



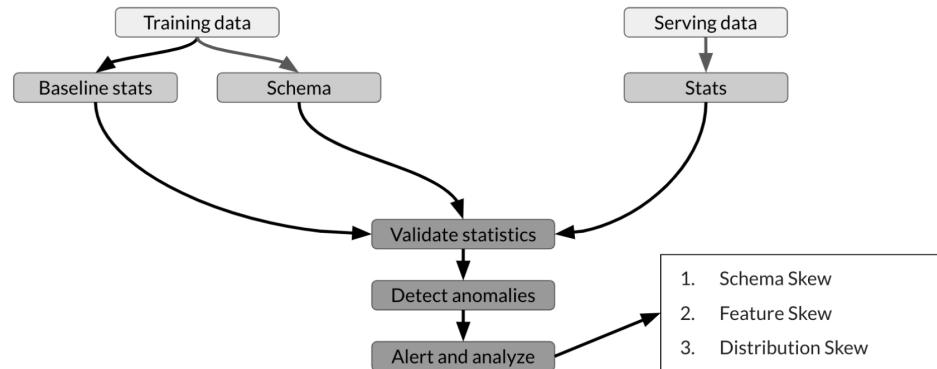
Ungraded Lab: TFDV Exercise

In this notebook, you will get to practice using [TensorFlow Data Validation \(TFDV\)](#), an open-source Python package from the [TensorFlow Extended \(TFX\)](#) ecosystem.

TFDV helps to understand, validate, and monitor production machine learning data at scale. It provides insight into some key questions in the data analysis process such as:

- What are the underlying statistics of my data?
- What does my training dataset look like?
- How does my evaluation and serving datasets compare to the training dataset?
- How can I find and fix data anomalies?

The figure below summarizes the usual TFDV workflow:



As shown, you can use TFDV to compute descriptive statistics of the training data and generate a schema. You can then validate new datasets (e.g. the serving dataset from your customers) against this schema to detect and fix anomalies. This helps prevent the different types of skew. That way, you can be confident that your model is training on or predicting data that is consistent with the expected feature types and distribution.

This ungraded exercise demonstrates useful functions of TFDV at an introductory level as preparation for this week's graded programming exercise. Specifically, you will:

- Generate and visualize statistics from a dataset
- Detect and fix anomalies in an evaluation dataset

Let's begin!

Package Installation and Imports

```
In [1]: import tensorflow as tf
import tensorflow_data_validation as tfdv
import pandas as pd

from sklearn.model_selection import train_test_split
from util import add_extra_rows

from tensorflow_metadata.proto.v0 import schema_pb2

print('TFDV Version: {}'.format(tfdv.__version__))
print('Tensorflow Version: {}'.format(tf.__version__))

TFDV Version: 0.24.1
Tensorflow Version: 2.3.1
```

Download the dataset

You will be working with the [Census Income Dataset](#), a dataset that can be used to predict if an individual earns more than or less than 50k US Dollars annually. The summary of attribute names with descriptions/expected values is shown below and you can read more about it [in this data description file](#).

- **age**: continuous.
- **workclass**: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
- **fnlwgt**: continuous.
- **education**: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
- **education-num**: continuous.
- **marital-status**: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
- **occupation**: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
- **relationship**: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
- **race**: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
- **sex**: Female, Male.
- **capital-gain**: continuous.
- **capital-loss**: continuous.
- **hours-per-week**: continuous.
- **native-country**: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinidad&Tobago, Peru, Hong, Holand-Netherlands.

Let's load the dataset and split it into training and evaluation sets. We will not shuffle them for consistent results in this demo notebook but you should otherwise in real projects.

```
In [2]: # Read in the training and evaluation datasets
df = pd.read_csv('data/adult.data', skipinitialspace=True)
```

```
# Split the dataset. Do not shuffle for this demo notebook.  
train_df, eval_df = train_test_split(df, test_size=0.2, shuffle=False)
```

Let's see the first few columns of the train and eval sets.

```
In [3]: # Preview the train set  
train_df.head()
```

Out[3]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	label
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

```
In [4]: # Preview the eval set  
eval_df.head()
```

Out[4]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	label
26048	30	Private	270886	Some-college	10	Never-married	Other-service	Own-child	White	Female	0	0	40	United-States	<=50K
26049	21	Private	216129	HS-grad	9	Never-married	Other-service	Own-child	White	Male	0	0	35	United-States	<=50K
26050	33	Private	189368	Some-college	10	Married-civ-spouse	Transport-moving	Husband	Black	Male	0	0	40	United-States	>50K
26051	19	?	141418	Some-college	10	Never-married	?	Own-child	White	Male	0	0	15	United-States	<=50K
26052	19	Private	306225	HS-grad	9	Never-married	Handlers-cleaners	Own-child	White	Male	0	0	25	United-States	<=50K

From these few columns, you can get a first impression of the data. You will notice that most are strings and integers. There are also columns that are mostly zeroes. In the next sections, you will see how to use TFDV to aggregate and process this information so you can inspect it more easily.

