Wikidata Query Service, retrieved on March 2nd, 2025.

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[3]Our library is available at https://github.com/nurulputri/paper-knowledge-wealth-framework
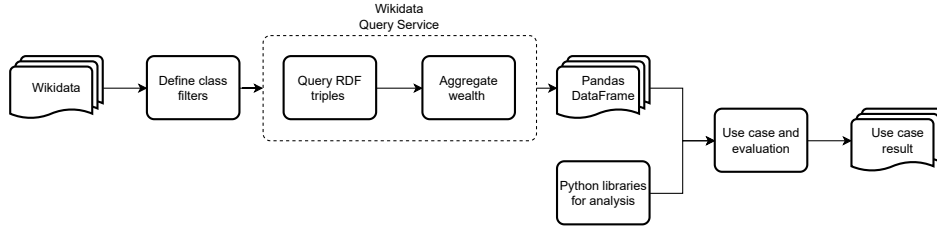
**Figure 5:** Model implementation and evaluation flow using Python Jupyter Notebook

## 4.1. Group-Level Gap in Representation in Wikidata

In this subsection, analysis is conducted to see whether any particular entity group in Wikidata is underrepresented compared to others. There are 2 analysis done: gender-based gap and regional gap.

For this analysis, we use $W_{bag,*,[out]}$ as the definition of wealth, i.e., the notion of bag of properties, including all property types, and assuming outgoing link direction. This choice is motivated by the need to capture the total volume of information associated with each entity, regardless of teh type of property. Moroever, using outgoing links ensures we measure the knowledge attached to an entity, which is more suitable for identifying disparities in how richly different groups are described in Wikidata.

**Gender-Based Knowledge Gap: Male vs. Female Representation.** Gender-based knowledge gap analysis in Wikidata will be performed on 10 Wikidata classes: computer scientist, American singer, American actress/actor, badminton player, businessperson, lawyer, American politician, American writer, American researcher, and American journalist. These classes are chosen to ensure variation in occupations, as gender representation differs across professions. Additionally, six of these classes are limited to American entities to manage scalability, as querying large, global datasets can lead to excessive query time and computational resource constraints. The United States, being a large and well-known country, is expected to provide a broadly reflective sample while keeping the analysis computationally feasible.

To analyze the gap, the first aspect that will be considered is the proportion of each gender in every class. We assumed that there are equal numbers of males and females in real-world and this will be the basis to determine if there is any gap in the data. Pearson's chi-square test (goodness-of-fit) is then performed to test the null and alternative hypotheses with significance level of $\alpha = 5\%$ as follows:

| Gender-Based Knowledge Gap: Entity Count Gap (Pearson's chi-square test) | |
|---|---|
| $H_0$ | The proportions of males and females in a particular class are equal to the assumed real-world proportion of 50%-50%. |
| $H_1$ | The proportions of males and females in a particular class are not equal to the assumed real-world proportion of 50%-50%. |
| **Insight 1:** | Across all 10 classes, male entities significantly outnumber female entities in all classes. This suggests a systematic underrepresentation of female entities in Wikidata. |

Table 3: Entity Count of 10 Wikidata Classes per Gender Category

| Class Name | Entity | Male | Female | %Male | %Female | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| American actress/actor | 38655 | 21787 | 16868 | 0.563627 | 0.436373 | 625.96 | 3.78e-138 |
| American journalist | 18033 | 12402 | 5631 | 0.687739 | 0.312261 | 2542.36 | 0.0 |
| American politician | 96507 | 85800 | 10707 | 0.889055 | 0.110945 | 58430.57 | 0.0 |
| American researcher | 5233 | 3634 | 1599 | 0.694439 | 0.305561 | 791.37 | 4.06e-174 |
| American singer | 16038 | 9198 | 6840 | 0.573513 | 0.426487 | 346.69 | 2.23e-77 |
| American writer | 33554 | 19656 | 13898 | 0.585802 | 0.414198 | 988.10 | 6.95e-217 |
| Computer scientist | 19049 | 16180 | 2869 | 0.849388 | 0.150612 | 9301.42 | 0.0 |
| Badminton player | 25427 | 13493 | 11934 | 0.530656 | 0.469344 | 95.59 | 1.42e-22 |
| Businessperson | 76758 | 68583 | 8175 | 0.893496 | 0.106504 | 47540.67 | 0.0 |
| Lawyer | 94479 | 83147 | 11332 | 0.880058 | 0.119942 | 54587.73 | 0.0 |

This table shows the entity count of 10 Wikidata classes per Gender Category. Chi-square test result shows the significance of difference between the entity count of the two genders male and female.

From Table 3, we can see that there are more male entities than female entities in all of the classes. In terms of entity count, the gender gaps in some classes such as American singer, American actress/actor, badminton player, and American writer, are slim. The gender gaps in some other classes are huge, and it can be observed in the classes of computer scientist, businessperson, lawyer, American politician, journalist, and researcher. This phenomenon can also be easily identified through visualization, as exhibited in Figure 6a, where the histogram of the female subclass is much smaller compared to the male. Looking at the chi-square test result, as p-value is well below the chosen significance level, the null hypothesis is rejected in all classes. Hence, we considered the difference of entity count to be significant and conclude that the proportions of males and females in each Wikidata class are not the same as the assumed real-world proportion of 50%-50%.

However, it is arguable that, for some classes, the gap in entity count between both genders is expected because, in reality, there are more men than women in the workforce, especially in particular fields such as engineering. As a consequence, it is not reasonable if we expect to have an equal number of males and females entities in Wikidata. Therefore, entity count may not be a good measure of gap because of the nature of the data itself. To address this, we need to evaluate other metrics which can quantify the gap at entity-level.

The next metrics to be considered are the measures of central tendency and dispersion to see where the wealth distribution is concentrated and how the data spread.

| Gender-Based Knowledge Gap: Measures of Central Tendency and Dispersion |
| --- |
| **Insight 1:**   For all 10 classes, female values for mean, median, and mode are generally lower than those of males. Only in the American Singer class does a female (Madonna) appear as the richest individual. |
| **Insight 2:**   Positive value of skewness and high value of kurtosis are observed across the board, indicating right-skewed distribution and frequent extreme outliers. |

Table 4: Measures of Central Tendency of 10 Wikidata Classes per
Gender Category

| Class Name | Mean (o/m/f) | Median (o/m/f) | Mode (o/m/f) |
| --- | --- | --- | --- |
| American actress/actor | 39.72/40.82/38.31 | 30.00/30.00/28.00 | 19/19/19 |
| American journalist | 31.30/33.12/27.29 | 24.00/25.00/21.00 | 14/15/14 |
| American politician | 19.15/19.31/17.90 | 15.00/15.00/15.00 | 9/9/12 |
| American researcher | 24.24/25.32/21.77 | 20.00/21.00/19.00 | 12/12/15 |
| American singer | 42.96/43.30/42.51 | 31.00/33.00/30.00 | 18/24/15 |
| American writer | 39.75/44.05/33.66 | 30.00/33.00/26.00 | 19/21/19 |
| Computer scientist | 24.30/24.65/22.33 | 19.00/19.00/18.00 | 8/8/11 |
| Badminton player | 21.90/21.64/22.19 | 16.00/16.00/16.00 | 14/14/14 |
| Businessperson | 17.06/16.98/17.73 | 13.00/13.00/13.00 | 10/10/9 |
| Lawyer | 22.58/23.16/18.33 | 19.00/19.00/15.00 | 14/16/12 |

This table shows the measures of central tendency of 10 Wikidata classes per gender category. Each measure will have 3 values: o (overall), m (male), and f (female).

