Automating the Generation of a Functional Semantic Types Ontology with Foundational Models

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Abstract

The rise of data science, the inherent dirtiness of data, and the proliferation of vast data providers have increased the value proposition of Semantic Types. Semantic Types are a way of encoding contextual information onto a data schema that informs the user about the definitional meaning of data, its broader context, and relationships to other types. We increasingly see a world where providing structure to this information, attached directly to data, will enable both people and systems to better understand the content of a dataset and the ability to efficiently automate data tasks such as validation, mapping/joins, and eventually machine learning. While ontological systems exist, they have not had widespread adoption due to challenges in mapping to operational datasets and lack of specificity of entity-types. Additionally, the validation checks associated with data are stored in code bases separate from the datasets that are distributed. In this paper, we address both challenges holistically by proposing a system that efficiently maps and encodes functional meaning on Semantic Types.

1 Introduction

Onboarding datasets at scale is human-intensive because recognizing semantics about how data was generated, its bounds or other idiosyncrasies is critical to how it is processed and eventually used. Normalization requires understanding the form/representation as it is ingested, as well as the target form used by other datasets or people in an organization. Much of the effort involved in semantic understanding can be automated when values are typed with something richer than the basic primitives (e.g. integer, float, or strings types). In fields like finance, medicine, or broadly-spanning AI systems, new data is constantly being added, and automation can defray some of the ingestion cost.

The underlying pain-point in data onboarding stems from humans inconsistently naming tables and columns without knowing who may use them, their assumptions, the amount of specificity, or how they may be joined with datasets from other sources. Therefore, even if a company ingests data from a high-quality source [21], they often invest in pipelines to normalize data to ingest, normalize, and map data to a canonical representation

Furthermore, there are many challenges associated with normalizing columnar tables at scale. In addition to handling null/not-a-number values, inconsistent data formats, or out-of-distribution values, it is critical to understand the units of the values, and this is either implicit (e.g. dollars when giving the price of housing in the US), written in prose (e.g. revenue may be in millions of dollars as noted in the text of a 10k filing), or easily inferred (e.g. a summer temperature of 100 degrees is Fahrenheit and not Kelvin or Celsius). Additionally, to compare, join, or group values from columns in different tables, it may be necessary to recast values (e.g. convert a 12-hour am/pm time value to a 24-hour clock value or a country code to a country name). Identifying these semantics is behind the reliance on humans during onboarding.

We introduce *Functional Semantic Types* (`FST`) to automatically annotate columnar data with Semantic Types and provide a library of functional attributes to normalize, validate, and cast real data values. `FST`s are placed in a synthetic-generated ontology, which directly maps columnar datasets to their hierarchically organized `FST`s. The generation of `FST`s relies upon the usage of Large Language Models (LLMs) to assign and generate a Python class definition that contains semantic details and functional characteristics about the data. By the breadth of their training, LLMs offer a more general solution for entity recognition [6], because they can leverage the distributional properties/real values of data, tabular metadata, and data dictionaries to construct more accurate type annotations. Furthermore, LLMs have shown the ability to generate code, and therefore are capable of transforming semantic context into functional attributes.

Our work takes advantage of the natural hierarchical organization of tabular data. We refer to a collection of tables as a product. The information within a product is assumed to be initially constructed, maintained, and labeled by the same community of interest. As such, columns and tables, as well as context, are correlated. Our system is likely to generate the same `FST` for multiple columns belonging to the tables within a product. The automatic generation of semantic types saves human labor, and even more so when multiple columns are assigned the same type. The system verifies this by merging a subset of values from these columns and checking that they all pass the same validation test.

At the final stage, we identify common `FSTs` across different products. First semantic types with the same name are agglomerated. Then all the uniquely named `FSTs` are turned into a graph by finding semantically similar `FSTs` in representation space and generating *cross-type-cast* functions to transfer data values between `FSTs`. Human verification shows that this first attempt identifies communities of semantically-*identical* entities.

There have been many other efforts to automatically assign semantic types to columnar data, but with some major differences (see Section 2). They assume the existence of an ontology or knowledge graph, they do not generate the functions that define the Semantic Type, and do not build a bespoke ontology that is used for cross-type casting. Hence, the contributions of this work are:

- Automatically generating *Functional Semantic Type* Python class definitions with fields and functional methods that characterize, transform, and validate columnar data values.
- Aggregating commonly named `FSTs` across products, and generating conversion code.
- Demonstrating success in real-world collections of data and evaluating the functionality and correctness of each of these ontologies.
- Showing that generated ontologies have utility in downstream data discovery, joining, validation, and normalization applications.

2 Related Works

The association of columnar tables with entities has been previously treated as a multi-class prediction problem over some user-defined distribution of entity types/properties. Methods such as Sherlock[9], SATO[25], DoDuo[22], and TableGPT[6] use 78 semantic types described by the T2Dv2 Gold Standard[4] which matches properties from the DBpedia ontology with column headers from the WebTables corpus. AutoType[24] made predictions over 112 manually procured types that spanned different industries. However, the types used in these works are often too broad for industry-specific datasets (e.g. in finance, EBITA is a commonplace term, but missing from DBPedia[1] and WordNet[5] knowledge graphs).

We summarize the related works along several dimensions (although TableGPT[6] and Foundational Models[17] cover nearly all of these). *Table Question and Answer:* Table Cell Identification[23], Semantic Parsing[18], TabFact[3]. *Row-to-Row Transformation:* TDE[7]. *Entity Matching Between Rows:* Ditto[13], Deep Entity Matching[16], Auto-EM[27]. *Schema Matching Between Tables:* Valentine[10], SMAT[26]. *Data Imputation:* DataWig[2], Eracer[14], IMP[15], HoloClean[20].