Adding extra rows

To demonstrate how TFDV can detect anomalies later, you will add a few extra rows to the evaluation dataset. These are either malformed or have values that will trigger certain alarms later in this notebook. The code to add these can be seen in the `add_extra_rows()` function of `util.py` found in your Jupyter workspace. You can look at it later and even modify it after you've completed the entire exercise. For now, let's just execute the function and add the rows that we've defined by default.

```
In [5]: # add extra rows  
eval_df = add_extra_rows(eval_df)  
  
# preview the added rows  
eval_df.tail(4)
```

Out[5]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	label
6513	46	Nan	257473	Bachelors	8	Married-civ-spouse	Plumber	Husband	Other	Male	1000	0	41	Australia	>50K
6514	0	Private	257473	Masters	8	Married-civ-spouse	Adm-clerical	Wife	Asian	Female	0	0	40	Pakistan	>50K
6515	1000	Private	257473	Masters	8	Married-civ-spouse	Prof-specialty	Husband	Black	Male	0	0	20	Cameroon	<=50K
6516	25	?	257473	Masters	8	Married-civ-spouse	gamer	Husband	Asian	Female	0	0	50	Mongolia	<=50K

Generate and visualize training dataset statistics

You can now compute and visualize the statistics of your training dataset. TFDV accepts three input formats: TensorFlow's TFRecord, Pandas Dataframe, and CSV file. In this exercise, you will feed in the Pandas Dataframes you generated from the train-test split.

You can compute your dataset statistics by using the `generate_statistics_from_dataframe()` method. Under the hood, it distributes the analysis via [Apache Beam](#) which allows it to scale over large datasets.

The results returned by this step for numerical and categorical data are summarized in this table:

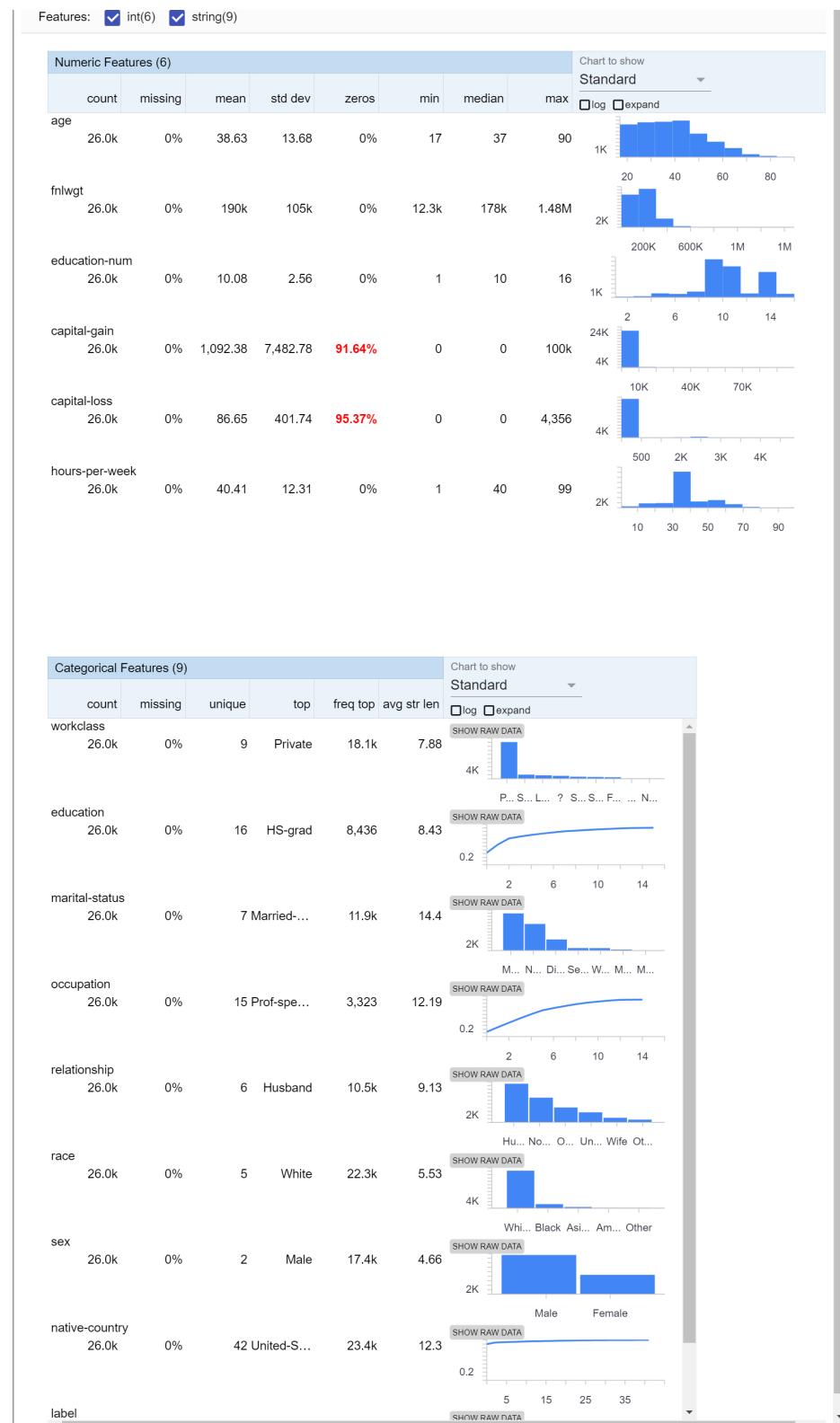
Numerical Data		Categorical Data	
Count of data records		Count of data records	
% of missing data records		% of missing data records	
Mean, std, min, max		unique records	
% of zero values		Avg string length	

```
In [6]: # Generate training dataset statistics  
train_stats = tfdv.generate_statistics_from_dataframe(train_df)
```