Table 5: Measures of Dispersion and Symmetry of 10 Wikidata Classes per Gender Category

| Class Name | Min (o/m/f) | Max (o/m/f) | Std. Deviation (o/m/f) | Skewness (o/m/f) | Kurtosis (o/m/f) |
| --- | --- | --- | --- | --- | --- |
| American actress/actor | 4/4/4 | 703/585/703 | 35.15/34.47/35.97 | 4.22/3.65/4.88 | 30.55/22.97/39.11 |
| American journalist | 4/4/4 | 418/418/363 | 27.78/29.22/23.82 | 4.21/4.17/4.15 | 30.60/29.94/29.09 |
| American politician | 4/4/4 | 564/564/334 | 15.05/15.07/14.90 | 6.98/7.01/6.83 | 112.45/115.94/84.91 |
| American researcher | 4/4/4 | 225/225/195 | 17.16/18.46/13.46 | 3.86/3.75/3.74 | 25.74/23.07/31.65 |
| American singer | 4/5/4 | 703/585/703 | 40.36/36.61/44.90 | 4.15/3.33/4.65 | 29.66/19.78/33.57 |
| American writer | 4/4/4 | 564/564/435 | 35.82/39.48/28.82 | 3.63/3.37/4.02 | 21.27/18.08/27.34 |
| Computer scientist | 3/3/3 | 452/452/178 | 19.69/20.35/15.35 | 3.48/3.52/2.25 | 28.77/28.90/9.89 |
| Badminton player | 9/9/9 | 360/240/360 | 15.98/15.15/16.88 | 4.28/3.94/4.52 | 31.54/23.57/36.62 |
| Businessperson | 3/3/3 | 585/585/434 | 15.06/14.39/19.81 | 8.07/7.80/8.17 | 142.31/144.95/106.75 |
| Lawyer | 3/3/3 | 608/608/334 | 17.02/17.34/13.73 | 5.78/5.79/5.67 | 82.87/82.78/78.35 |

This table shows the measures of dispersion and symmetry of 10 Wikidata classes per gender category. Each measure will have 3 values: o (overall), m (male), and f (female).

From Table 4, female entities generally have lower values of measure of central tendency (mean, median, mode). These characteristics can also be observed from the histogram in Figure 6a: female histograms' peak and dense area are located on the left of the male's. However, there are some classes in which the richest entity is a female. An example for this is the class of American Singer, which is shown by Figure 6b. Though the value of mean, median, and mode of count of properties are lower for female compared to male, the richest entity on that class is a

female entity *Madonna* (Q1744) with bag of property count of 703, with a significant difference with *Michael Jackson* (Q2831) with bag of property count of 585.

From Table 5, we also observed positive values of skewness (skewness > 0) and high kurtosis values (kurtosis > 3) in all classes, denoting the wealth distribution is right-skewed and leptokurtic. The high skewness values indicate that a small number of individuals accumulate disproportionately large property counts. Moreover, high kurtosis values across all genders suggest wealth distributions with heavy tails, meaning that extreme outliers are relatively frequent. Furthermore, we saw higher variability among males, as reflected in their generally wider range of property counts and higher standard deviations. These statistical properties point toward a more unequal wealth distribution among male entities, while females tend to cluster within a lower and more compressed wealth range.
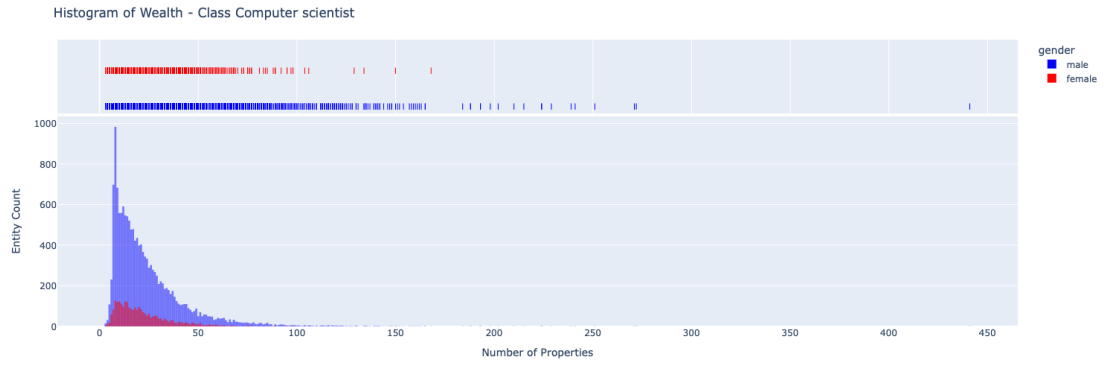
(a) Histogram and Marginal Distribution Plot of Wealth for Class Computer Scientist

(b) Histogram and Marginal Distribution Plot of Wealth for Class American Singer

**Figure 6:** Histogram of wealth

At a glance we saw female classes are poorer compared to the male classes. To test this, we used t-test and Welch's test. First, we performed F-test to check if the male and female classes have equal variance. The result of F-test is then used to determine the appropiate test to be used in each class. Those with equal variance, i.e., if the p-value is more than 0.05, will use t-test; otherwise Welch's test is used. Then, we performed the appropiate tests to verify the null and

alternative hypotheses with significance level of $\alpha = 5\%$ as follows:

| Gender-Based Knowledge Gap: Mean of Wealth Gap (two-sided t-test and Welch's test) | |
| --- | --- |
| $H_0$ | The means of wealth of males and females in a particular class are equal. |
| $H_1$ | The means of wealth of males and females in a particular class are not equal. |
| **Insight 1:** | 9 out of 10 classes shows unequal mean, with 7 of them are in favor of males. |

Table 6: F-Test, t-Test, and Welch's Test Result of 10 Wikidata Classes

| Class Name | F-Test statistic | F-Test p-value | t-Test statistic | t-Test p-value | Welch's Test statistic | Welch's p-value |
| --- | --- | --- | --- | --- | --- | --- |
| American actress/actor | 0.92 | 0.00 | - | - | 6.93 | 4.27e-12 |
| American journalist | 1.50 | 1.00 | 13.12 | 4.05e-39 | - | - |
| American politician | 1.02 | 0.94 | 9.11 | 8.46e-20 | - | - |
| American researcher | 1.88 | 1.00 | 6.92 | 4.91e-12 | - | - |
| American singer | 0.66 | 0.00 | - | - | 1.19 | 0.23 |
| American writer | 1.88 | 1.00 | 26.44 | 1.98e-152 | - | - |
| Computer scientist | 1.76 | 1.00 | 5.83 | 5.80e-09 | - | - |
| Badminton player | 0.81 | 0.00 | - | - | -2.75 | 0.01 |
| Businessperson | 0.53 | 0.00 | - | - | -3.34 | 0.00 |
| Lawyer | 1.60 | 1.00 | 28.47 | 1.69e-177 | - | - |

This table shows the result of F-test, t-test, and Welch's test of 10 Wikidata classes to compare the significance difference between the males and females within each class.