A trend that spans most of these works is the success of LLMs as natural language processing engines for directly operating on real data values. LLMs have also shown success in code generation tasks [12], specifically, for data processing and ingestion coding [8, 11]. Our work builds on these efforts but is unique in that it directly attaches any functional normalization during the entity recognition process (encapsulated in a `FST`), and hierarchically groups `FSTs` to build an ontology that identifies semantically identical entities across products.

3 Problem Formulation

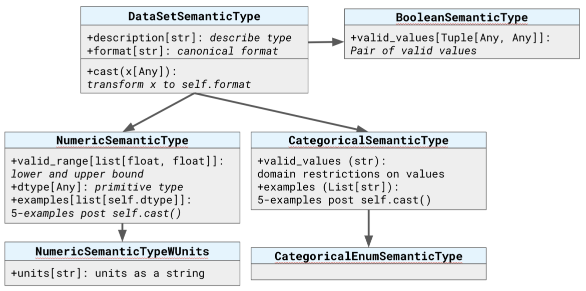
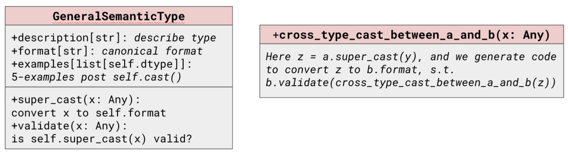

DataSetSemanticType
+description[str]: describe type
+format[str]: canonical format
+cast(x[Any]):
transform x to self.format
BooleanSemanticType
+valid_values[Tuple[Any, Any]]:
Pair of valid values
NumericSemanticType
+valid_range[list[float, float]]:
lower and upper bound
+dtype[Any]: primitive type
+examples[list[self.dtype]]:
5-examples post self.cast()
CategoricalSemanticType
+valid_values (str):
domain restrictions on values
+examples (List[str]):
5-examples post self.cast()
NumericSemanticTypeWUnits
+units[str]: units as a string
CategoricalEnumSemanticType

Figure 1: The subclasses of `DatasetSemanticType` . Each class has specific and inherited instance fields, as well as an implementation of the `cast()`.

Our `FST` system is applied to a *universe* of data, hierarchically composed of *tables* and *products*. A product consists of at least one columnar table. Columns, tables, and products all have labels. The tables within a product are assumed to have some informational similarity. In addition, our set of FSTs can either be a subclass of DatasetSemanticType (Fig. 1), or of GenericSemanticType (Fig. 2). DatasetSemanticType FSTs correspond to the standard types of data: numeric (with/without units), boolean, strings, and categorical. Examining the values in a column, as well as its relation to other columns, is all that is needed to make this type of assignment. In addition to a human-readable name, its definition includes descriptive characteristics about the type's semantics, domain, and example values, as well as a functional transformation from raw data to normalized, types. GenericSemanticTypes collate identically-named ColumnSemanticTypes across products by applying a standardized normalization procedure that undergoes self-validation (see Fig. 2). The FSTs generated at the table and product levels are called T-FSTs and P-FSTs (each a subclass of DatasetSemanticType), while those generated at the universe level are called G-FSTs (subclass of GenericSemanticType).



```
GeneralSemanticType
+description[str]: describe type
+format[str]: canonical format
+examples[list[self.dtype]]:
5-examples post self.cast()
+super_cast(x: Any):
convert x to self.format
+validate(x: Any):
is self.super_cast(x) valid?
```

```
+cross_type_cast_between_a_and_b(x: Any)
Here z = a.super_cast(y), and we generate code
to convert z to b.format, s.t.
b.validate(cross_type_cast_between_a_and_b(z))
```

Figure 2: Class definition of GenericSemanticType and the cross_type_cast() method.

Goal: Given a table, extract the underlying semantic entities (if any) per column and generate a DatasetSemanticType with a descriptive class name, instance fields, and a cast() that transforms a single columnar value to the format dictated by the class. Commonly named FSTs across products are used to generate a subclass of a GenericSemanticType that merges the semantics of all the input DatasetSemanticType definitions, consolidates their transform logic into a single cross_type_cast(), and evaluates the correctness with validate(). Finally, create a synthetic ontology from these GenericSemanticTypes that identifies relations between types which are used to cast values of a source to a destination FST.

4 FSTO-*Gen*

Step 1: table → T-FST - For each table in our universe, an LLM is provided with a serialized format of the table (App. A.1) and identifies the *subset* of columns that correspond to semantic entities. For each identified column, the LLM generates the corresponding T-FST definitions and a mapping from column name to generated subclass. Abstract syntax trees are used to parse the output string and store any class definition and this mapping dictionary. In our experiments, the LLM tends to create identical subclass names (but not always identical fields) for columns in the same product.

Step 2: T-FST → P-FST (product) - There exists many identical T-FSTs within a product, so we agglomerate identically-named ones into a single P-FST (App. A.2). For a given T-FST group, the unique columnar values spanned by the T-FSTs are aggregated and iteratively tested via the cast() to assess the # of values that pass and the # of values that changed. The T-FST that achieves the max criteria was selected as the P-FST for the group.

Step 3: P-FST → G-FST (general) - Across products there exist identically-named, but functionally/semantically different P-FSTs. Therefore, an LLM is necessary to understand the differences in each P-FST and generate a G-FST whose super_cast() handles the output of each P-FST's cast(). By performing two consecutive transformations at the product and general levels, we must also sanity-check the values. The validate() is responsible for performing type, bound, or value-based checks on the output, and is where we witnessed LLMs use external lookups to establish a ground truth.

Step 4: G-FST → G-FST (cross) - There exist many G-FSTs that may represent identical (differently named) or distinct entities, that may be castable. For a given source G-FST, we identify the k-nearest G-FSTs neighbors, by vectorizing each G-FST using an embedding model (App.A.3). An LLM determines the subset of the k neighbors that are convertible and for each, it generates a cross_type_cast() that transforms any output of the source G-FST to a value that would be accepted by the neighbors validate().