Once you've generated the statistics, you can easily visualize your results with the `visualize_statistics()` method. This shows a [Facets interface](#) and is very useful to spot if you have a high amount of missing data or high standard deviation. Run the cell below and explore the different settings in the output interface (e.g. Sort by, Reverse order, Feature search).

```
In [7]: # Visualize training dataset statistics  
tfdv.visualize_statistics(train_stats)
```

Sort by
Feature order ▾ Reverse order Feature search (regex enabled)



Infer data schema

Next step is to create a data schema to describe your train set. Simply put, a schema describes standard characteristics of your data such as column data types and expected data value range. The schema is created on a dataset that you consider as reference, and can be reused to validate other incoming datasets.

With the computed statistics, TFDV allows you to automatically generate an initial version of the schema using the `infer_schema()` method. This returns a Schema `protocol buffer` containing the result. As mentioned in the [TFX paper](#) (Section 3.3), the results of the schema inference can be summarized as follows:

- The expected type of each feature.
- The expected presence of each feature, in terms of a minimum count and fraction of examples that must contain the feature.
- The expected valency of the feature in each example, i.e., minimum and maximum number of values.
- The expected domain of a feature, i.e., the small universe of values for a string feature, or range for an integer feature.

Run the cell below to infer the training dataset schema.

```
In [8]: # Infer schema from the computed statistics.
schema = tfdv.infer_schema(statistics=train_stats)

# Display the inferred schema
```

```
tfdv.display_schema(schema)
```

Feature name	Type	Presence	Valency	Domain
'age'	INT	required	-	-
'workclass'	STRING	required	-	'workclass'
'fnlwgt'	INT	required	-	-
'education'	STRING	required	-	'education'
'education-num'	INT	required	-	-
'marital-status'	STRING	required	-	'marital-status'
'occupation'	STRING	required	-	'occupation'
'relationship'	STRING	required	-	'relationship'
'race'	STRING	required	-	'race'
'sex'	STRING	required	-	'sex'
'capital-gain'	INT	required	-	-
'capital-loss'	INT	required	-	-
'hours-per-week'	INT	required	-	-
'native-country'	STRING	required	-	'native-country'
'label'	STRING	required	-	'label'

Domain	Values
'workclass'	"?", "Federal-gov", "Local-gov", "Never-worked", "Private", "Self-emp-inc", "Self-emp-not-inc", "State-gov", "Without-pay"
'education'	'10th', '11th', '12th', '1st-4th', '5th-6th', '7th-8th', '9th', 'Assoc-acdm', 'Assoc-voc', 'Bachelors', 'Doctorate', 'HS-grad', 'Masters', 'Preschool', 'Prof-school', 'Some-college'
'marital-status'	'Divorced', 'Married-AF-spouse', 'Married-civ-spouse', 'Married-spouse-absent', 'Never-married', 'Separated', 'Widowed'
'occupation'	"?", "Adm-clerical", "Armed-Forces", "Craft-repair", "Exec-managerial", "Farming-fishing", "Handlers-cleaners", "Machine-op-inspc't", "Other-service", "Priv-house-serv", "Prof-specialty", "Protective-serv", "Sales", "Tech-support", "Transport-moving"
'relationship'	'Husband', 'Not-in-family', 'Other-relative', 'Own-child', 'Unmarried', 'Wife'
'race'	'Amer-Indian-Eskimo', 'Asian-Pac-Islander', 'Black', 'Other', 'White'
'sex'	'Female', 'Male'
'native-country'	"?", "Cambodia", "Canada", "China", "Columbia", "Cuba", "Dominican-Republic", "Ecuador", "El-Salvador", "England", "France", "Germany", "Greece", "Guatemala", "Haiti", "Holand-Netherlands", "Honduras", "Hong", "Hungary", "India", "Iran", "Ireland", "Italy", "Jamaica", "Japan", "Laos", "Mexico", "Nicaragua", "Outlying-US(Guam-USVI-etc)", "Peru", "Philippines", "Poland", "Portugal", "Puerto-Rico", "Scotland", "South", "Taiwan", "Thailand", "Trinidad-and-Tobago", "United-States", "Vietnam", "Yugoslavia"
'label'	'<=50K', '>50K'