Based on F-test on the 10 classes, variance between male and female subclasses was found to be unequal (p < 0.05) in 4 classes, requiring the use of Welch's test. From the test results in Table 6, we rejected the null hypothesis in 9 out of 10 class, with the American singer being the only exception with p-value > 0.05. Among them, 7 classes' means are in favor of male. The other 2 classes, badminton player and businessperson, deviate from this trend, where Welch's test results indicate that the female subclasses actually have a higher mean wealth. The extremely small p-values in classes such as American writer and lawyer indicate a very strong statistical signal that the mean wealth differs significantly between genders. Finally, we may conclude that female classes are more likely to have smaller means than male classes, although certain classes may reflect localized or domain-specific representation imbalances. These results reinforce our earlier observations that female entities tend to be poorer in terms of knowledge wealth.

Entity count alone might not be a reliable measure of gap because the nature of the data itself. For instance, in real world, the number of male computer scientists is greater than that of female computer scientists. Therefore, expecting an equal number of male and female entities in Wikidata for this class would be unreasonable. Similarly, measures of central tendency, such as the mean or median, may offer a general overview but fail to capture the distributional nuances of individual entities within a class. To address this, a more holistic metric is needed.

Here, we introduced a new measure: the ratio of top $x\%$ representation (of male/female) relative to expectation. The value of expectation of a gender in a class is equal to the percentage of that particular in the class. Top $x\%$ male relative to expectation is the ratio of percentage of

| Gender-Based Knowledge Gap: Relative Expectation Ratios | |
| --- | --- |
| **Insight 1:** | A ratio value of 1 indicates a balanced distribution, where the group's actual share of wealth aligns with its expected share under equal representation. |
| **Insight 2:** | On average across all 8 classes, the bottom six quantiles (i.e., the lower wealth segments) are predominantly composed of female entities, while the top four quantiles (i.e., the wealthier segments) are predominantly male. |
| **Insight 3:** | At the individual class level, 6 out of 8 classes show male dominance in the upper wealth quantiles. The exceptions are the businessperson and badminton player classes. |
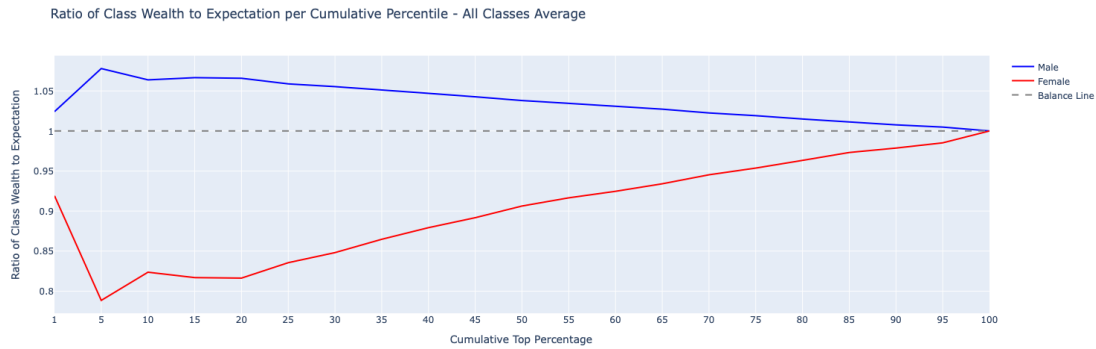


(a) Ratio of Class Wealth to Expectation per Cumulative Top Percentage - All Classes Average
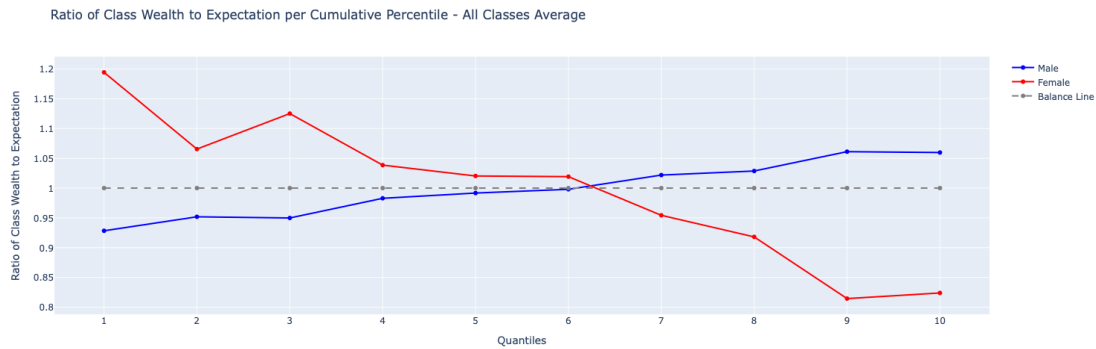


(b) Ratio of Class Wealth to Expectation per Quantile - All Classes Average

**Figure 7:** Ratio of each gender wealth to expectation

male entities in the top $x\%$ to the expectation. Similarly, top $x\%$ female relative to expectation is the ratio of percentage of female entities in the top $x\%$ to the expectation.

When the shape of distribution of male and female of a class is the same (in other word, the wealth is distributed equivalently to male and female entities), then the value of top $x\%$ relative to expectation should be 1 for both male and female subclasses. A value higher than 1 indicates domination by that particular gender. Conversely, a value lower than 1 indicates

underrepresentation.

From Figure 7 the value of ratio between top $x\%$ potion to the expectation in the above tables, we can see that on average, the rich entities are dominated by male. Exceptions are held for 2 classes, that is classes businessperson, and badminton player. In the businessperson class, female dominance in the top quantile (Q10) creates an exception. However, quantiles 2–9 are predominantly male-dominated, albeit only slightly and very close to the balance line. Meanwhile, the lowest quantile (Q1) is significantly female-dominated. The badminton player class deviates from all other classes by exhibiting a distinct zig-zag pattern across quantiles, indicating alternating dominance between males and females, without a clear upward or downward trend.

Moreover, as we set bigger portions (higher percentage), the gap of ratio between the two ender in each class decreases i.e. the value of top $x\%$ relative to expectation of both genders converge to 1.

**Regional Knowledge Gap: Western vs. Non-Western Representation.** Regional knowledge gap analysis in Wikidata will be performed on 5 Wikidata classes: computer scientist, singer, memorial, university, and river. For each class, we collected the data for the western portion from 8 countries: Canada, France, Germany, Ireland, Poland, Switzerland, the United Kingdom (UK), and the United State of America (USA). For the non-western portion, we also selected 8 countries: China, Egypt, India, Indonesia, Japan, Morocco, Nigeria, and South Africa. The selected countries represent different continents to capture a diverse geographic distribution. Additionally, we focused on large and well-known countries to ensure the dataset is representative, as data from smaller countries may not provide meaningful insights due to limited coverage in Wikidata.