5 Experimental Evaluation

We evaluated the P-FSTs, G-FSTs, and cross_type_cast()'s on three data universes, two of which are freely available to the public (as well as all our code and prompts) with results shown here and code definitions in the Appendix.

Universe Curation - Our universes source from

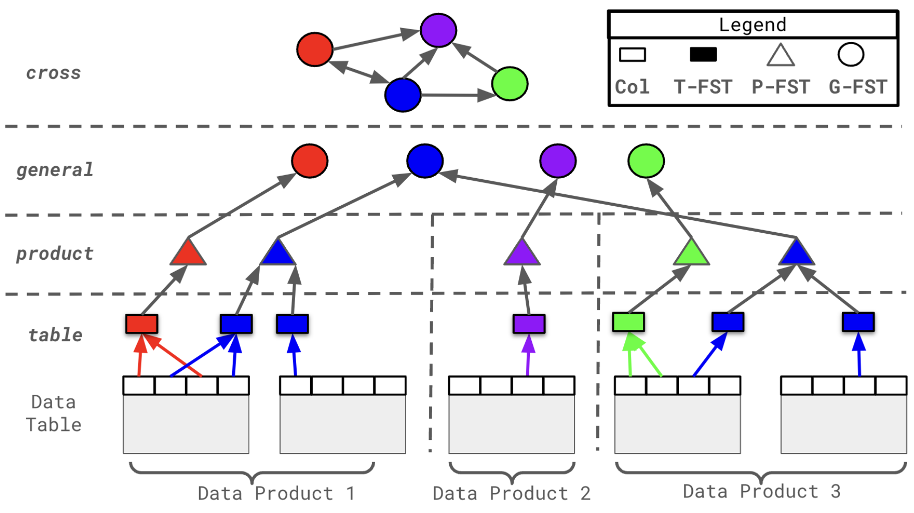


Figure 3: Unshaded rectangles represent columns, shaded rectangles represent `T-FST`s, triangles represent `P-FST`s, and shaded circles represent `G-FST`s. Each color represents a specific semantic entity (i.e. ZipCode, City, State, etc). Circles at the `general` level are the generalization of the `P-FST`s. At the `cross` level is a graph representing the relationship between `G-FST`s.

Data-Verse	Data-Verse Properties			Ontology Properties			
	# Cols.	# Tables	# Data Prod.	# Cols.	# Data Set Types	# Data Prod. Types	# Gen Types
Kaggle	8649	707	237	7051	4730	3196	2043
Harvard	7007	484	12	5898	2998	2325	2057
Factset	3535	428	13	3203	1681	853	664

Table 1: Properties of each universe and their ontologies.

two open-source data providers, Kaggle and Harvard Dataverse, as well as a commercial financial dataset vendor, Factset. For Kaggle, we selected the 707 most commonly used Kaggle-*datasets* and extracted their associated tabular data files (files and datasets are represented as tables and products in our nomenclature). For Harvard, we selected the top 484 most downloaded datasets and organized them similarly to Kaggle, but Harvard required additional preparation due to the large number of fully null columns (App. A.4). Factset consists of 428 tables containing a wide breadth of financial terminology. Table 1 shows the aggregated details of each universe. Notice that Kaggle contains the largest number of tables, products, and columns while Harvard and Factset contain differing levels of product granularity and table widths, which are both factors that affected the performance of the `product` and `general` stages.

LLM Choice - We used OpenAI's `gpt-4-0613` LLM with 8k context for the `table`, `general`, and `cross` stages of `FSTO`-*Gen*.

Evaluation Criteria - To evaluate the functionality of `FSTO`-*Gen*, we considered the throughput performance of each pipeline stage. Our analysis of the functional characteristics of each stage provides intuition about the behavior of each transformation; however, to demonstrate correctness, a human evaluation of the `P-FST`s and `cross_type_cast()`'s was needed to assess the LLM's ability to select subsets of information (relevant columns that refer to semantic entities in `table` or relevant semantically similar general FSTs that are castable), as well generate accurate code.

For each `P-FST`, we iterated over each child `FST`, sampled 1000 values from the columns covered by the `FST`, and aggregated a unique set. For each x in this set, we applied `P-FST`'s `cast()` to x to obtain a value w. For the `G-FST` parent of `P-FST`, we applied `G-FST`'s `super_cast()` to w to obtain a value y, which we validated using `G-FST`'s `validate()`. Then for a neighboring `G-FST`, we applied a `cross_type_cast()` on y to obtain a value z, which we validated in the neighbor's `validate()`. For each cast function (`cast()`, `super_cast()`, `cross_type_cast()`), we record if it passes (indicated by ✓) or errors out (χ). The result of a cast can either be Complex (differs from the original), Identity (identical to the original), or an Exception (erroneous input or cast logic).

5.1 Functional Throughput Results

Column $\rightarrow$ **`P-FST`:** The results are summarized in Table 2. Non-Null values mostly pass through unchanged, i.e. the data is already well-formatted and fits the canonical form of the `P-FST`. Some values change after casting, indicating normalization was necessary. Complex transformations range from rounding floats (App. A.6.1, A.6.2) to mapping

Col Value (x)	Cast Func	Return Val	Universe		
			Kaggle	**Harvard**	**Factset**
Non-Null	✓	Complex	17.14	19.97	15.21
		Identity	68.26	54.25	48.81
	χ	Exception	0.86	1.30	0.71
Null	✓	Complex	12.12	14.72	34.22
	χ	Identity	1.62	9.76	1.05

Table 2: The distribution of `cast()` outcomes for product `FSTs` across all universes. Trends indicate that data is already in the correct form, or it performs a Complex transformation.

country abbreviations to full names with lookup tables (App. A.6.3). A few times, a `RunTimeError` in the `cast()` is thrown.