Generate and visualize evaluation dataset statistics

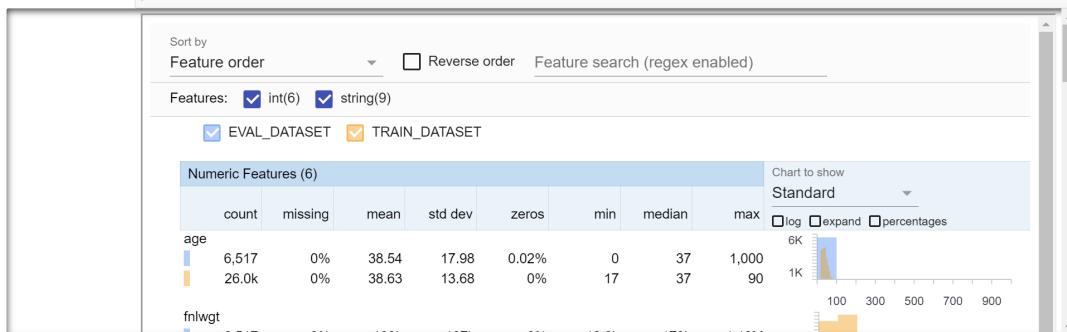
The next step after generating the schema is to now look at the evaluation dataset. You will begin by computing its statistics then compare it with the training statistics. It is important that the numerical and categorical features of the evaluation data belongs roughly to the same range as the training data. Otherwise, you might have distribution skew that will negatively affect the accuracy of your model.

TFDV allows you to generate both the training and evaluation dataset statistics side-by-side. You can use the `visualize_statistics()` function and pass additional parameters to overlay the statistics from both datasets (referenced as left-hand side and right-hand side statistics). Let's see what these parameters are:

- `lhs_statistics`: Required parameter. Expects an instance of `DatasetFeatureStatisticsList`.
- `rhs_statistics`: Expects an instance of `DatasetFeatureStatisticsList` to compare with `lhs_statistics`.
- `lhs_name`: Name of the `lhs_statistics` dataset.
- `rhs_name`: Name of the `rhs_statistics` dataset.

```
In [9]: # Generate evaluation dataset statistics
eval_stats = tfdv.generate_statistics_from_dataframe(eval_df)

# Compare training with evaluation
tfdv.visualize_statistics(
    lhs_statistics=eval_stats,
    rhs_statistics=train_stats,
    lhs_name='EVAL_DATASET',
    rhs_name='TRAIN_DATASET'
)
```



We encourage you to observe the results generated and toggle the menus to practice manipulating the visualization (e.g. sort by missing/zeros). You'll notice that TFDV detects the malformed rows we introduced earlier. First, the `min` and `max` values of the `age` row shows `0` and `1000`, respectively. We know that those values do not make sense if we're talking about working adults. Secondly, the `workclass` row in the Categorical Features says that `0.02%` of the data is missing that particular attribute. Let's drop these rows to make the data more clean.