To analyze the gap, the first aspect that will be considered is the proportion of each regional category in every class. We assumed that there are equal numbers of western and non-western and this will be the basis to determine if there is any gap in the data. Pearson's chi-square test (goodness-of-fit) is then performed to test the null and alternative hypotheses with significance level of $\alpha = 5\%$ as follows:

| Regional Knowledge Gap: Entity Count Gap (Pearson's chi-square test) | |
| --- | --- |
| $H_0$ | The proportions of western and non-western entities in a particular class are equal. |
| $H_1$ | The proportions of western and non-western entities in a particular class are not equal. |
| **Insight 1:** | Across all 5 classes, the proportions of western and non-western entities differ significantly. Western entities dominate in 4 out of 5 classes, with the only exception being the university class, which is skewed toward non-western entities. |

Table 7: Entity Count of 5 Wikidata Classes per Regional Category

| Class Name | Entity | Western | Non-western | %Western | %Non-western | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| Computer scientist | 6063 | 5446 | 617 | 0.90 | 0.10 | 3846.15 | 0.0 |
| Singer | 43240 | 31039 | 12201 | 0.72 | 0.28 | 8206.99 | 0.0 |
| Memorial | 4011 | 3836 | 175 | 0.96 | 0.04 | 3341.54 | 0.0 |
| University | 6124 | 2398 | 3726 | 0.39 | 0.61 | 287.98 | 1.37e-64 |
| River | 125567 | 70059 | 55508 | 0.56 | 0.44 | 1686.20 | 0.0 |

This table shows the entity count of 5 Wikidata classes per regional category. Chi-square test result shows the significance of difference between the entity count of the two regions.

From Table 7, we can observe that the proportion of western entities exceeds that of non-western entities in 4 out of the 5 classes. In the memorial and computer scientist classes, the gap is particularly striking, with western entities making up over 90% of the total population. Similarly, in the singer and river classes, western entities also represent the majority. The university class is the only exception, where non-western entities slightly outnumber western ones, comprising 61% of the total. Based on the results of the chi-square test, the p-values in all five classes are well below the significance threshold ($\alpha = 0.05$), leading us to reject the null hypothesis. This indicates that the differences in entity proportions between western and non-western entities are statistically significant and not due to random variation.

However, similar to entity count in gender-based knowledg gap analysis, it is debatable that some of these gaps are expected. For instance, the dominance of western representation in the computer scientist or memorial classes is not necessarily a result of data entry errors or systemic bias within Wikidata alone. Instead, it may mirror general historical and sociopolitical factors, such as unequal access to documentation, global academic visibility, and archival infrastructure. Conversely, the university class, where the number of non-western entities are higher, might be a reflection of population-driven realities, as countries like China, India, and Indonesia possess massive populations and have established a vast number of higher education institutions to serve their demographic needs. The greater number of non-western universities represented in Wikidata is probably a result of this population scale. Due to this, raw entity count alone may not be an ideal measure of gap. To more accurately assess representation and equity, we must consider other metrics that analyze wealth distribution and prominence at the entity level.

The next step in our analysis is examining the measures of central tendency and dispersion to evaluate where the knowledge wealth is concentrated and how it varies between western and non-western entities.

| Regional Knowledge Gap: Measures of Central Tendency and Dispersion |
|---|
| **Insight 1:** In 4 out of 5 classes, western entities have higher mean, median, and mode values than non-western entities, indicating greater concentration of knowledge wealth. |
| **Insight 2:** Western entities generally exhibit higher standard deviations, skewness, and kurtosis, suggesting greater variability, more frequent outliers, and stronger right-skewed distributions. |

Table 8: Measures of Central Tendency of 5 Wikidata Classes
per Regional Category

| Class Name | Mean (o/w/n) | Median (o/w/n) | Mode (o/w/n) |
|---|---|---|---|
| Computer scientist | 35.00/35.87/27.24 | 29.00/29.00/22.00 | 21/15/16 |
| Singer | 34.99/39.14/24.43 | 25.00/29.00/18.00 | 15/18/14 |
| Memorial | 11.04/11.04/11.13 | 9.00/9.00/9.00 | 9/9/9 |
| University | 23.11/31.61/17.63 | 17.50/24.00/16.00 | 6/6/6 |
| River | 7.69/8.55/6.60 | 7.00/7.00/6.00 | 7/7/7 |

This table shows the measures of central tendency of 5 Wikidata classes per regional category. Each measure will have 3 values: o (overall), w (western), and n (non-western).

Table 9: Measures of Dispersion and Symmetry of 5 Wikidata Classes per Regional Category

| Class Name | Min (o/w/n) | Max (o/w/n) | Std. Deviation (o/w/n) | Skewness (o/w/n) | Kurtosis (o/w/n) |
|---|---|---|---|---|---|
| Computer scientist | 4/4/5 | 441/441/145 | 25.15/25.67/18.15 | 3.02/3.02/2.37 | 20.90/20.83/8.49 |
| Singer | 3/4/3 | 687/687/379 | 33.27/36.60/18.94 | 4.49/4.28/3.15 | 35.56/31.09/21.59 |
| Memorial | 2/3/2 | 142/142/52 | 5.89/5.82/7.28 | 8.50/8.95/2.98 | 143.57/156.15/12.79 |
| University | 2/2/2 | 234/234/166 | 20.00/25.88/12.25 | 2.37/1.65/2.22 | 10.34/5.33/12.70 |
| River | 2/2/2 | 452/452/148 | 5.24/6.46/2.68 | 21.71/19.54/14.67 | 1152.84/868.56/465.42 |

This table shows the measures of dispersion and symmetry of 5 Wikidata classes per regional category. Each measure will have 3 values: o (overall), w (western), and n (non-western).

From Table 8, we observed that in 4 out of 5 classes, western entities consistently show higher values across all measures of central tendency (mean, median, and mode) compared to non-western entities. This suggests that western entities tend to be richer in knowledge wealth. The memorial class is the only exception, where both groups exhibit nearly identical values. A particularly extreme disparity is observed in the university class, where the mean property count for western entities (31.61) is nearly double that of non-western entities (17.63), highlighting a strong central tendency skew. This extreme pattern can also be seen in the singer class.

Turning to the measures of dispersion and symmetry in Table 9, we saw that standard deviation is generally higher for western entities across all classes except memorial, suggesting greater wealth variability among western entities. Furthermore, in the university class, western entities show a standard deviation of 25.88, more than double that of non-western entities at 12.25. We also observed positive skewness and high kurtosis across all classes and both regions, indicating that knowledge wealth distributions are right-skewed and leptokurtic. However, western entities often exhibit higher values, implying more extreme outliers and longer tails. For example, in the river class, the skewness and kurtosis for western entities are 19.54 and 868.56, respectively, compared to 14.67 and 465.42 for non-western entities.

Taken together, these statistics suggest that western entities tend not only to accumulate more knowledge wealth on average but also to dominate the extreme high end of the distribution. In contrast, non-western entities tend to cluster around lower values with tighter distribution, reinforcing regional disparity in knowledge representation.