`P-FST` → `G-FST`: The results are summarized in Table 2. In general, values are left unchanged, indicating that data already achieved normalization in the `P-FST`, which is expected considering that there are many 1-1 correspondences between `P-FSTs` and `G-FSTs` (per Table 1). When the `super_cast()` is a Complex transformation, this indicates that different communities of interest (in this case products) have differing, yet locally standardized ways of representing the same data (App. A.6.4). In some of these cases, the `validate()` fails, indicating insufficient normalization in the `P-FST` or `G-FST`, incorrect `validate()`, or deeper insights are needed into the domain restriction of the `G-FST` (App. A.6.5). However, more frequently, Complex transforms pass `validate()` (App. A.6.6 A.6.7), indicating that LLMs can derive a common standard for a large variety of entity types at scale.

Col Entry	Cast Func	Return Val	Validate Func	Dataset		
				Kaggle	**Harvard**	**Factset**
Non-Null	✓	Complex	Pass	11.59	7.02	9.83
			Fail	2.14	2.08	0.37
		Identity	Pass	79.86	84.96	83.68
			Fail	2.61	4.12	2.59
	χ	Exception	Fail	2.87	1.38	1.29
Null	✓	Complex	Pass	0.04	0.28	2.00
			Fail	0.88	0.15	0.24
		Identity	Pass	0.00	0.00	0.00
			Fail	0.00	0.00	0.00
	χ	Exception	Fail	0.00	0.00	0.00

Table 3: The distribution of outcomes after the application of a `G-FST`'s `super_cast()` and `validate()`. The most common outcome is when Non-Null data undergoes an Identity transformation, the result of which generally passes the `validate()`. When data undergoes a Complex transformation, this indicates that differing product-level normalization was used for the same semantic entity.

`G-FST` → `G-FST`: We found (Table 4) many semantically-*identical* entities that differed only by class name (App: A.6.8). The generation of `T-FSTs` is a generative process with no source of truth, and since LLMs are stochastic, it is likely to name identical semantic entities with slightly differing naming conventions. An artifact of generating ontologies from the bottom-up is that entities at the most general level may be too specific or too broad; however, this is the fundamental purpose of the `cross_type_cast()`. While these `FSTs` differ by name, they shouldn't differ in their semantics (and therefore are close in the vectorized representation space of their corresponding classes). The next most common outcomes were Complex transforms, where we witnessed nontrivial behavior involving lookups, mappings, etc.(App. A.6.9, A.6.10), as well as Identity mappings that failed the neighbor's `validate()` (App. A.6.11). We attribute these cases to hallucinations, whereby the LLM will justify a `cross_type_cast()` with faulty logic.

Col Entry	Cast Func	Return Val	Validate Func	Dataset		
				Kaggle	**Harvard**	**Factset**
Non-Null	✓	Complex	Pass	14.26	18.34	11.10
			Fail	0.95	2.30	0.97
		Identity	Pass	77.30	63.55	78.75
			Fail	7.16	14.69	5.78
	χ	Exception	Fail	0.29	0.45	0.20
Null	✓	Complex	Pass	0.00	0.22	1.52
			Fail	0.00	0.40	1.67
		Identity	Pass	0.00	0.00	0.00
			Fail	0.00	0.05	0.00
	χ	Exception	Fail	0.04	0.00	0.00

Table 4: The distribution of outcomes after the application of `cross_type_cast()` between general `FSTs` and the target's `validate()`. Values tend to undergo Identity transformation, indicating the existence of semantically-duplicative `FSTs`.

5.2 Human Evaluation Results

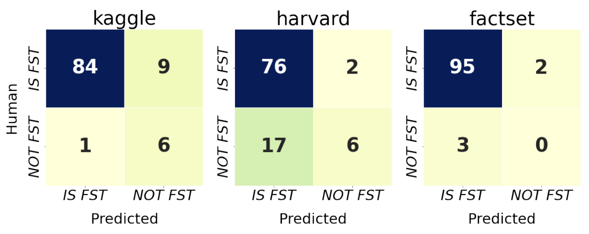


Figure 4: Confusion Matrices of the LLM's ability to recognize and generate `P-FSTs`. We witness high True Positive, low False Positive, and low False Negative rates, indicating both high precision and recall.

As there is no ground truth, we performed a human evaluation to assess *quality* and *correctness*. The *quality* of `P-FSTs` was based on a sample of 50 tables from Kaggle, and 20 tables each from Factset and Harvard for a total of 1̃000 columns. Our results show (Figure 4) that LLMs have high precision and recall in *recognizing semantic entities* and were able to *generate correctly-scoped*, and functionally correct `FSTs`.

We counted when `P-FSTs` were either too broad or too specific (Table 5). For those with correct scope, we labeled cases of when the generated

	Incorrect Scope		Correct Scope		
dataverse	Too Broad	Too Specific	Totally Incorrect	Slightly Wrong	Just Right
kaggle	15.44	1.52	2.78	5.06	75.19
harvard	17.54	0.88	1.32	0.44	79.82
factset	49.07	0	3.27	1.87	45.79

Table 5: Quality Distribution of True Positive, product-level `FSTs`. The LLM generates types that are too broad, or perfect.

class completely differed from the semantics of the entity (Totally Incorrect), contained slightly erroneous fields or functional attributes (Slightly Wrong), or was (Just Right). In Kaggle and Harvard, these types were generally right, while in Factset they were either too broad or perfect. We hypothesize LLMs tend to generalize unfamiliar concepts (e.g. it labeled a finance-specific growth rate with "Growth Rate"), making any cast or validation ineffectual. Finally, even when `P-FSTs` were scoped properly, some contained errors such as mismatches between its name or description or made a false assertion (App. A.6.11).