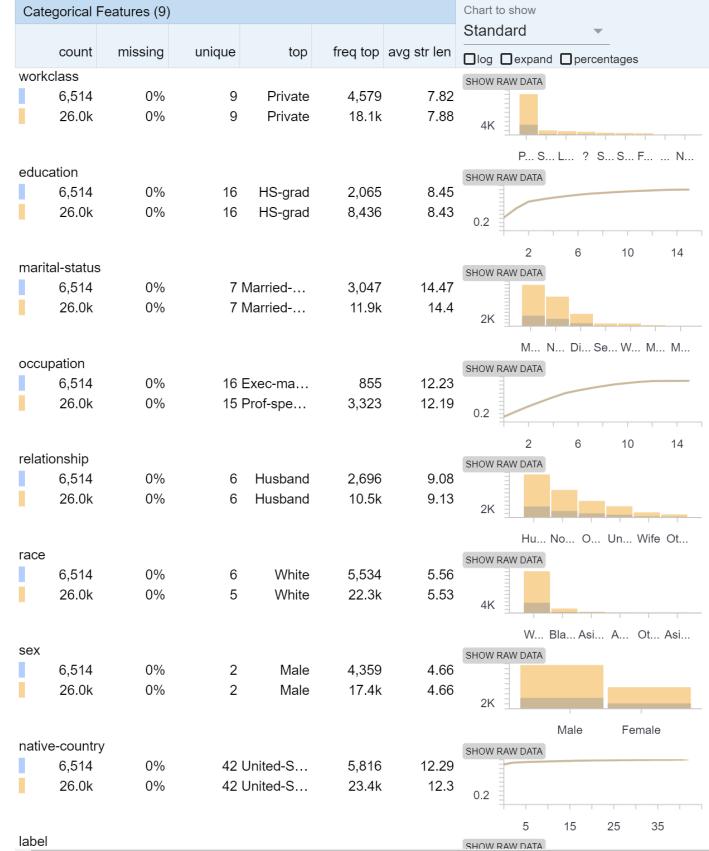
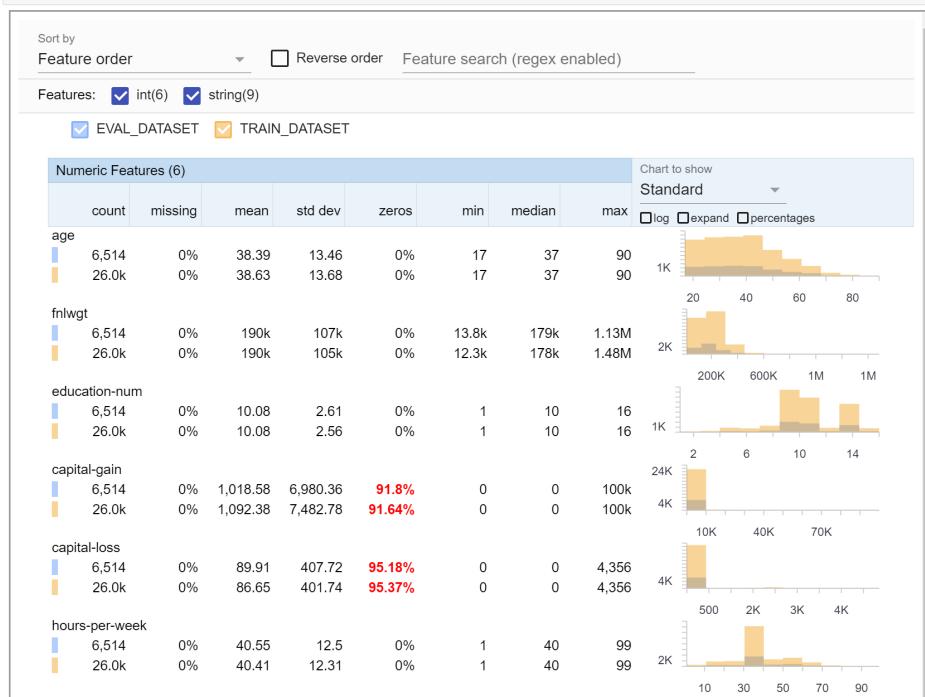
```
In [10]: # filter the age range
eval_df = eval_df[eval_df['age'] > 16]
eval_df = eval_df[eval_df['age'] < 91]

# drop missing values
eval_df.dropna(inplace=True)
```

You can then compute the statistics again and see the difference in the results.

```
In [11]: # Generate evaluation dataset statistics
eval_stats = tfdv.generate_statistics_from_dataframe(eval_df)

# Compare training with evaluation
tfdv.visualize_statistics(
    lhs_statistics=eval_stats,
    rhs_statistics=train_stats,
    lhs_name='EVAL_DATASET',
    rhs_name='TRAIN_DATASET'
)
```



Calculate and display evaluation anomalies

You can use your reference schema to check for anomalies such as new values for a specific feature in the evaluation data. Detected anomalies can either be considered a real error that needs to be cleaned, or depending on your domain knowledge and the specific case, they can be accepted.

Let's detect and display evaluation anomalies and see if there are any problems that need to be addressed.

```
In [12]: # Check evaluation data for errors by validating the evaluation dataset statistics using the reference schema
anomalies = tfdv.validate_statistics(statistics=eval_stats, schema=schema)

# Visualize anomalies
tfdv.display_anomalies(anomalies)
```

Feature name	Anomaly short description	Anomaly long description
'race'	Unexpected string values	Examples contain values missing from the schema: Asian (<1%).
'native-country'	Unexpected string values	Examples contain values missing from the schema: Mongolia (<1%).
'occupation'	Unexpected string values	Examples contain values missing from the schema: gamer (<1%).

Revising the Schema

As shown in the results above, TFDV is able to detect the remaining irregularities we introduced earlier. The short and long descriptions tell us what were detected. As expected, there are string values for `'race'`, `'native-country'` and `'occupation'` that are not found in the domain of the training set schema (you might see a different result if the shuffling of the datasets was applied). What you decide to do about the anomalies depend on your domain knowledge of the data. If an anomaly indicates a data error, then the underlying data should be fixed. Otherwise, you can update the schema to include the values in the evaluation dataset.

TFDV provides a set of utility methods and parameters that you can use for revising the inferred schema. This [reference](#) lists down the type of anomalies and the parameters that you can edit but we'll focus only on a couple here.