At a glance, western entities appear to be richer compared to their non-western counterparts. To statistically verify this, we conducted a series of mean comparison tests between the two groups. We began by applying the F-test to assess whether the western and non-western subsets within each class have equal variance. The result of the F-test determines the appropriate test to be used: if the p-value is greater than 0.05, indicating equal variance, we use the standard t-test; otherwise, we apply Welch's test, which does not assume equal variance.

| Regional Knowledge Gap: Mean of Wealth Gap (two-sided t-test and Welch's test) | |
| --- | --- |
| $H_0$ | The means of wealth of western and non-western entities in a particular class are equal. |
| $H_1$ | The means of wealth of western and non-western entities in a particular class are not equal. |
| **Insight 1:** | In 4 out of 5 classes, western entities have significantly higher mean knowledge wealth than non-western entities. |

Table 10: F-Test, T-Test, and Welch's Test Result of 5 Wikidata Classes

| Class Name | F-Test statistic | F-Test p-value | T-Test statistic | T-Test p-value | Welch's Test statistic | Welch's p-value |
| --- | --- | --- | --- | --- | --- | --- |
| Computer scientist | 2.00 | 1.00 | 8.13 | 5.10e-16 | - | - |
| Singer | 3.73 | 1.00 | 42.22 | 0.0 | - | - |
| Memorial | 0.64 | 0.00 | - | - | -0.16 | 0.88 |
| University | 4.46 | 1.00 | 28.40 | 8.23e-167 | - | - |
| River | 5.83 | 1.00 | 66.91 | 0.0 | - | - |

The result of the F-test in Table 10 shows that only one class, that is, memorial, has unequal variance ($p < 0.05$), thus requiring the use of Welch's test. For the remaining four classes, the t-test was applied. From the test results, we rejected the null hypothesis in 4 out of 5 classes, indicating that the difference in mean wealth between western and non-western entities is statistically significant. The only exception is the memorial class, where Welch's test yields a p-value of 0.88, suggesting no significant difference in mean. Among the classes with significant results, the direction of difference consistently favors Western entities. This can be seen clearly in classes such as university and singer, where the t-statistics are noticeably high (28.40 and 42.22, respectively) and the p-values are zero. These findings align with our previous observations that western entities dominate in terms of quantity and average information richness. We conclude that western entities are more likely to have higher mean knowledge wealth than non-western ones, although exceptions like the memorial class suggest that certain domains may present a more balanced knowledge distribution.

As with gender-based knowledge gap, measuring regional gap in Wikidata cannot rely solely on entity counts. The number of entities associated with western and non-western regions may reflect real-world disparities in documentation or notability, making raw counts an unreliable indicator of gap. Similarly, measures of central tendency, such as the mean or median, fail to capture how representation is distributed across the full spectrum of prominence

or wealth. To address these limitations, we applied the same metric introduced in the gender-based gap analysis: the relative expectation ratio. This measure compares a region's share of entities within a given quantile to its expected share under equal representation. A ratio of 1 indicates proportional representation, while values above or below 1 signal overrepresentation or underrepresentation, respectively. This allows for a more nuanced, quantile-level understanding of how western and non-western entities are distributed in knowledge graphs like Wikidata.

| Regional Knowledge Gap: Relative Expectation Ratios | |
| --- | --- |
| **Insight 1:** | On average across all 5 classes, the less prominent segments are dominated by non-western entities, while the more prominent ones are dominated by western entities. The middle quantiles exhibit a zig-zag pattern, reflecting inconsistent representation between the two groups. |
| **Insight 2:** | At the individual class level, 2 out of 5 classes display a particularly strong western dominance. The rests exhibit a zig-zag trend. |

On average across all classes, the lower four quantiles (i.e., the less prominent or "poorer" segments) are predominantly composed of non-western entities, while the top three quantiles (i.e., the more prominent or "wealthier" segments) are dominated by western entities. The middle quantiles exhibit a zig-zag pattern, reflecting inconsistent representation between the two groups. At the individual class level, the computer scientist and singer classes display a particularly strong western bias. In both classes, non-western entities are consistently overrepresented in the lower quantiles (Q1–Q4), while western entities are consistently overrepresented in the upper quantiles (Q5–Q6). This pattern suggests a clear stratification, with non-western entities disproportionately concentrated in less prominent positions. The memorial, university, and river classes, however, deviate from this pattern and exhibit a zig-zag trend across quantiles. This suggests a more unstable distribution of western and non-western entities across the quantiles.

## 4.2. Impact of Wealth Type on Knowledge Inequality

| Impact of Wealth Type on Knowledge Inequality | |
| --- | --- |
| **Insight 1:** | Wealth based on the bag of properties is always higher than that based on the set of properties, leading to higher value of Gini coefficient. |
| **Insight 2:** | Wealth measured using incoming links shows significantly higher inequality than outgoing links. Lorenz curves confirm that very few entities have incoming links, while most have none. |
| **Insight 3:** | In general, the order of Gini coefficient values from smallest to largest is: object properties, literal properties, and ID properties. |

In this subsection, we analyze how each wealth type affects the level of knowledge inequality of Wikidata classes. This analysis is carried out in two ways: quantitatively by using the Gini coefficient and qualitatively by examining the Lorenz curve. The analysis is performed on 8 Wikidata classes, in which 4 of them are human-related class while the other 4 are not.
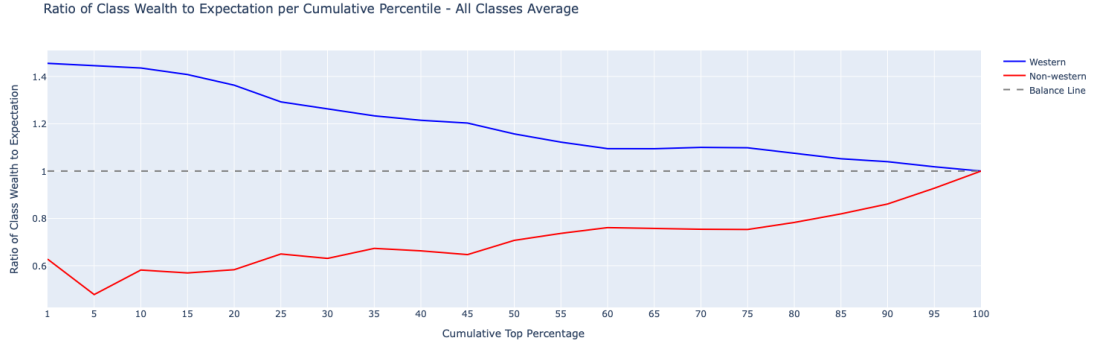
(a) Ratio of Class Wealth to Expectation per Cumulative Top Percentage - All Classes Average
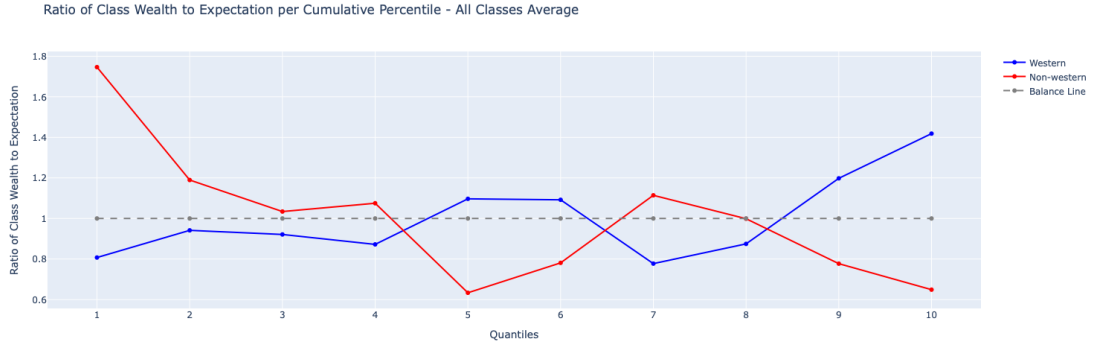