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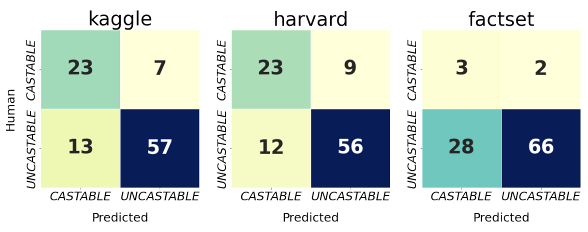

Figure 5: Confusion Matrices of LLM's ability to recognize true, castable relationships between `G-FSTs`. We witness lower levels of recall and precision, due to the LLMs hallucination.

To assess the quality of the `cross_type_cast()`, we sampled 20 `G-FSTs` from each universe, as well as its k=20 neighbors in representation space. For each neighbor, we recorded whether there should exist a `cross_type_cast()` between the source and destination. This served as a ground-truth comparison to the edges present in the generated ontology, with which we classified if the LLM was able to recognize when two `G-FSTs` were truly cross-type-castable. As seen in Fig 5, we witnessed acceptable recall on Kaggle and Harvard, low recall on Factset, and low precision across all universes. The reasons for low recall on Factset are related to the analysis in Table 5: when an LLM can't recognize semantic entities, it's difficult to assess whether a cross-type-cast is allowed. Additionally, because LLMs tend to hallucinate, the false positive rate was large across all universes, especially for Factset, which is an artifact of the generality of the `FSTs`. LLMs found cross-type-casts between types like "Percent" and "Ratio", which might refer to entirely different entities, but when generalized, hallucinations become more likely.

6 Conclusion and Applications

`FSTO`-*Gen* is an LLM-powered framework for automating the generation of `G-FSTs` and their relations from columnar data. Despite inaccuracies sourcing from domain-specific language or hallucination, `FSTO`-*Gen* shows promise in challenging data onboarding tasks: normalization, validation, fusion, and discovery. Normalization and Validation are automatically unlocked in the declaration of `G-FSTs` because columns must undergo two stages of normalization (`cast()`, `super_cast()`) before `G-FST` validation, and this process was shown to reveal invalid values. One such example was the identification of negative values for a `timeduration` type. Fusion is achievable by joining columns within or across `G-FSTs`. For the former case, `FSTO`-*Gen* created a `G-FST` for `temperature` that handled `P-FSTs` that declared temperature in Celsius, Fahrenheit, or even Kelvin. For the latter case, `FSTO`-*Gen* created `super_cast()`'s that converted gender data, from string representations like "Male|Female|Other" to boolean "True=male|False=female" or numeric "0=other|1=male|2=female". Finally, Discovery is achieved by allowing practitioners to semantically search over the informational/functional properties of `FSTs` that would otherwise be challenging with raw data. For example, `FSTO`-*Gen* generated a `FST` for `lifeexpectancy` that included four products, two of which came from the "world happiness" product where a column was named "Tooltip", one from the "US Health report" product, and one from a "Brussels Open Data" product where a column was named "longevity". It is doubtful that someone searching for data related to life expectancy would have known that these products would be related, but automated contextualization with LLMs combined with the hierarchical composition of `FSTO`-*Gen* found these relations. We have begun searching for ways to improve this framework, such as using retrieval-augmented-generation or batched inference to reduce hallucination, but even in its current state, `FSTO`-*Gen* shows promise in reducing the tedious job of data onboarding.

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A Appendix

A.1 Table Serialization in Step 1 of `FSTO`-*Gen* (`table`)

In step 1 of `FSTO`-*Gen*, an LLM is tasked with converting a table into a mapping dictionary which maps some subset of the tables' columns to `FSTs` names and the definition of `FSTs` themselves. The motivation for this scheme sources from the serialization process in Sherlock[9] and DoDuo[22], which showed that semantic type annotation is enhanced when the annotation engine can understand table-level and column-level semantics. In fact, in our experiments, there were many cases where columns were badly named, but table/product names helped the LLM perform inference. The problem with table serialization is fitting it into the context window of the LLM, so given a table as a `pandas` dataframe, we convert it to a string using `serialize()` as defined in Listing 1.

```python
import pandas as pd

def serialize(df: pd.DataFrame, data_dict:
     dict[str, str]) -> str:
    string = ''
    for col in df.columns:
        is_numeric = ... # check if col is
             numeric/categorical
        quartile_1, median, quartile_3 =
             df['col'].quantile([0.25,0.5,0.75])
        if is_numeric:
            string += f"""
            -col: {col}
            *description: {data_dict[col]}
            *mean: {df[col].mean()}
            *std: {df[col].std()}
            *min: {df[col].min()}
            *0.25: {quartile_1}
            *0.5: {median}
            *0.75: {quartile_3}
            *max: {df[col].max()}
            *first_five: {df[col].iloc[:5].values}
            *num_na: {df[col].isna().sum()}
            """
        else:
            string += """
            -col: {col}
            *description: {data_dict[col]}
            *num_na: {len(df[col].unique())}
            *top_5_most_frequent:
                {df[col].value_counts().nlargest(5)}
            *num_na: {df[col].isna().sum()}
            """
    return string
```

Listing 1: `serialize()` function which converts a pandas dataframe table to a string.