- You can relax the minimum fraction of values that must come from the domain of a particular feature (as described by `ENUM_TYPE_UNEXPECTED_STRING_VALUES` in the [reference](#)):
`tfdv.get_feature(schema, 'feature_column_name').distribution_constraints.min_domain_mass = <float: 0.0 to 1.0>`
- You can add a new value to the domain of a particular feature:
`tfdv.get_feature(schema, 'feature_column_name').value.append('string')`

Let's use these in the next section.

Fix anomalies in the schema

Let's say that we want to accept the string anomalies reported as valid. If you want to tolerate a fraction of missing values from the evaluation dataset, you can do it like this:

```
In [13]: # Relax the minimum fraction of values that must come from the domain for the feature 'native-country'
country_feature = tfdv.get_feature(schema, 'native-country')
country_feature.distribution_constraints.min_domain_mass = 0.9

# Relax the minimum fraction of values that must come from the domain for the feature 'occupation'
occupation_feature = tfdv.get_feature(schema, 'occupation')
occupation_feature.distribution_constraints.min_domain_mass = 0.9
```

If you want to be rigid and instead add only valid values to the domain, you can do it like this:

```
In [14]: # Add new value to the domain of the feature 'race'
race_domain = tfdv.get_domain(schema, 'race')
race_domain.value.append('Asian')
```

In addition, you can also restrict the range of a numerical feature. This will let you know of invalid values without having to inspect it visually (e.g. the invalid age values earlier).

```
In [15]: # Restrict the range of the 'age' feature
tfdv.set_domain(schema, 'age', schema_pb2.IntDomain(name='age', min=17, max=90))

# Display the modified schema. Notice the 'Domain' column of 'age'.
tfdv.display_schema(schema)
```

Feature name	Type	Presence	Valency	Domain
'age'	INT	required	-	[17,90]
'workclass'	STRING	required	-	'workclass'
'fnlwgt'	INT	required	-	-
'education'	STRING	required	-	'education'
'education-num'	INT	required	-	-
'marital-status'	STRING	required	-	'marital-status'
'occupation'	STRING	required	-	'occupation'
'relationship'	STRING	required	-	'relationship'
'race'	STRING	required	-	'race'
'sex'	STRING	required	-	'sex'
'capital-gain'	INT	required	-	-
'capital-loss'	INT	required	-	-
'hours-per-week'	INT	required	-	-
'native-country'	STRING	required	-	'native-country'
'label'	STRING	required	-	'label'

Domain	Values
'workclass'	"?", "Federal-gov", "Local-gov", "Never-worked", "Private", "Self-emp-inc", "Self-emp-not-inc", "State-gov", "Without-pay"
'education'	"10th", "11th", "12th", "1st-4th", "5th-8th", "9th", "Assoc-acdm", "Assoc-voc", "Bachelors", "Doctorate", "HS-grad", "Masters", "Preschool", "Prof-school", "Some-college"
'marital-status'	"Divorced", "Married-AF-spouse", "Married-civ-spouse", "Married-spouse-absent", "Never-married", "Separated", "Widowed"
'occupation'	"?", "Adm-clerical", "Armed-Forces", "Craft-repair", "Exec-managerial", "Farming-fishing", "Handlers-cleaners", "Machine-op-inct", "Other-service", "Priv-house-serv", "Prof-specialty", "Protective-serv", "Sales", "Tech-support", "Transport-moving"
'relationship'	"Husband", "Not-in-family", "Other-relative", "Own-child", "Unmarried", "Wife"
'race'	"Amer-Indian-Eskimo", "Asian-Pac-Islander", "Black", "Other", "White", "Asian"
'sex'	"Female", "Male"
'native'	"?", "Cambodia", "Canada", "China", "Columbia", "Cuba", "Dominican-Republic", "Ecuador", "El-Salvador", "England", "France", "Germany", "Greece", "Guatemala", "Haiti", "Ireland", "Italy", "Jamaica", "Mexico", "Nepal", "Peru", "Portugal", "Russia", "Spain", "Sweden", "Thailand", "United-Kingdom", "United States", "USA", "West Bank-Judea", "Yugoslavia", "Zimbabwe"

```
country'    'Holand-Netherlands', 'Honduras', 'Hong', 'Hungary', 'India', 'Iran', 'Ireland', 'Italy', 'Jamaica', 'Japan', 'Laos', 'Mexico', 'Nicaragua', 'Outlying-US(Guam-USVI-etc)',  
          'Peru', 'Philippines', 'Poland', 'Portugal', 'Puerto-Rico', 'Scotland', 'South', 'Taiwan', 'Thailand', 'Trinidad&Tobago', 'United-States', 'Vietnam', 'Yugoslavia'  
'label'          '<=50K', '>50K'
```

With these revisions, running the validation should now show no anomalies.

```
In [16]: # Validate eval stats after updating the schema  
updated_anomalies = tfdv.validate_statistics(eval_stats, schema)  
tfdv.display_anomalies(updated_anomalies)
```

No anomalies found.

Examining dataset slices

TFDV also allows you to analyze specific slices of your dataset. This is particularly useful if you want to inspect if a feature type is well-represented in your dataset. Let's walk through an example where we want to compare the statistics for male and female participants.