(b) Ratio of Class Wealth to Expectation per Quantile - All Classes Average

**Figure 8:** Ratio of each regional wealth to expectation

In this analysis, wealth definitions are chosen for consistency and fair comparison. For multiplicity comparison (bag-set), we use $W_{bag,*,[out]}$ and $W_{set,*,[out]}$, which include all property types with outgoing links. For property type comparison (object-literal-ID), we apply $W_{bag,[obj],[out]}$, $W_{bag,[ltr],[out]}$, and $W_{bag,[id],[out]}$, using the bag of properties approach with outgoing links for each property types. For link direction comparison (outgoing-incoming), we use $W_{bag,*,[out]}$ and $W_{bag,*,[in]}$, both of which include all property types. These choices ensure representativeness while isolating the effect of each factor on the results.

Table 11: Knowledge Wealth Type on Gini Coefficient

| Class Name | Gini Bag | Gini Set | Gini Object | Gini Pure Literal | Gini ID | Gini Outgoing | Gini Incoming |
|---|---|---|---|---|---|---|---|
| American researcher | 0.33 | 0.31 | 0.26 | *0.65 | 0.50 | 0.33 | 0.77 |
| American singer | 0.40 | 0.39 | 0.29 | 0.36 | 0.53 | 0.40 | 0.82 |
| Badminton player | 0.29 | 0.14 | 0.30 | *0.14 | 0.60 | 0.29 | 0.68 |
| Computer scientist | 0.41 | 0.37 | 0.36 | *0.64 | 0.56 | 0.41 | 0.81 |
| Historical painting | 0.23 | 0.15 | 0.25 | 0.26 | 0.45 | 0.23 | 0.87 |
| Memorial | 0.22 | 0.19 | 0.20 | 0.31 | 0.41 | 0.22 | 0.99 |
| Sci-fi book | 0.30 | 0.21 | 0.31 | 0.33 | 0.44 | 0.30 | 0.82 |
| University | 0.44 | 0.41 | 0.39 | 0.49 | 0.53 | 0.44 | 0.91 |

This table shows the comparison of Gini coefficient of 8 Wikidata classes

When looking at the notion of wealth using the characteristics of (non-)uniqueness of individual properties, it is intuitive that the measure of the bag of properties will always give higher (or at least, equal) amount of wealth compared to the measure of set. Set of property will have an upper bound of number of unique property, while the bag of properties does not have any upper bound. Moreover, using the bag of properties, a large number of triples having the same property may inflate the wealth substantially (though this is not necessarily a problem nor an advantage). This characteristics has a direct impact on inequality measure and it is well depicted on the value of Gini coefficient. From Table 11, in all clasess, the Gini coefficient using the bag of properties is always higher than of set of properties.

Using the notion of wealth by type of property, in general the smallest Gini coefficient value comes from wealth using object properties, followed by literal properties, with ID properties having the highest value. This condition holds for the four non-human classes that are being observed. However, there are anomalies in the human classes, as illustrated in Figure 9.
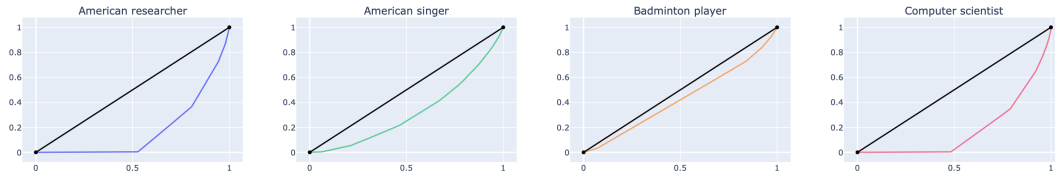


**Figure 9:** Lorenz curve of wealth using literal properties

In the classes of American researchers and computer scientists, the Gini coefficients for wealth using pure literal properties are significantly higher than those of other classes. This is due to approximately 50% of the entities in these classes having zero pure literal properties, not even basic human-related literal properties such as *date of birth* (P569). For example, an American researcher *John Heidemann* (Q29354581) has a total wealth of 61 (using the bag of properties) and is among the top 4% entities in his class, yet this entity has 0 literal properties. In contrast, only 818 out of 16150 (just about 5%) entities of American singer class have 0 literal properties. Moreover, an instance of American singer, *Kris Allen* (Q216927), who also has a total wealth of 61 (using the bag of properties), has 6 literal properties.

Another anomaly is observed in the class of badminton player where the Gini coefficient for wealth using pure literal is significantly lower than that of other classes. Upon inspection, three main reasons for this anomaly were identified. First, there are no entities in this class with 0 literal properties; all entites have at least 1 literal. Second, the range of wealth in this class is smaller, with a minimum value of 1 and maximum value of 10, in comparison to the classes of American researcher, American singer, and computer scientist which all have a minimum value of 0 and maximum values of 16, 26, and 54, respectively. This smaller range means the difference between the poorest and richest entities in the class of badminton player is minimal, and a small wealth range generally leads to a low Gini coefficient because inequality is limited by the narrow spread of wealth. The third reason is the large number of entities in this class, which totals 25,402. With such a high population size, the wealth of each individual, whether the poorest, middle, or the richest entity, contributes only a tiny fraction to the total wealth of the class. Combined with the small wealth range, this further reduces the inequality measure, resulting in a low Gini coefficient.