A.2 Merging `T-FSTs` into a `P-FST` in Step 2 of `FSTO`-*Gen* (`product`)

After Step 1 of `FSTO`-*Gen*, for each product, there exist many `T-FSTs` with the same name, which tend to also have the same semantics, so we perform an agglomeration of them into a single `P-FST`

```python
import numpy as np

def agglomerate(tfsts: list[DataSetSemanticType],
     unique_set: list[Any]):
    mat = np.zeros((len(tfsts), 2))
    for ix in range(len(tfsts)):
        num_passes = 0
        num_changes = 0
        for x in unique_set:
            try:
                y = tfsts[ix].cast(x)
                num_passes += 1
                num_changes += y != x
            except Exception as e:
                pass
        mat[ix] = [num_passes, num_changes]
    max_ix = mat[mat[:, 0] == mat[:,
         0].max()].argmax()
    return tfsts[max_ix]
```

to reduce the number of LLM calls at the `general` stage. Given a grouping `G` of `T-FSTs`, we ideally would perform an agglomeration similar to the `general` stage, because while the `T-FSTs` have the same name, they may still have different fields or `cross_type_cast()`'s. However, this is computationally expensive across the many groupings in the `product` stage, so instead we pick the most functionally general `T-FST` that performs meaningful normalization on the columnar input. We seek to maximize throughput through the `cast()`, so we pick the `T-FST` that throws the least errors and performs the most Complex transformation on a set of columnar values. To assemble this set, we sample 1000 values from each column associated with a `T-FST` and create a unique set. We show this in the `agglomerate()` which takes in a grouping of `T-FSTs` and a unique set of values, and generates a `P-FST`.

A.3 Finding k `G-FSTs` pairs in Step 4 of `FSTO`-*Gen* (`cross`)

There exist many `G-FSTs` that are semantically similar, or even identical, so to identify joins across products, we generate `cross_type_cast()`'s between similar `G-FSTs`. First, we serialize each `G-FST` into a string by concatenating the class name with its `description` instance field. Then for each string we vectorize the class using an embeddings model (we use the `all-MiniLM-L6-v2` model[19]) to convert the model into a 384-length vector and find the nearest k neighbors using kNN (we use $k = 20$ to reduce the number of tokens in the `cross` LLM prompt). For each `G-FST`, we concatenate the `cross` prompt with the `G-FST` and each of its 20 neighbors to receive a maximum of 20 output `cross_type_cast()`'s.

A.4 Data Curation Details

The Kaggle dataverse was sourced from the top 1000 most downloaded Kaggle Datasets, and we extracted the ".csv" files present into each dataset. Each Kaggle dataset was termed as a product, while the ".csv" files as a table. Across all universes, we selected tables that had at least 80% of columns with at least more than one-null value. From the set of 1000, we selected the top 707. In the end, there were 237 products with an average of 3 tables per product. We performed a similar process for the Harvard dataverse, except we selected the top 500 by filtering on whether the datasets contained ".tab" files (tabular data files) and if they were released publicly. Additionally, Harvard datasets are generally mapped directly to a single tabular file, so to enhance the product stage we categorized datasets by their subject tag, which could be any one of: "agriculturalsciences, businessandmangement, earthandenvironmentalsciences, law, socialsciences, artsandhumanities, chemistry, engineering, mathematicalsciences, astronomyandastrophysics, computerandinformationscience, medicinehealthandlifesciences". With a small number of products, there is less opportunity for aggregation to occur at the `product` stage as columns are less likely to have semantically similar information in wider groupings. This explains the greater decrease in the number of types from `FST`s to `P-FST`s in Kaggle versus Harvard (Table 1). The Factset universe is a commercial, proprietary universe and its details can't be revealed under confidentiality agreements.

A.5 `FST` allowed Imports

To perform data manipulation tasks and lookups, in the declaration of each `FST`, we allowed the following set of imports:

1. `numpy` - to perform array manipulation.
2. `pandas` - to handle na/null values.
3. `datetime` - to perform date string operations.
4. `math` - to perform rounding.
5. `pycountry/countryinfo` - to perform geographic lookups.

A.6 Examples

A.6.1 BodyAcceleration

This `P-FST` (Listing 2) was generated from the "human-activity-recognition-with-smartphones" product from Kaggle. This `FST` represents accelerometer values, and the generated cast() function will float-cast and round the number. However, these values are stored as strings and contain various rounding conventions. The `cast()` standardizes the number of decimal points to 6, and converts all strings to floats. Additionally, using its understanding of accelerometer data, the LLM it assigned a `unit` of "1g" for acceleration. It also used the min/max values from App. A.1 to create bounds. These may not be right, but these are rules enforced by the data and the LLM's knowledge about accelerometer values.

```python
class
    bodyacceleration(NumericSemanticTypeWithUnits):

    def __init__(self, *args, **kwargs):
        self.description = 'The mean body acceleration in a certain direction'
        self.valid_range = [-1.0, 1.0]
        self.dtype = float
        self.format = 'Body acceleration should be a floating point number between -1 and 1'
        self.units = 'The unit of body acceleration is 1g, where g is the acceleration due to gravity'
        self.examples = [-1.0, -0.5, 0.0, 0.5, 1.0]

    def cast(self, val):
        num = float(val)
        if num < -1.0 or num > 1.0:
            raise Exception('Invalid body acceleration')
        return round(num, 6)
```

Listing 2: Body Acceleration `P-FST`

A.6.2 Precipitation

```python
class precipitation(NumericSemanticTypeWithUnits):
    def __init__(self, *args, **kwargs):
        self.description = 'Precipitation levels in inches'
        self.valid_range = [0, float('inf')]
        self.dtype = float
        self.format = 'Precipitation should be a floating point number indicating inches of precipitation.'
    self.units = 'Inches'
        self.examples = [0, 0.254, 0.508, 0.762, 1.016]

    def cast(self, val):
        if val == 'T':
            return 0.0
        return round(float(val), 3)
```

Listing 3: Precipitation `P-FST`

In the construction of a *precipitation* `FST` (Listing 3) in the "weatherww2" product from Kaggle, the product contains weather information during World War 2, and each table contains data relative to specific geographic locations. A column, named "precip.", consists of a mixture of floating-point values and a single letter 'T'. Without context, it could be confusing to any user of the data, or even cause failures in any downstream pipelines that rely upon the column being floating-point. The `table` and `product` stages of FSTO-*Gen* identified a few important features: 1) the table corresponded to U.S. weather conditions 2) "precip." refers to "precipitation" 3) precipitation in the U.S. is measured in inches, so it subclassed a `NumericSemanticTypeWithUnits` and added "inches" as a unit 4) identified the existence of a value 'T', which canonically refers to when *trace* amounts of rain occur and replaced 'T' with 0. Encapsulated in an FST, this type allows any user to understand how it was processed.