First, you will use the `get_feature_value_slicer` method from the `slicing_util` to get the features you want to examine. You can specify that by passing a dictionary to the `features` argument. If you want to get the entire domain of a feature, then you can map the feature name with `None` as shown below. This means that you will get slices for both `Male` and `Female` entries. This returns a function that can be used to extract the said feature slice.

```
In [17]: from tensorflow_data_validation.utils import slicing_util  
  
slice_fn = slicing_util.get_feature_value_slicer(features={'sex': None})
```

With the slice function ready, you can now generate the statistics. You need to tell TFDV that you need statistics for the features you set and you can do that through the `slice_functions` argument of `tfdv.StatsOptions`. Let's prepare that in the cell below. Notice that you also need to pass in the schema.

```
In [18]: # Declare stats options  
slice_stats_options = tfdv.StatsOptions(schema=schema,  
                                         slice_functions=[slice_fn],  
                                         infer_type_from_schema=True)
```

You will then pass these options to the `generate_statistics_from_csv()` method. As of writing, generating sliced statistics only works for CSVs so you will need to convert the Pandas dataframe to a CSV. Passing the `slice_stats_options` to `generate_statistics_from_dataframe()` will not produce the expected results.

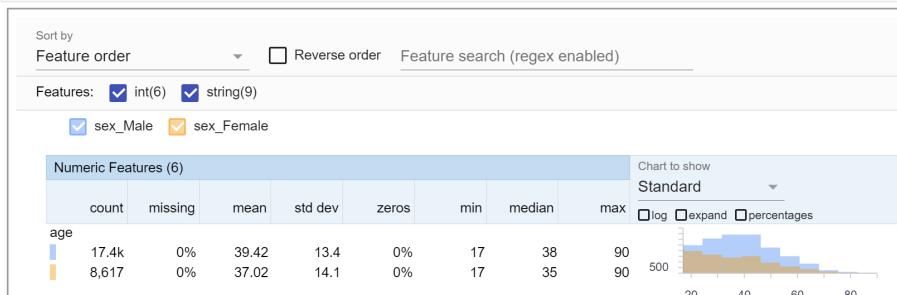
```
In [19]: # Convert dataframe to CSV since 'slice_functions' works only with `tfdv.generate_statistics_from_csv`  
CSV_PATH = 'slice_sample.csv'  
train_df.to_csv(CSV_PATH)  
  
# Calculate statistics for the sliced dataset  
sliced_stats = tfdv.generate_statistics_from_csv(CSV_PATH, stats_options=slice_stats_options)  
  
WARNING:tensorflow:From /opt/conda/lib/python3.8/site-packages/tensorflow_data_validation/utils/stats_util.py:229: tf_record  
_iterator (from tensorflow.python.lib.io.tf_record) is deprecated and will be removed in a future version.  
Instructions for updating:  
Use eager execution and:  
'tf.data.TFRecordDataset(path)'  
  
WARNING:tensorflow:From /opt/conda/lib/python3.8/site-packages/tensorflow_data_validation/utils/stats_util.py:229: tf_record  
_iterator (from tensorflow.python.lib.io.tf_record) is deprecated and will be removed in a future version.  
Instructions for updating:  
Use eager execution and:  
'tf.data.TFRecordDataset(path)'
```