Using the notion of wealth by the direction of the link, the Gini coefficient when using incoming link is always higher than using outgoing link. By inspecting the Lorenz curve, we can see that most entities do not have any incoming link, and only the small percentage of entites has some incoming link. Figure 10 shows the comparison of Lorenz curve of knowledge wealth based on the direction of the link from 3 Wikidata classes. The difference between the two is very significant, because in Figure 10a the Lorenz curves are closer to the perfect equality line, meanwhile in Figure 10b the diagonal and the Lorenz curve almost form a right triangle which is very close to maximum inequality.
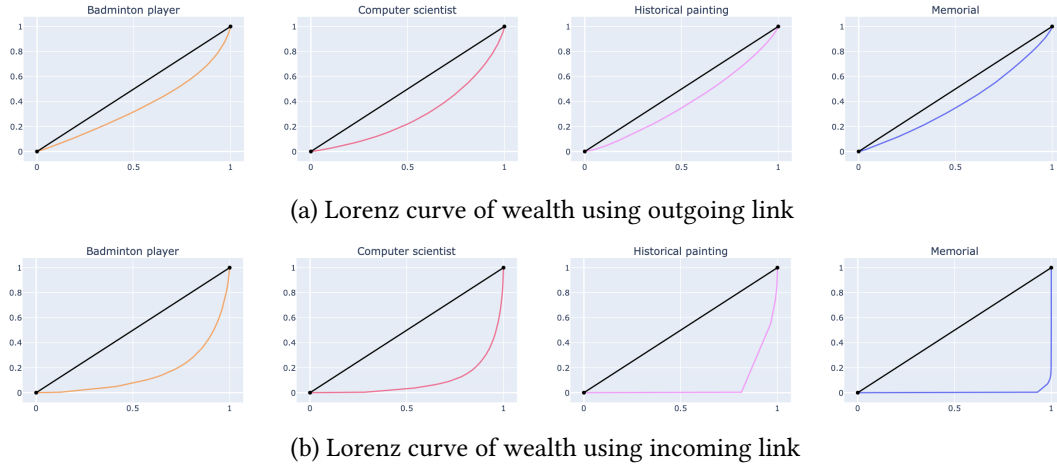


(a) Lorenz curve of wealth using outgoing link



(b) Lorenz curve of wealth using incoming link

**Figure 10:** Comparison of Lorenz curve of wealth based on the direction of link

### 4.3. Structural Gap Across Property Types in Knowledge Wealth

In this subsection, we analyze the contribution of different property types to the knowledge wealth of Wikidata classes. We only use outgoing links because, for incoming links, only object properties ($I_{objProp}$) are valid, which would exclude literal and ID properties. The analysis

| Structural Gap Across Property Types in Knowledge Wealth | |
|---|---|
| **Insight 1:** | The usage of literal properties is lower than of object and ID. |
| **Insight 2:** | Generally, the majority of knowledge wealth comes from internal resources (object and literal types). |

is performed on 8 classes, in which 4 of them are human-related class while the other 4 are non-human. For each class, the wealth measures assessed are: $W_{bag,[obj],[out]}$, $W_{bag,[ltr],[out]}$, $W_{bag,[id],[out]}$, $W_{bag,[obj,ltr],[out]}$, $W_{set,[obj],[out]}$, $W_{set,[ltr],[out]}$, $W_{set,[id],[out]}$, and $W_{set,[obj,ltr],[out]}$. These measures capture both the bag of properties and set of properties approaches, applied separately to object, literal, and ID property types, as well as the combination of object and literal properties, which represents knowledge wealth sourced from internal Wikidata. This setup allows us to observe structural disparities in how different types of information contribute to the overall wealth of entities.

Two methods of averaging are used in this analysis: global percentage and average contribution per individual entity. The first method is done by calculating the total sum of each property across all entities and then dividing it by the grand total of all properties combined, providing a holistic view of each property's overall contribution. The second method is done by first determining the percentage contribution of each property within each individual entity and then averaging these percentages across all entities, ensuring that every entity is equally represented regardless of its scale. While the global percentage method highlights absolute contributions, the average per-entity method captures relative contributions within each entity, making it more robust to variations in scale and less sensitive to outliers since every data point contributes equally to the final result.

From Table 12 and Table 13, generally, the usage of pure literal properties is lower than of object and ID. This aligns with the principle of knowledge graph to use URI for internal connections and ID for external resources.

We can say that object properties and literal properties combined represent wealth sourced internally from Wikidata, whereas ID properties originate from external sources. In general, more than half of the wealth is attributed to internal resources.

Table 12: Contribution of Property Type to Knowledge Wealth Using Bag of Properties

| Class Name | % Object Bag | % Literal Bag | % ID Bag | % Object + Literal Bag |
|---|---|---|---|---|
| American researcher | 59.55 / 65.65 | 3.32 / 2.8 | 37.12 / 31.55 | 62.88 / 68.45 |
| American singer | 40.44 / 48.42 | 7.47 / 8.48 | 52.09 / 43.1 | 47.91 / 56.9 |
| Badminton player | 79.34 / 78.96 | 10.14 / 11.68 | 10.52 / 9.36 | 89.48 / 90.64 |
| Computer scientist | 59.36 / 65.93 | 4.19 / 3.71 | 36.44 / 30.36 | 63.56 / 69.64 |
| Historical painting | 66.35 / 66.46 | 25.48 / 25.85 | 8.17 / 7.69 | 91.83 / 92.31 |
| Memorial | 62.82 / 64.16 | 21.0 / 20.4 | 16.18 / 15.44 | 83.82 / 84.56 |
| Sci-fi book | 62.96 / 62.62 | 14.44 / 15.78 | 22.59 / 21.6 | 77.41 / 78.4 |
| University | 37.59 / 44.79 | 18.11 / 18.31 | 44.3 / 36.9 | 55.7 / 63.1 |

This table shows the contribution of each property type of 8 Wikidata classes based on the notion of bag of properties. Each record has 2 values separated by "/". The first value is the contribution rate when calculated with global percentage method, and the second one is when using the average contribution per individual entity

Table 13: Contribution of Property Type to Knowledge Wealth Using Set of Properties

| Class Name | % Object Set | % Literal Set | % ID Set | % Object + Literal Set |
|---|---|---|---|---|
| American researcher | 51.25 / 59.69 | 3.97 / 3.29 | 44.78 / 37.02 | 55.22 / 62.98 |
| American singer | 33.91 / 43.58 | 8.1 / 9.18 | 57.99 / 47.24 | 42.01 / 52.76 |
| Badminton player | 71.75 / 74.13 | 13.79 / 13.9 | 14.46 / 11.97 | 85.54 / 88.03 |
| Computer scientist | 50.53 / 60.54 | 4.98 / 4.27 | 44.49 / 35.19 | 55.51 / 64.81 |
| Historical painting | 60.57 / 61.91 | 28.88 / 28.61 | 10.55 / 9.48 | 89.45 / 90.52 |
| Memorial | 60.06 / 62.01 | 22.41 / 21.59 | 17.54 / 16.4 | 82.46 / 83.6 |
| Sci-fi book | 59.36 / 61.91 | 13.86 / 14.59 | 26.78 / 23.5 | 73.22 / 76.5 |
| University | 33.93 / 42.74 | 17.67 / 18.32 | 48.4 / 38.95 | 51.6 / 61.05 |

This table shows the contribution of each property type of 8 Wikidata classes based on the notion of set of properties. Each record has 2 values separated by "/". The first value is the contribution rate when calculated with global percentage method, and the second one is when using the average contribution per individual entity

Typically, an ID property has exactly one associated value because it serves as a unique identifier in external resources, preventing ambiguity. In contrast, object properties can have multiple values. For example, the computer scientist *Noam Chomsky* (Q9049) has an ID property, *VIAF cluster ID* (P214), with exactly one value: *89803084*. At the same time, he has an object property, *work location* (P937), with four values: *Pennsylvania* (Q1400), *Cambridge* (Q350), *Tucson* (Q18575), and *Massachusetts* (Q771). When using the bag of properties, *VIAF cluster ID* (P214) contributes 1 to the total wealth, while *work location* (P937) contributes 4. Under the set of properties, both properties contribute equally, each accounting for 1. This explains why the percentage contribution of object properties to wealth is smaller when using the set of properties compared to the bag of properties. Since the overall property count is lower in the set of properties, the percentage contribution of ID properties to wealth is correspondingly higher than in the bag of properties.