A.6.3 NationalityName

```python
class nationalityname(CategoricalEnumSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'Name of a nationality'
        self.valid_values = 'Name should be a
            string and a valid country name'
        self.format = 'Names should be capitalized'
        self.examples = ['United States', 'France',
            'Germany', 'Canada', 'Brazil']

    def cast(self, val):
        country = pycountry.countries.get(name=val)
        if country is None:
            raise Exception('Invalid country name')
        return country.name
```

Listing 4: NationalityName P-FST

Each table in the "fifa-22-complete-player-dataset" product contains information about individual players in the soccer videogame, FIFA 2022. One type that arose in this product was a P-FST (Listing 4) that represents the *nationality* of a soccer player, and the generated `cast()` function checks that the country is valid by using a lookup from the `pycountry` library. It produced an Exception for the value "China PR", which is the name of the soccer team, not a nationality name.

A.6.4 Latitude

These two T-FSTs (Listing 5) were generated in Harvard's "earthandenvironmentalsciences" product, and merged during the `product` stage of FSTO-*Gen*. This example shows how table-level generation can produce a class with the same name, but slightly different semantics. The first class signifies that the *latitude* corresponds to a loss event, while the second class refers to the most general notion of *latitude* and contains a bound check within its `cast()`.

```python
class latitude(NumericSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'Latitude where the loss
            event occurred'
        self.valid_range = [32.548, 41.867]
        self.dtype = float
        self.format = 'Latitude should be a
            floating point number'
        self.examples: list = [39.739, 39.747,
            39.763, 39.78, 39.133]

    def cast(self, val):
        return float(val)

class latitude(NumericSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'Geographical latitude'
        self.valid_range = [-90.0, 90.0]
        self.dtype = float
        self.format = 'Latitude should be a
            floating point number between -90.0
            and 90.0'
        self.examples = [32.516372, 32.478485,
            32.442435, 32.408118, 32.373841]

    def cast(self, val):
        num = float(val)
        if num < -90.0 or num > 90.0:
            raise Exception('Invalid latitude')
        return num
```

Listing 5: Latitude P-FSTs

A.6.5 Duration

```python
class duration(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'Duration in seconds'
        self.format = 'Should be a positive
            floating point number representing
            seconds'
        self.examples = [22.534, 22.745, 22.105,
            23.477, 22.684]

    def super_cast(self, val):
        if isinstance(val, str):
            val = float(val)
        return round(val, 3)

    def validate(self, val):
        casted_val = self.super_cast(val)
        if not isinstance(casted_val, float) or
            casted_val < 0:
            return False
        return True
```

Listing 6: Duration G-FST

The duration G-FST in Listing 6 represents the temporal *duration* between events and correctly throws an error when the value is less than 0, indicating that an event was in the past. Generally, the duration between events is seen as a scalar, regardless of whether the event was passed in or not, so this function failed `validate()` on the column value of "-27.83". Whether or not this is the correct behavior, alerts any user of this G-FST about how negative numbers are being handled and allows them to alter the behavior.

A.6.6 Gender

```python
class gender(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'A gender'
        self.format = 'In lower-case and as a string'
        self.examples = ['male', 'female', 'male', 'female', 'male']

    def super_cast(self, val):
        str_val = str(val).lower()
        if str_val in ['male', 'female', 'm', 'f', '1', '2']:
            if str_val == 'male' or str_val == 'm' or str_val == '1':
                return 'male'
            elif str_val == 'female' or str_val == 'f' or str_val == '2':
                return 'female'
        else:
            return 'other'

    def validate(self, val):
        casted_val = self.super_cast(val)
        if casted_val in ['male', 'female', 'other']:
            return True
        else:
            return False
```

Listing 7: Gender G-FST

A.6.7 Timestamp

The timestamp G-FST in Listing 8 represents a timestamp in a specific format. The P-FSTs that it agglomerates each use a unique format, so as seen in the super_cast(), it performs an exhaustive normalization process of each type to that of self.format.

```python
class timestamp(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'A timestamp'
        self.format = "A string in the format 'YYYY-MM-DD HH:MM:SS'"
        self.examples = ['2020-01-01 00:00:00', '2019-12-31 23:59:59', '2020-02-29 12:34:56', '2019-02-28 01:23:45', '2020-12-31 11:11:11']

    def super_cast(self, val):
        if isinstance(val, int) or isinstance(val, float):
            return datetime.utcfromtimestamp(
                val
            ).strftime('%Y-%m-%d %H:%M:%S')
        elif isinstance(val, str):
            try:
                return datetime.strptime(
                    val, '%Y-%m-%d %H:%M:%S'
                ).strftime('%Y-%m-%d %H:%M:%S')
            except ValueError:
                try:
                    return datetime.strptime(
                        val, '%m/%d/%Y %H:%M:%S'
                    ).strftime('%Y-%m-%d %H:%M:%S')
                except ValueError:
                    try:
                        return datetime.strptime(
                            val, '%d/%m/%Y %H:%M:%S'
                        ).strftime('%Y-%m-%d %H:%M:%S')
                    except ValueError:
                        try:
                            return datetime.strptime(
                                val,
                                '%Y-%m-%d %H:%M:%S%z'
                            ).isoformat()
                        except ValueError:
                            try:
                                return datetime \
                                .strptime(
                                    val,
                                    '%H:%M:%S'
                                ).strftime(
                                '%Y-%m-%d %H:%M:%S'
                                )
                            except ValueError:
                                raise Exception(
                                'Invalid timestamp'
                                )
        else:
            raise Exception('Invalid timestamp')

    def validate(self, val):
        casted_val = self.super_cast(val)
        try:
            datetime.strptime(casted_val, '%Y-%m-%d %H:%M:%S')
            return True
        except ValueError:
            return False
```

Listing 8: Timestamp G-FST

A.6.8 Redundant G-FST Names

In Listing 9, we show the generated G-FSTs related to Covid-19 Case Counts. Each class contains differing levels of granularity in its name, but the descriptions are all relatively similar. In cases like these, the super_cast()'s between any pair is a Identity mapping.

