Understanding Python’s pandas source code

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<https://github.com/pandas-dev/pandas>

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# Preliminaries and third-party packages

## Preliminaries

The reader is assumed to have working knowledge of python v3 and C++ v14.

## Google Flatbuffers

<https://google.github.io/flatbuffers/>

<https://github.com/google/flatbuffers>

From Flatbuffers Programmers Guide <https://google.github.io/flatbuffers/usergroup0.html>

Flatbuffers is efficient serialization library supporting various languages.

Benefits of using Flatbuffers:

* Access to serialized data without parsing/unpacking – what sets Flatbuffers apart is that it represents hierarchical data in a flat binary buffer in such way that it still can be accessed without parsing / unpacking while also still supporting data structure evolution (forward/backward compatibility)
* Memory efficiency and speed- the only memory needed to access your data. It requires 0 additional allocations in C++. Flatbuffers is also very suitable for use of mmap (or streaming) requiring only a part of the buffer to be in memory. Access is close to the speed of raw struct access with only one extra indirection (a kind of vtable) to allow for format evolution and optional fields. It is aimed at projects where spending time and space (many memory allocations) to be able to access or construct serialized data is undesirable such as in games or any other performance sensitive applications
* Flexible – Optional fields means not only do you get forwards and backwards compatibility (do not have to update all data with each new version). It also means you have a lot of choice in what data you write and what data you don’t and how you design data structures.
* Tiny code footprint – small amounts of generated code and just a single small header as the minimum dependency which is very easy to integrate.
* Strongly typed – Errors happen at compile time rather than manually having to write repetitive and error prone run-time checks. Useful code can be generated for you.
* Convenient to use – generated C++ code allows for terse access and construction code.
* Cross platform code with no dependencies

How to use Flatbuffers:

* Write a schema file that allows you to define the data structures you may want to serialize. Fields can have scalar types (int / floats of all sizes) or they can be : string, array of any type; reference to yet another object; or a set of possible objects (unions). Fields are optional and have defaults so they do not need to be present for every object instance.
* Use flatc (the FlatBuffer compiler) to generate C++ header (or Java/Kotlin/C#/Go/Python classes) with helper classes to access and construct the serialized data. This header (say mydata\_generated.h) only depends on flatbuffers.h which defines the core functionality.
* User the FlatBufferBuilder class to construct a flat binary buffer. The generated functions allow you to add objects to this buffer recursively often as simply as making a single function call.
* Store or send the buffer somewhere
* When reading it back you can obtain a pointer to the root object from the binary buffer and from there traverse it conveniently in place with object->field().

Small example:

Writing the Monster’s FlatBuffer Schema

To start working with FlatBuffers you first need to create a schema file which defines the format of each schema file you wish to serialize. Here is the schema that defines the template for our monsters:

// Example IDL file for our monster’s schema

namespace MyGame.Sample;

enum Color:byte { Red = 0, Green, Blue = 2}

union Equipment { Weapon } // optionally add more tables

struct Vec3 {

x:float;

y:float;

z:float;

}

table Monster {

pos:Vec3; // Struct

mana:short = 150;

hp:short = 100;

name:string;

friendly:bool = false (deprecated);

inventory:[ubyte]; // Vector of scalars

color:Color = Blue; // Enum

weapons:[Weapon]; // Vector of tables

equipped:Equipment; // Union

path:[Vec3]; // Vector of structs

}

table Weapon {

name:string;

damage:short;

}

root\_type Monster;

The schema starts with a namespace declaration. This determines the corresponding package/namespace for the generated code. In our example we have Sample namespace inside the MyGame namespace. Next we have an enum definition. In this example, we have enum of type byte, named Color. We have three values in this enum: Red , Green and Blue. We specify Red = 0 and Blue = 2, but we do not specify an explicit value for Green. Since the behavior of an enum is to increment if unspecified Green will receive the implicit value of 1. Following the enum is a union. The union in this example is not very useful as it only contains the one table (named Weapon). If we had created multiple tables that we would want the union to be able to reference we could add more elements to the union Equipment. After the union comes a struct Vec3, which represents a floating point vector with *3* dimensions. We use struct here instead of table as structs are ideal for modeling data structures which will not change since they use less memory and have faster lookup. The Monster table is the main object in our FlatBuffer. This will be used as a template to store our orc monster. We specify some default values for fields such as mana:short = 150. If unspecified, scalar fields like int, uint or float will be given a default of 0 while strings and tables will be given a default of null. Another thing to note is the line friendly: bool = false (deprecated); . Since you cannot delete fields from a table (to support backwards compatibility), you can set fields as deprecated, which will prevent the generation of accessors for this field in the generated code. The keyword deprecated can break legacy code that used that accessor. The Weapon table is a sub-table used within our FlatBuffer. It is used twice: once within the Monster table and once within the Equipment union. For our Monster it is used to populate a vector of tables via the weapons field within our Monster.

It is also the only table referenced by the Equipment union. The last part of the schema is the root\_type. The root type declares what will be the root table for the serialized data. In our case the root type is our Monster table. The scalar types can also use alias type names such as int16 instead of short and float32 instead of float. Thus we could also write the Weapon table as:

table Weapon {

name:string;

damage:int16;

}

More information about Flatbuffers Schema

Let us look into another example of Flatbuffers schema:

// example IDL file

namespace MyGame;

attribute “priority”;

enum Color : byte { Red = 1; Green; Blue }

## Apache Arrow

<https://github.com/apache/arrow>

<https://arrow.apache.org/docs/format/Columnar.html>

From <https://arrow.apache.org/overview/> :

Apache Arrow defines language-independent columnar memory format for flat and hierarchical data, organized for efficientanalytic operations on modern hardware like CPUs and GPUs. The Arrow memory format supports zero copy reads for fast data access without serialization overhead.

Apache Arrow is software development platform for building high-performance applications that process and transport large data sets. It is designed to both improve the performance of analytical algorithms and the efficiency of moving data from one system or one programming language to another. The defining component of Arrow is its in-memory columnar format which is a standardized, language-agnostic specification for representing structured, table-like datasets in memory. This format has rich data type system including nested and user-defined data types designed to support the needs for analytic database systems, data frame libraries, etc.

The Apache Arrow format allows computational routines and execution engines to maximize their efficiency when scanning and iterating large chunks of data. In particular, the contiguous columnar layout enables vectorization using the latest SIMD operations included in modern processors.

Assuming standard format for the data speeds up execution

Without standard format there are potentially a lot of conversion and transforming of data which is lots of unnecessary operations. Moving data from one system to another involves costly serialization and deserialization. In addition, common algorithms must be transformed / rewritten for each data format.

Arrow’s in-memory columnar format provides a solution to these kinds of problems allowing data transfers between between disparate systems to be achieved with very low cost. Additionally, the standardized format allows for reuse of libraries and algorithms.

The Arrow Columnar Format

The Arrow Columnar Format includes a language-agnostic in-memory data structure specification, metadata serialization, and a protocol for serialization and generic data transport. The new columnar format is created without the aid of existing implementation. For the implementation of the columnar format [Flatbuffers](https://github.com/google/flatbuffers) is used for metadata serialization purposes.

## Numpy

<https://github.com/numpy/numpy>

<https://numpy.org/doc/stable/user/>