## 5. Discussion

**Generality of Framework.** The framework that is proposed in this study is applicable to any kind of knowledge graph. However, the library that we built for experimentation is specifically for Wikidata, because the query service, structure, and response is very unique for each knowledge graph. If further experimentation is to be conducted for other knowledge graph, then the library needs to be modified.

**Scalability.** In our Wikidata use case, we analyzed both human-related and non-human classes based on predefined filters. While analyzing the entire human class (i.e., all entities $s$ that satisfy the triple $(s, instanceOf(P31), human(Q5))$) would provide valuable insights, we opted for smaller classes due to practical constraints. The primary limitation comes from the Wikidata Query Service itself, particularly its restrictions on query execution time.

The largest class we successfully retrieved in a single query was "American politicians" which contained 96,507 entities and required 34 seconds for query execution. However, when attempting to query significantly larger classes, such as all politicians without filtering by nationality, we encountered system limitations, including timeouts and out-of-memory errors.

For Wikidata or other KGs developer, a potential solution to overcome these limitations is to host them on a more reliable infrastructure with optimized indexing and caching mechanisms. This would allow for faster query execution and improved scalability for large-scale data retrieval.

That said, it is important to note that the analysis performed in this study is non-transactional, meaning it does not require real-time execution. Instead, it is designed for periodic analyses (e.g., monthly or quarterly), where latency constraints and query limitations are less critical. Given this characteristic, our current approach remains viable despite the performance limitations of the Wikidata Query Service.

**Issue of Incoming Link.** Wikidata is an entity-centric knowledge graph which means in the editathon efforts, the subject $s$ is always be the subject of interest and the starting point to be edited by contributors. It is very unlikely that the opposite approach is done, that is, an object $(o)$ is given and a pair subject and property $(s, p)$ is to be searched. Not only from the contributors, the platform itself does not support the later view. This explains the phenomenon that we observed in Subsection 4.2 regarding outgoing and incoming link. With existing subject-centric point of view, the number of new outgoing link introduced to the knowledge graph will grow in a much higher rate as opposed to incoming link. As a result, incoming link will be very rare, or even only present in certain entites.

**Weight of Property** Set of properties might be more suitable if the main concern is the presence of properties, instead of the abundance of information it contains. We will take *William Shakespeare* (Q692) in Wikidata as an example. It is reasonable if property like *date of birth* (P569) to be treated using set of properties, but for a well-known playwright and poet, we shall expect the property *notable work* (P800) to incorporate all or most of his well-known works. If only few works registered in $G$ despite he has dozens of works, then we might conclude

the entity is poor. For this case, treating the property using the notion of set is not preferable because it will fail to capture the aforementioned poor condition, while blatantly using bag of properties might skew the wealth amount. Due to this, the notion of (non-)uniqueness can be extended to a weighted form. The weight is given independently for each property and can be defined in such a way that is most appropriate for the nature of the property.

Another phenomena that should also be considered is that an entity might have several occurrences of the same property, but this property might just be 'trivial'. This is similar to a document having a lot of 'the' or 'a' (stopwords). Conversely, an entity might just have a single occurrence of a property, but it is a non-trivial one. Perhaps, the property is a highly relevant one for the entity's class. For example, *time period* (P2348) for *William Shakespeare* (Q692) will be a highly relevant one for prominent poets. However, the property *sibling* (P3373) might not be too relevant for Shakespeare's career. One idea to handle such trivial is to regard those properties using the notion of set of properties. In this way, we care only on its existence rather than its actual count. Another approach that we can consider is to use threshold function to set a tolerance for how much of such trivial we allow.

**Multiclass Entity and Misclassification.** In data classification, entities may belong to multiple classes or be misclassified due to inconsistencies in data sources. For instance, the richest entity in the computer scientist class based on pure literal properties count, *Bruno Darcet* (Q71055086), has a total wealth of 54, which accounts from 1 value in *date of birth* (P569) and 53 values in *Elo rating* (P1087). The same case is also observed in the second richest entity, *Daniel José Queraltó* (Q23906907). From their profiles, we may say these 2 entities are not actually computer scientists, highlighting an occupational misclassification issue. A similar problem occurs with the classification of American researcher, where the wealthiest by pure literal count, *Alexander Julien* (Q61249179), is not a university researcher. In the case of badminton players, *Dirk Stikker* (Q194654), the richest individual in the class based on ID properties count, is more of a politician with badminton affiliations rather than a prominent player. These examples illustrate that an entity can belong to multiple classes, or be entirely misclassified. These classification inconsistencies reveal data quality issues, necessitating careful data querying, cleaning, and validation to ensure accuracy prior to analysis.

## 6. Conclusions

In this study, we introduce a novel framework for analyzing knowledge wealth in knowledge graphs, using Wikidata as a case study. By drawing an analogy between financial wealth and information richness, we develop the formal model of 3 notions of knowledge wealth based on property cardinality, property type, and link direction. Complementing this, we introduce an insight model that includes statistical summaries, Gini coefficients, and Lorenz curves, providing interpretable diagnostics of wealth distribution. We make the Python-based implementation library for both the formal model and the insight model available at https://github.com/nurulputri/paper-knowledge-wealth-framework.

We demonstrate how these formal definitions, when analyzed through the insight model, yield varying inequality levels, as reflected in measures such as the Gini coefficient and Lorenz

curves. Our proposed metric, the relative expectation ratio, offers a powerful and intuitive way to assess representation bias across different entity groups. Unlike raw entity counts or central tendency measures, this metric captures the distributional imbalances of information across quantiles, providing a more nuanced understanding of how knowledge is allocated within Wikidata.

Future work may explore several things in order to improve the knowledge wealth framework. At the moment, our evaluation is limited to Wikidata. However, the framework itself is designed to be general, and our Python library is openly available. It can be extended to other KGs by simply modifying the SPARQL endpoint and adapting the query structure, making it feasible to assess the framework's generalizability and to further explore the overall quality of other KGs. Another promising direction is to explore *property-weighted knowledge wealth*, where not all properties are treated equally. In the current framework, each property contributes uniformly to an entity's wealth, regardless of its importance or informativeness. Incorporating weights based on factors such as semantic significance, frequency of use, or relevance to the class could offer a more nuanced and realistic estimation of an entity's information richness. Last but not least, it is also of our interest to explore the use of machine learning algorithms to classify entities into "rich" and "poor" groups based on their knowledge wealth. This goes beyond simply sorting entities and selecting the top $x\%$ or bottom $y\%$, as different distribution shapes across classes may imply different thresholds or grouping patterns. Such clustering could assist contributors in identifying which segments require additional enrichment efforts, enabling more targeted and efficient improvements to KGs completeness.

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