A.6.9 Nontrivial Education super_cast()

In Listing 10, we show a Complex transformation between two G-FSTs, where the source represents education as a set of enum strings, while the latter represent it as numbers. Using the set of unique values in the former and the range bounds in the latter, the LLM generates a cross_type_cast() that works on real-data values. The reasoning string was generated by the LLM to justify its behavior.

A.6.10 Nontrivial Currency super_cast()

In Listing 11, we show a Complex transformation from a United States Dollar G-FST to an Indian Rupee G-FST. While in App. A.5, we stated only a fixed set of libraries could be used – the LLM ignored this rule and used a completely valid currency conversion library, forex_python, to perform conversions using the most up-to-date exchange rate.

A.6.11 Incorrect Weight super_cast()

In Listing 12, we show an incorrect Identity transformation from a crop yield weight G-FST in kg/ha (ha=hectare, a unit of area) to a fish yield

```python
class confirmedcases(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'Number of confirmed
            COVID-19 cases'
        self.format = 'The number should be a
            non-negative integer'

class covidcases(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'COVID-19 Cases'
        self.format = 'COVID-19 cases should be a
            positive integer, representing the
            number of cases'

class casescount(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'Count of COVID-19 cases'
        self.format = 'Count of cases should be an
            integer with no decimal places'

class numcases(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'Number of COVID-19
            cases'
        self.format = 'Number of cases should be a
            positive integer'
```

Listing 9: Covid-19 Case G-FSTs (only the name and its description and format fields are shown for brevity)

```python
class education(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'Level of education'
        self.format = 'In capitalized string form'
        self.examples = ['Secondary / Secondary
            Special', 'Higher Education',
            'Incomplete Higher', 'Lower
            Secondary', 'Academic Degree']

class mothereducation(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = "Education level of the
            student's mother"
        self.format = 'Education level should be an
            integer'
        self.examples = [0, 1, 2, 3, 4]

def cross_type_cast_between_education_\
    and_mothereducation(val):
    reason = 'Both the Education and
        mothereducation classes represent the same
        real-world entity, which is the education
        level. However, they represent this
        information in different formats. The
        education class represents education
        levels as strings, while mothereducation
        represents them as integers. We can map
        the string representation to the integer
        representation by identifying keywords in
        the string that correspond to different
        integer values.'
    mapping = {'no education': 0, 'education level
        1': 1, 'education level 2': 2, 'education
        level 3': 3, 'education level 4': 4,
        'education level 5': 5, 'education level
        6': 6, 'higher education': 7}
    return mapping.get(val.lower(), 0)
```

Listing 10: Conversion Between Two Categorical Enum G-FSTs representing education (only the name and its description and format fields are shown for brevity).

G-FST in (kg). The LLM incorrectly asserts that the two types are castable and hallucinate in its rea-

```python
class currencyvalue(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'A USD currency value'
        self.format = 'Currency Value should be a
            floating point number'
        self.examples = [113524789243.0,
            63497164978.0, 49124317794.0,
            9572240391.0, 1918358283.0]

class currencyinr(GeneralSemanticType):

    def __init__(self, *args, **kwargs):
        self.description = 'Currency value in INR'
        self.format = 'Currency should be
            represented as a floating point number'
        self.examples = [450000, 370000, 158000,
            225000, 130000]

def cross_type_cast_between_currencyvalue_\
    and_currencyinr(val):
    reason = 'Here, the real-world entity is the
        same, i.e., a currency amount. However, it
        is represented in a different unit. We are
        converting from an unspecified currency to
        INR. As a default, I am assuming the
        source currency is USD. If this assumption
        is incorrect, this mapping would not be
        valid and you would need to adjust the
        source currency accordingly.'
    from forex_python.converter import CurrencyRates
    cr = CurrencyRates()
    conversion_rate = cr.get_rate('USD', 'INR')
    return val * conversion_rate
```

Listing 11: Conversion Between USD and Indian Rupee G-FSTs (only the name and its description and format fields are shown for brevity).

```python
class yieldweight(GeneralSemanticType):
    def __init__(self, *args, **kwargs):
        self.description = 'The yield weight in
            kg/ha of an entity'
        self.format = 'Yield weight should be
            formatted as a floating point number
            (in kg/ha units)'

class fishweight(GeneralSemanticType):
    def __init__(self, *args, **kwargs):
        self.description = 'The weight of the fish
            in kg'
        self.format = 'Weight should be a
            non-negative number, representing the
            weight in kg'

def cross_type_cast_between_yieldweight_\
    and_fishweight(val):
    reason = 'Both yieldweight and fishweight
        represent the real-world entity, weight.
        No conversion is required as both are
        represented as float.'
    return val
```

Listing 12: Incorrect Conversion Between yieldweight and fishweight G-FSTs because of differing units (only the name and its description and format fields are shown for brevity).

soning. We hypothesize that batching outputs from the LLM and performing a consensus, or using more examples in the prompt, could help alleviate these issues.