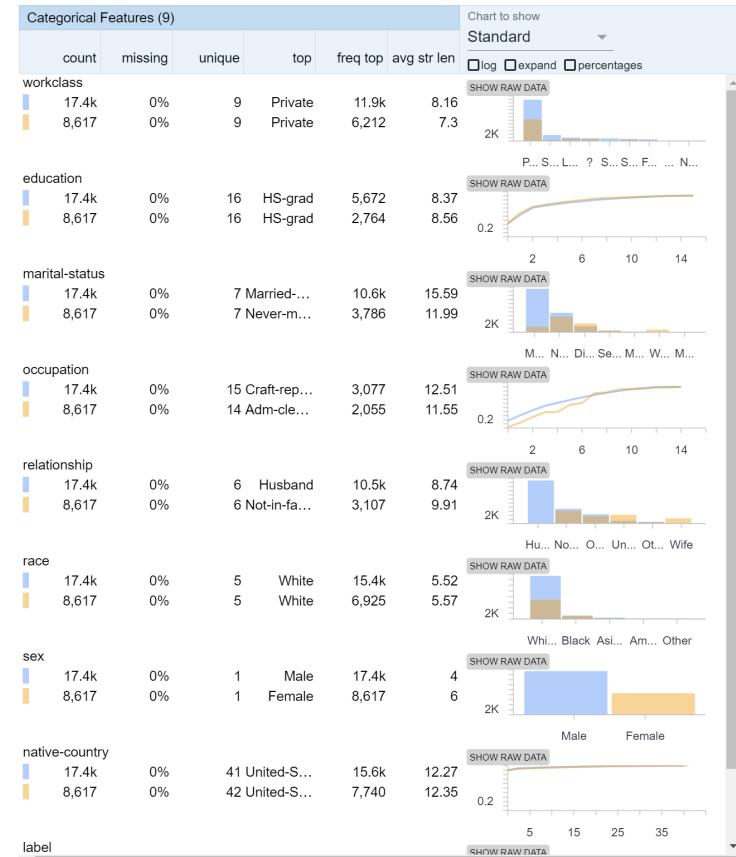
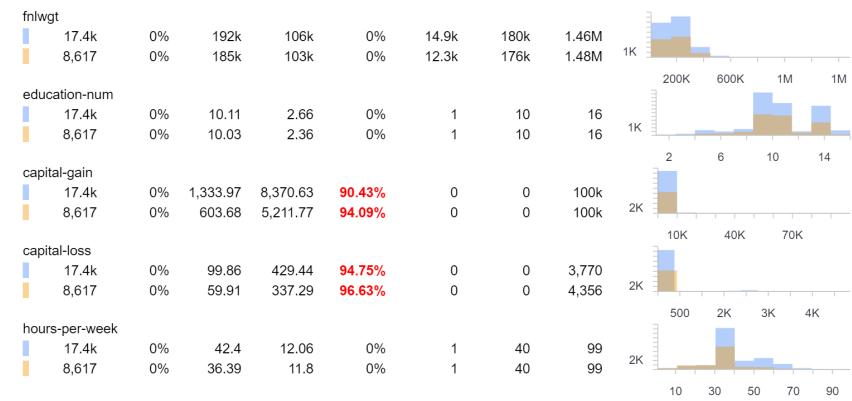
With that, you now have the statistics for the set slice. These are packed into a `DatasetFeatureStatisticsList` protocol buffer. You can see the dataset names below. The first element in the list (i.e. `index=0`) is named `All_Examples` which just contains the statistics for the entire dataset. The next two elements (i.e. named `sex_Male` and `sex_Female`) are the datasets that contain the stats for the slices. It is important to note that these datasets are of the type: `DatasetFeatureStatistics`. You will see why this is important after the cell below.

```
In [20]: print(f'Datasets generated: {[sliced.name for sliced in sliced_stats.datasets]}')  
  
Datasets generated: ['All Examples', 'sex_Male', 'sex_Female']  
Type of sliced_stats elements: <class 'tensorflow_metadata.proto.v0.statistics_pb2.DatasetFeatureStatistics'>
```

You can then visualize the statistics as before to examine the slices. An important caveat is `visualize_statistics()` accepts a `DatasetFeatureStatisticsList` type instead of `DatasetFeatureStatistics`. Thus, at least for this version of TFDV, you will need to convert it to the correct type.

```
In [21]: from tensorflow_metadata.proto.v0.statistics_pb2 import DatasetFeatureStatisticsList  
  
# Convert 'Male' statistics (index=1) to the correct type and get the dataset name  
male_stats_list = DatasetFeatureStatisticsList()  
male_stats_list.datasets.extend([sliced_stats.datasets[1]])  
male_stats_name = sliced_stats.datasets[1].name  
  
# Convert 'Female' statistics (index=2) to the correct type and get the dataset name  
female_stats_list = DatasetFeatureStatisticsList()  
female_stats_list.datasets.extend([sliced_stats.datasets[2]])  
female_stats_name = sliced_stats.datasets[2].name  
  
# Visualize the two slices side by side  
tfdv.visualize_statistics(  
    lhs_statistics=male_stats_list,  
    rhs_statistics=female_stats_list,  
    lhs_name=male_stats_name,  
    rhs_name=female_stats_name  
)
```





You should now see the visualization of the two slices and you can compare how they are represented in the dataset.

We encourage you to go back to the beginning of this section and try different slices. Here are other ways you can explore:

- If you want to be more specific, then you can map the specific value to the feature name. For example, if you want just `Male`, then you can declare it as `features={'sex': [b'Male']}.` Notice that the string literal needs to be passed in as bytes with the `b'` prefix.
- You can also pass in several features if you want. For example, if you want to slice through both the `sex` and `race` features, then you can do `features={'sex': None, 'race': None}.`

You might find it cumbersome or inefficient to redo the whole process for a particular slice. For that, you can make helper functions to streamline the type conversions and you will see one implementation in this week's assignment.

Wrap up

This exercise demonstrated how you would use Tensorflow Data Validation in a machine learning project.

- It allows you to scale the computation of statistics over datasets.
- You can infer the schema of a given dataset and revise it based on your domain knowledge.
- You can inspect discrepancies between the training and evaluation datasets by visualizing the statistics and detecting anomalies.
- You can analyze specific slices of your dataset.

You can consult this notebook in this week's programming assignment as well as these additional resources:

- [TFDV Guide](#)
- [TFDV blog post](#)
- [Tensorflow Official Tutorial](#)
- [API Docs](#)

