

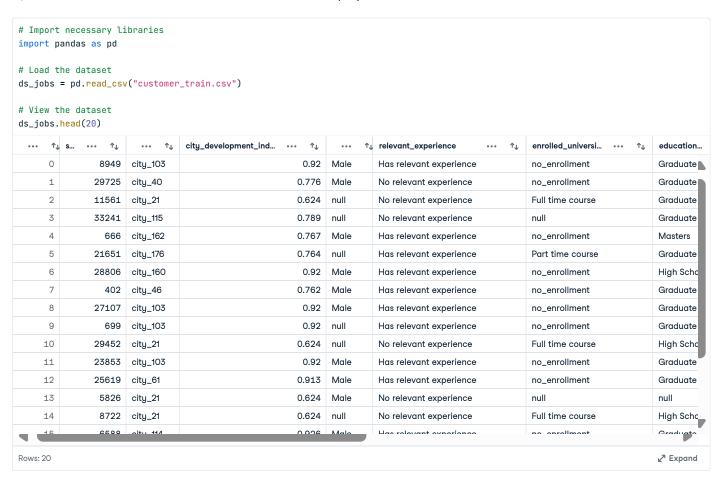


A common problem when creating models to generate business value from data is that the datasets can be so large that it can take days for the model to generate predictions. Ensuring that your dataset is stored as efficiently as possible is crucial for allowing these models to run on a more reasonable timescale without having to reduce the size of the dataset.

You've been hired by a major online data science training provider called *Training Data Ltd.* to clean up one of their largest customer datasets. This dataset will eventually be used to predict whether their students are looking for a new job or not, information that they will then use to direct them to prospective recruiters.

You've been given access to customer_train.csv, which is a subset of their entire customer dataset, so you can create a proof-of-concept of a much more efficient storage solution. The dataset contains anonymized student information, and whether they were looking for a new job or not during training:

Column	Description
student_id	A unique ID for each student.
city	A code for the city the student lives in.
city_development_index	A scaled development index for the city.
gender	The student's gender.
relevant_experience	An indicator of the student's work relevant experience.
enrolled_university	The type of university course enrolled in (if any).
education_level	The student's education level.
major_discipline	The educational discipline of the student.
experience	The student's total work experience (in years).
company_size	The number of employees at the student's current employer.
company_type	The type of company employing the student.
<pre>last_new_job</pre>	The number of years between the student's current and previous jobs.
training_hours	The number of hours of training completed.
job_change	An indicator of whether the student is looking for a new job ($\boxed{1}$) or not ($\boxed{0}$).



```
# Create a copy of ds_jobs for transforming
ds_jobs_transformed = ds_jobs.copy()
# Start coding here. Use as many cells as you like!
# convert columns with in64 -> int32
ds_jobs_transformed["student_id"] = ds_jobs_transformed["student_id"].astype("int32")
ds_jobs_transformed["training_hours"] = ds_jobs_transformed["training_hours"].astype("int32")
# convert columns with float64 -> float16
ds_jobs_transformed = ds_jobs_transformed.astype({
    "city_development_index":"float16",
    "job_change":"float16"
})
# two-factor categories -> bool:
relevent_map = {"Has relevant experience":1,
               "No relevant experience":0}
ds_jobs_transformed["gender"].replace(gender_map, inplace = True)
ds_jobs_transformed["relevant_experience"].replace(relevent_map, inplace = True)
ds_jobs_transformed = ds_jobs_transformed.astype({
    "relevant_experience":"bool",
    "job_change":"bool",
})
# convert nominal columns(doesn't have natural order eg: orange,blue,... or it's not comparable) -> category
ds_jobs_transformed = ds_jobs_transformed.astype({
    "city":"category",
   "gender":"category",
   # "relevant_experience":"category", 2 factor category -> bool
   "major_discipline":"category",
    "company_type":"category"
})
# convert ordinal columns -> ordered categories.
enrolled_university_order = ["no_enrollment", "Part time course", "Full time course"]
education_level_order = ["High School", "Graduate", "Masters"]
experience_order = ["<1"] + [str(i) for i in range(1,21)] + [">20"]
company_size_order = ["<10","10-49", "50-99", "100-499","500-999","1000-4999","5000-999","10000+"]
last_new_job_order = ["never","1","2","3","4",">4"]
ds_jobs_transformed["enrolled_university"] = pd.Categorical(ds_jobs_transformed["enrolled_university"],
                                                           categories = enrolled_university_order,
                                                           ordered = True)
ds_jobs_transformed["education_level"] = pd.Categorical(ds_jobs_transformed["education_level"],
                                                       categories = education_level_order,
                                                       ordered = True)
ds_jobs_transformed["experience"] = pd.Categorical(ds_jobs_transformed["experience"],
                                                  categories = experience_order,
                                                  ordered= True)
ds_jobs_transformed["company_size"] = pd.Categorical(ds_jobs_transformed["company_size"],
                                                    categories = company_size_order,
                                                    ordered= True)
ds_jobs_transformed["last_new_job"] = pd.Categorical(ds_jobs_transformed["last_new_job"],
                                                    categories= last_new_job_order,
                                                    ordered=True)
```

```
# filtring the dataframe: (only contain students with 10 or more years of experience at companies with at least 1000 employees, as
their recruiter base is suited to more experienced professionals at enterprise companies.)
is_experience_sup_than10 = ds_jobs_transformed["experience"] >= "10"
is\_comp\_size\_1000 = ds\_jobs\_transformed["company\_size"] >= "1000-4999"
{\tt ds\_jobs\_transformed} = {\tt ds\_jobs\_transformed[is\_experience\_sup\_than10~\&~is\_comp\_size\_1000]}
# View the dtypes
print(ds_jobs_transformed.dtypes)
print("!-----!")
# memory usage check:
print("Our initial data:")
print(ds_jobs.info())
print("-----")
print("After processing the data:")
print(ds_jobs_transformed.info())
student_id
                          int32
city
                       category
city_development_index float16
gender
                     category
relevant_experience
                       bool
enrolled_university category
education_level category
major_discipline category
experience
                     category
                    category
company_size
company_type
                     category
last_new_job
                     category
training_hours
                       int32
job_change
                          bool
dtype: object
Our initial data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19158 entries, 0 to 19157
Data columns (total 14 columns):
# Column
                         Non-Null Count Dtype
0 student_id 19158 non-null int64
1 city 19158 non-null object
                         19158 non-null object
1
   citv
2
   city_development_index 19158 non-null float64
                        14650 non-null object
3
    gender
 4
    relevant_experience 19158 non-null object
5
    enrolled_university 18772 non-null object
    education_level 18698 non-null object
```